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Abstract

Drawing upon a cross-country panel data for developing countries, the present study sheds new empirical light on dynamic and long-term linkages among growth, inequality and poverty. First, agricultural sector growth is found to be consistently the most important factor in reducing inequality and poverty not only through its direct effects but also through its indirect effects. Second, there is a significant and negative association between inequality and GDP per capita, with macro institutional quality as one of the important factors in determining the inequality-growth relationship. Third, policies designed to prevent conflicts and mitigate their disruptive effects and violence, stabilise commodity prices, and enhance institutional quality would help eliminate worst forms of deprivation. Our analysis points to a drastic shift away from rural- urban migration and urbanisation as main drivers of growth and elimination of extreme poverty, and towards revival of agriculture in the post-2015 policy discourse. Indeed, the case for urbanisation rests on not just shaky empirical foundations but could mislead policy makers and donors.

Keywords: Inequality, Poverty, Growth, Agriculture, Non-agriculture, MDG

JEL Codes: C20, I15, I39, O13

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I. Introduction

MDG 1A[1] of halving extreme poverty by 2015, it is claimed by Brookings (2011) and the World Bank (2013a), was achieved in 2010-5 years ahead of the deadline. Yet 970 million will remain poor in 2015, with 84 per cent concentrated in South Asia and Sub-Saharan Africa. The latter is also the only region that will not achieve MDG 1A by 2015.

Global poverty remains a *rural* problem with more than three-fourths of the extremely poor located in rural areas. However, as global poverty fell, so did the gap between rural-urban poverty. It reduced by half in East Asia and the Pacific by 2008, while in Sub-Saharan Africa, Latin America and the Caribbean, and South Asia, there was less progress.

The Global Monitoring Report 2013 (hereafter GMR 2013/World Bank, 2013) makes an important contribution to the discourse on MDGs by disaggregating progress into rural and urban. In doing so, it offers striking examples of the continuing rural-urban disparities in several MDGs. It does not, however, disaggregate the 970 million that are expected to remain in extreme poverty in 2015 into those who will be in rural and urban areas. This is crucial for designing appropriate policy interventions for rural and urban areas.

The GMR 2013 makes a powerful case for rapid and efficient urbanisation as key to overall poverty reduction. It rests on better utilisation of agglomeration economies and efficient rural-urban migration. Indeed, it is argued that these could also result in speedier rural poverty reduction. An important link in the chain is small cities (somewhat controversially referred to as

[1] MDG1A refers to "Millennium Development Goal, Target 1.A", "Halve, between 1990 and 2015, the proportion of people whose income is less than $1.25 a day" (http://www.un.org/millenniumgoals/poverty.shtml).

“the missing middle”). Their weak infrastructure, and poor hygiene and sanitation are likely to turn them into slums with growing rural-urban migration. So the refrain is that investment must be directed to such cities to better exploit their growth potential.

Curiously, rural-urban migration contributing 40 per cent of the increase in urban population over the period 2010-2030 has two sides to it. One is the poverty reduction through the growth of small cities and rapid urbanisation. The premise is that more rural-urban migration will have a substantial payoff in terms of higher wages in rural areas and greater diversification of rural economies. If this is turned on its head, it could be argued that more efficient land, labour and credit markets and better infrastructure in rural areas would not only help raise agricultural productivity but also enable diversification of rural economies. In particular, the dynamic between farm and non-farm activities has assumed greater significance with the diversification of the former (Thapa and Gaiha, 2014). Non-farm activities are not just remunerative but also help stabilise rural incomes. Consequently, the rapid pace of rural-urban migration - highest in Latin America and the Caribbean and lowest in South Asia and Sub-Saharan Africa - will slowdown. Better and more diversified livelihood opportunities in rural areas cannot be discarded as the inferior option relative to the more rapid and efficient urbanisation thesis with considerable risks of uncontrollable growth of slums with pervasive multiple deprivations (malnutrition and infectious diseases). In any case, available evidence is not robust enough to clinch the argument developed by the World Bank and other researchers[2].

Much of sustained reduction in poverty hinges on how growth and inequality interact - a subject that has gained prominence in a context of rising inequality in a large part of the developing world in the last two decades. As argued in a recent UN report (2013), addressing

[2] For a detailed critique, see Gaiha (2014).

inequality is not just a moral imperative but also a necessity for sustainable development[3]. Evidence points to the powerful and corrosive effects of inequality on poverty reduction, social cohesion and stability. A major part of the solution may lie in fostering inclusive and sustainable rural transformation through a comprehensive approach to food security and nutrition, addressing the linkages between agriculture, health, education, water, energy, gender equality and poverty.

The purpose of this study is to analyse the dynamic linkages between economic growth - disaggregated into agricultural growth and non-agricultural growth - and inequality or poverty using a cross-country panel data for developing countries. In analysing these relationships, due attention is given to conflict intensity, and institutional quality, such as political stability or vulnerability at macro level. Both poverty headcount ratios and poverty gaps will be used as measures of poverty.

The present study departs from the extant literature in the following three ways. First, drawing upon Christiaensen et al. (2011), it will estimate dynamic linkages between agricultural growth and non-agricultural growth, using a dynamic panel model applied to cross-county panel data (Blundell and Bond, 1998)[4]. Following Christiaensen et al. (2011), we apply this model separately for non-agricultural sector growth and agricultural sector growth in which both lagged agricultural growth and lagged non-agricultural growth are used as explanatory variables in each model after taking account of the endogeneity of the past growth. This will enable us to estimate effects from the non-agricultural sector to the agricultural sector, and *vice versa*. For instance, the improvement in productivity in the agricultural sector (e.g. through the shift from basic staple

[3] As noted by Doyle and Stiglitz (2014), "There are ….substantial links between violence and "horizontal inequalities" that combine economic stratification with race, ethnicity, religion or region. When the poor are from one race, ethnicity, religion or region, and the rich are from another, a lethal destabilizing dynamic often emerges" (p.4).

[4] It is referred to as system generalized method of moments (SGMM) estimator which enables us to explicitly model the dynamics of agricultural growth and non-agricultural growth over time.

food production to high yield varieties or non-staple food production) is likely to have positive effects on non-agricultural growth, while the non-agricultural sector growth may impact the agricultural sector through the change in demand patterns for primary goods.[5] In the first stage, we will estimate these dynamic relationships between agricultural and non-agricultural sectors. In the second stage, we will estimate how agricultural sector growth and non-agricultural sector growth affect the change in income inequality using the cross-county panel data.[6] This is important as the (overall) economic growth mainly originating from the agricultural sector may have a different impact on poverty as well as inequality from that of the non-agricultural sector. For instance, growth in the agricultural sector, which tends to be more labour- intensive than non-agricultural sector, can employ more poor people in developing countries. Also, most agricultural activities take place in rural areas where a majority of the poor reside and thus agricultural growth is likely to have a greater poverty-reducing effect, at least in the short-run (Christiaensen et al., 2011). If poverty reducing potentials are different for agricultural and non-agricultural sectors, their impact on income inequality is likely to be different too. As the data for sectoral growth are limited in terms of the coverage of countries, the analysis will be applied to the unbalanced panel for 41 countries in the period 1970-2010.

Second, given that the first set of analyses cover only a subset of developing countries[7], we will take a different approach based on a larger panel for 119 developing countries to explore the long-term relationship between overall economic growth and income inequality, with a focus on not only the overall relationship between them, but also at the individual country level as well as

[5] See Christiaensen et al. (2011) or de Janvry and Sadoulet (2010) for more detailed discussions on the linkages between these sectors.

[6] Pesaran's (2006) common correlated effects mean group (CCEMG) estimator will also be applied to take account of the cross-country dependence of error terms. Another advantage of this model is to derive the (time-series) regression results for each country with the shocks common to countries modelled. See Appendix 1 for details.

[7] See Appendix 2 for the list of countries.

the underlying determinants of the inequality-growth relationships. This analysis draws upon Pesaran's (2006) innovative and influential estimator[8]. Drawing upon a recent seminal paper by Herzer and Vollmer (2012), we estimate the long-term effect of inequality on income growth (that is, estimate the GDP per capita by inequality) after taking account of the country-level heterogeneity as well as cross-sectional correlations of unobservable factors which change over time. The estimation is based on an unbalanced panel data - reflecting the nature of inequality data - for 119 countries from 1970 to 2008. The results are disaggregated before and after 2000 to check whether the inequality-growth relation changed over time.

The third distinguishing feature is investigation of the dynamic relationship among poverty gap (or poverty headcount), income inequality, and income growth, based on the larger panel dataset covering 118 developing countries. We will extend the system equation approach (or 3 Stage Least Squares or 3SLS) used by Imai et al. (2010). In this model, using the unbalanced panel data, the feedback effect, that is, the effect from growth on inequality as well as that from inequality to growth is considered by a simple model of 3SLS applied to the panel data. Recently, the World Bank has been hard-selling a "shared prosperity index": the per capita income growth of the bottom 40 percent (Narayan et al. 2013), reflecting a dominant concern about the poor not being able to share the fruits of growing affluence. Narayan et al. (2013) emphasise that shared prosperity is strongly correlated with overall prosperity and that the former is conditional on equality of opportunities, such as human capital development of children. However, "the shared prosperity index" is essentially a relative index insensitive to the income distribution of the extreme poor. The shift of policy emphasis from absolute measures (e.g. poverty headcount or poverty gap) to relative measures, such as shared prosperity index,

[8] This is referred to as system generalized method of moments (SGMM) estimator which enables us to explicitly model the dynamics of agricultural growth and non-agricultural growth over time.

may obscure the importance of absolute poverty in many low income countries, in particular, in Sub- Saharan Africa (SSA) where poverty headcount ratios are still very high[9]. We argue that the poverty gap should be used as a policy goal and, in the second part of this analysis, we will examine the determinants of reducing poverty gaps after taking account of the dynamic relationship between inequality and economic growth. The effect of (instrumented) poverty gap on inequality (as well as that of inequality on poverty gap) is also estimated by 3SLS.

The rest of the paper is structured in three sections corresponding to the above three distinct research contributions. Section II will first elaborate the model and describe the data to capture the dynamics of agricultural growth and non-agricultural growth over time as well as the relationships between (predicted) agricultural and non-agricultural growth and inequality (or poverty) change. Regression results will be summarised in the latter half of Section II. In Section III, we will give a brief exposition of the econometric model to address the long-term relationship between economic growth and inequality for a larger set of countries, followed by the econometric results. Section IV will discuss the model of the dynamic relationship among poverty gap (or poverty headcount), income inequality, and income growth as well as the regression results. The final section offers concluding remarks with policy implications.

II. The dynamic relationship between agricultural growth and non-agricultural growth and effects on inequality and poverty

Despite the large body of literature demonstrating the role of agricultural growth in overall economic growth and poverty,[10] rigorous empirical analyses of the role of growth in *both*

[9] As argued in Gaiha (2014), whether this index can be justified on the Rawlsian maximin principle is far from convincing as there are several countries that have headcount ratios well below 40 %. Besides, the 40 % cut-off is arbitrary while the poverty gap measure is defined by a universal poverty cut-off point.

[10] See Imai et al. (2010), de Janvry and Sadoulet (2010) or Chistiaensen et al. (2011) for a review of the literature.

agricultural and non-agricultural sectors and their interactions are still few and far between with a few exceptions such as Haggblade and Hazell (1989), Haggblade et al. (2007), de Janvry and Sadoulet (2010) and Christiaensen et al. (2011). Haggblade and Hazell (1989) used cross-country data (43 countries) and illustrated the close interaction between these sectors, based on statistical comparisons of agricultural income and non-farm sector employment share. Haggblade et al. (2007) reported large multiplier or indirect effect from agricultural sector to non-agricultural sector.[11] de Janvry and Sadoulet (2010) reviewed several empirical studies, including their own on China and Vietnam, that confirm substantial sectoral linkages and their poverty reduction potential. They used time-series estimations (based on VAR model) for China in 1980-2001 and showed that non-agricultural growth has a substantial indirect effect on agricultural growth (Figure 4, p.8 of de Janvry and Sadoulet).[12] Using the Vietnam Living Standard Survey (VLSS) Panel on Vietnam in the 1990s, they also showed that agricultural households with more market access experienced the faster pace of poverty reduction than subsistence- oriented households (Table 3, p.16). Chistiaensen et al. (2011) is the first rigorous work to estimate the dynamic linkages between agricultural growth and non-agricultural growth as well as those between these sectoral growth components and poverty, drawing upon a cross-country panel dataset. They applied a dynamic panel model (SGMM) to take into account the dynamic realisation of agricultural growth (or non-agricultural growth) by having lagged dependent variables, while considering the dynamic effect of non-agricultural growth (or agricultural growth) on the agricultural growth (or non-agricultural growth) over time. Their estimation strategy is based on Arellano and Bover (1995) and Blundell and Bond (1998) with the finite sample correction of

[11] Haggblade et al. (2007) give evidence on multiplier effects of agricultural sector using an input-output model for developing countries.
[12] That China in this period is an exceptional case is not sufficiently emphasised in de Janvry and Sadoulet (2010).

the two-step standard errors proposed by Windmeijer (2005). The present analysis also uses the Blundell and Bond (1998) estimator with the correction of Windmeijer (2005).

More specifically, our model consists of two stages where in the first stage agricultural (or non-agricultural) growth is estimated by non-agricultural (or agricultural) growth and in the second inequality (or poverty) is estimated by (predicted) values of agricultural and non-agricultural growth.

Data Sources

The data for the first set of analyses of the effects of agricultural and non-agricultural growth on inequality or poverty in Section II are mainly based on *World Development Indicators (WDI)* 2011, 2012 and 2013 (e.g. World Bank, 2013b). The data on education and a few other variables are based on Barro and Lee (2010). To construct the proxy for institutional qualities, we have used the World Bank's World Governance Indicators (http://info.worldbank.org/governance/wgi/index.asp).

Following Herzer and Vollmer's (2012) work which estimated the relationship between economic growth and inequality, we have used the inequality data based on the EHII data - combining the UNIDO and the Deininger and Squire datasets - taken from the University of Texas Inequality Project (http://utip.gov.utexas.edu/data.html)- and 46 countries have been selected to avoid the problem of missing observations given that they apply the panel co-integration method. The EHII data is based on Theil's T statistic[13] measured across sectors within each country where the classifications of sectors are standardized based on UNIDO's Industrial Statistics and Eurostat to facilitate international comparisons. While we use the EHII

[13] Theil's T statistic is a measure of inequality under the Generalised Entropy measures and is defined as $\sum_{i=1}^{n} p_i ln \frac{p_i}{q_i}$ where n is the number of the groups in the country, p_i is the income share of the population in the i^{th} group, and q_i is the population share of the i[th] group. For an exposition of different inequality measures and their (relative) merits, see Sen (1997).

data on inequality, it will not be sufficient to use the data for only 18 developing countries, as in Herzer and Vollmer (2012) for the purpose of deriving any useful policy implications for developing countries. Apart from policy considerations, it may not be appropriate either - as a serious empirical work to test economic theories - to pool both developed and developing countries overlooking the structural difference between developed and developing economies. We have thus constructed an unbalanced panel data for inequality based on the EHII data covering a larger number of countries (86 countries) for the longer period (1970-2008). As an extension we have further expanded the EHII data on inequality by extending them with the World Bank data on inequality (the Gini Index[14]) on the PovcalNet, by estimating the EHII data inequality by the World Bank data using Ordinary Least Squares and replacing the missing observations by the predicted values. With this method, we have managed to cover 119 countries, which cover all the 41 countries in the first set of analyses. While the data quality and comparability are not ideal, this method has the advantage of covering more countries (about six times more developing countries than in Herzer and Vollmer (2012).

These data will be supplemented by data from other sources in the second and the third sets of our analyses (to be discussed in detail in Sections III and IV). They include a physical isolation index (McArthur and Sachs, 2002) and conflict data obtained from CSCW and Uppsala Conflict Data Program (UCDP) at the Department of Peace and Conflict Research, Uppsala University (available at http://www.pcr.uu.se/research/UCDP/). The latter covers armed conflicts, both internal and external, in the period 1946 to the present. We have also used the data on price uncertainty of 46 export commodities downloaded from WITS (World Integrated Trade Solution—an interface that provides UNCOMTRADE data) for all available countries, from the

[14]The Theil index is unavailable in the PovcalNet.

period 1960 - 2006. GARCH (1, 1) method has been applied to capture the uncertainty of export commodities.[15]

1st Stage: Estimation of Non- agricultural Growth and agricultural growth

Given the persistence of non-agricultural income growth (defined as the first difference in value added in the industrial and service sectors), the dynamic panel data model is specified as follows.

$$\Delta Y^{NA}{}_{it} = \sum_{j=1}^{P} \alpha_j \, \Delta Y^{NA}{}_{it-j} + \sum_{j=1}^{Q} \gamma_j \Delta Y^{A}{}_{it-j} + \boldsymbol{X}_{it} \cdot \beta_1 + \boldsymbol{Z}_{it} \cdot \beta_2 + \eta_i + \varepsilon_{it} \qquad (1)$$

where *i* and *t* denote country and time (either 3- year averages, that is, from 1969-72, 73-75,…, 2008-2010, or years, 1969, …, 2010[16]), $\Delta Y^{NA}{}_{it}$ is the first difference in log of growth in non-agricultural value added per capita, and $\Delta Y^{NA}{}_{it-j}$ is its j^{-th} lag. $\Delta Y^{A}{}_{it}$ is the first difference in log of growth in agricultural value added per capita, which is modelled as an endogenous variable. $\boldsymbol{X}_{it}$ is a vector of explanatory variables (exogenous variables, such as precipitation) and $\boldsymbol{Z}_{it}$is a vector of endogenous variables. $\boldsymbol{Z}_{it}$ includes the Share of Mining Sector Income in GDP (second lagged), the first difference in investment[17], and log of schooling years (first lag). While we will see the effects of predicted agricultural and non-agricultural growth on inequality in the second stage, we will insert the (endogenous) inequality in one of the specifications to see whether inequality has any impact on non-agricultural growth. In one specification, we have interacted $\Delta Y^{A}{}_{it}$with the Sub-Saharan African dummy (SSA) to see if the effect of agricultural growth on non-agricultural growth is different in SSA and elsewhere following Christiaensen et al. (2011). η_i is the country specific unobservable effect (e.g. social and cultural factors) and ε_{it} is an error term, independent, and identically distributed (or *i.i.d.*).

15 Estimation results of GARCH (1, 1) will be furnished on request.

16 Christiaensen et al. (2011) used a three-year average panel, but we have used both three -year panel and annual panel to see if the results change. The latter captures the effects realised in the shorter run.

17 Here investment is based on the data of physical capital formation in WDI 2013 (in log) on the assumption that the physical capital formation is mainly related to non-agricultural sector investment. Estimates of investment specific to non-agricultural sector are unavailable and thus omitted in Christiaensen et al. (2011). We have tried the cases with and without investment.

As an alternative to the standard first differencing approach[18] [19], we can use the lagged differences of all explanatory variables as instruments for the level equation and combine the difference equation (1) and the level equation (that is, the equation where $\Delta Y^{NA}{}_{it}$ is replaced by $Y^{NA}{}_{it}$ in equation (1)) in a system whereby the panel estimators use instrument variables based on previous realisations of the explanatory variables as the internal instruments, using the Blundell-Bond (1998) system GMM estimator based on additional moment conditions. Such a system gives consistent results under the assumptions that there is no second order serial correlation and the instruments are uncorrelated with the error terms. The Blundell-Bond System GMM (SGMM) estimator is used in the present study. This estimator is useful to address the problem of endogenous regressors, $\boldsymbol{Z}_{it}$ (e.g. lagged agricultural growth in equation (1)). In the system of equations, endogenous variables can be treated similarly to lagged dependent variables. The second lagged levels of endogenous variables could be specified as instruments for the difference equation. The first lagged differences of those variables could also be used as instruments for the level equation in the system.

In a similar way, agricultural growth is estimated by replacing $\Delta Y^{NA}{}_{it}$ with $\Delta Y^{A}{}_{it}$ in equation (1). We have dropped log of investment from $\boldsymbol{Z}_{it}$.[20] We have also included precipitation.[21]

[18] Two issues have to be resolved in estimating the dynamic panel model. One is endogeneity of the regressors and the second is the correlation between$(\Delta Y_{it-1} - \Delta Y_{it-2})$ and$(\varepsilon_{it-}\varepsilon_{it-1})$ (e.g. see Baltagi, 2005, Chapter 8). Assuming that ε_{it} is not serially correlated and that the regressors in $\boldsymbol{X}_{it}$ are weakly exogenous, the generalized method-of-moments (GMM) first difference estimator (e.g. Arellano and Bond, 1991) can be used.

[19] We have presented Arellano-Bond test for zero autocorrelation in first-differenced errors and Sargan test of overidentifying restrictions for each table. In most cases, the results of the former show the first-order correlations of the first differenced errors which justifies including the one-period lagged dependent variable. Reflecting the fact that $\boldsymbol{Z}_{it}$, endogenous variables - which are instrumented by their own lags - tend to be persistent over time and thus Sargan test rejects the null hypothesis that overidentifying restrictions are valid in some cases and the results in these cases should be interpreted with caution. Using different specifications (e.g. including external instruments, treating $\boldsymbol{Z}_{it}$ as exogenous) does not overcome this difficulty.

[20] Comprehensive data on agricultural investment comparable across different countries are not available. The share of agricultural land and the number of tractors - which are admittedly inappropriate proxies for agricultural investment - are available from *WDI 2013* and the use of these data will not significantly change the final results. Because they are not appropriate as a proxy for agricultural investment, we show the results without using it.

$$\Delta Y^{A}{}_{it} = \sum_{j=1}^{P} \alpha_j \, \Delta Y^{A}{}_{it-j} + \sum_{j=1}^{Q} \gamma_j \Delta Y^{NA}{}_{it-j} + \boldsymbol{X}_{it} \cdot \beta_1 + \boldsymbol{Z}_{it} \cdot \beta_2 + \eta_i + \varepsilon_{it} \tag{2}$$

Tables 1 and 2 report the estimation results of equations (1) and (2) for both three-year average panel (the upper panel of each table) and for annual panel (the lower panel) and for three cases - the case with a full sample as well as their subsets, such as middle income countries and low income countries. For each case, two sets of results are shown. The first case is the parsimonious case only with the first difference of log of non-agricultural (or agricultural) value added per capita (the first lag), the log of agricultural (or non-agricultural) value added per capita and the share of mining industry (the second lag)[22]. Additional explanatory variables, such as log of schooling years or log of investment, are added in the second case.

Table 1: Effect of Agricultural Growth on Non-Agricultural Growth Dynamic Panel Regressions (Blundell and Bond (1998) SGMM): Dependant Variable: D.Log Non Agricultural Value Added per capita

Panel A: Based on 3- Year Average Panel Data

VARIABLES	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
	Full Sample		Middle Income Countries		Low Income Countries	
D.Log Non Agricultural Value Added per capita (-1)	**0.261*** **	**0.309*** **	**0.223** **	**0.211** **	**0.502*** **	**0.504*** **
	(0.0988)	**(0.0535)**	**(0.105)**	**(0.102)**	**(0.129)**	**(0.129)**
D.Log Agricultural Value Added per capita [Endogenous]	**0.224*** **	**0.143* **	0.122	**0.171** **	0.0702	0.088
	(0.0865)	**(0.0761)**	(0.0761)	**(0.0840)**	(0.141)	(0.153)
The Share of Mining Sector Income in GDP (-2) [Endogenous]	0.000488	0.000773	-0.00398	-0.00254	0.000118	-0.00172
	(0.00781)	(0.00586)	(0.00926)	(0.00738)	(0.00593)	(0.00542)
D.Log Investment [Endogenous]	-	**0.214*** **	-	-	-	-
	-	**(0.0310)**	-	-	-	-
Log Schooling Years (-1) [Endogenous]	-	**0.0205* **	-	-	-	-
	-	**(0.0117)**	-	-	-	-
Log Inequality [Endogenous]	-	**0.00186* **	-	-	-	-
	-	**(0.000971)**	-	-	-	-
D.Log Agricultural Value Added per capita * SSA Dummy [Endogenous]	-	-	-	-0.0719	-	0.0201
	-	-	-	(0.121)	-	(0.146)
Constant	0.0443	-0.0686	0.0455	0.0436	0.0540	0.0534
	(0.0128)	(0.0484)	(0.0155)	(0.0150)	(0.0194)	(0.0194)
Observations	532	400	414	414	113	113
Number of Countries	59	50	44	44	14	14
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)						
Prob > z						

[21] The case with precipitation is shown only for low income countries because it yielded insignificant or counter-intuitive results in other cases (Case 6B and Case 12B in Table 2).
[22] Inclusion of mining share follows Christiaensen et al. (2011).

Order 1	0.0030***	0.0032***	0.0098***	0.0094***	0.1308	0.1266
2	0.1916	0.2548	0.1894	0.1853	0.2813	0.2379
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)						
	Chi2(316)	Chi2(399)	Chi2(307)	Chi2(366)	Chi2(133)	Chi2(143)
	375.66	414.60	392.864	457.17	170.30	183.08
Prob > chi2	0.00118**	0.2848	0.0007***	0.0008***	0.0161**	0.0133**

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Panel A of Table 1 (based on three-year average panel) shows that the growth in agricultural sector has a statistically significant effect on non-agricultural growth, based on the full sample (regardless of the specification, that is, in Cases 1 and 2) and in Case 4 (for only middle income countries with other explanatory variables). It is not significant for low income countries. This is consistent with the observation that, as the country grows and shifts from the low income category and the middle income category, the nature of agriculture typically changes from subsistence-oriented farming to more commercialised and market farming and has a closer linkage with non-agricultural sector. The elasticity of non-agricultural growth rate with respect to agricultural growth rate ranges from 0.14 to 0.22, that is, a 10% increase in *the growth rate* in agricultural value added per capita (e.g. from 10% growth to 11% growth) tends to be associated with 1.4% to 2.2% increase in *the growth rate* of non-agricultural value added per capita (e.g. from 10% growth to 10.1% to 10.2% growth). This is in contrast with Christiaensen et al. (2011) who showed that there is no effect from agricultural growth to non-agricultural growth. The reason for difference is not clear, but this may be because we have used a more recent sample comprising a different set of countries.

As in Christiaensen et al. (2011), there is a strong persistent effect in non-agriculture and that mining sector does not affect non-agricultural growth. In Case 2 in Panel A, investment growth, schooling years, and inequality (which are treated as endogenous, and instrumented by their own lags) are found to be positive and significant. Positive effects of physical and human capital are consistent with the empirical growth literature. In Case 2, we observe positive effects of (endogenous) inequality on growth. Why inequality (in level) leads to higher non-agricultural growth is not clear and needs further investigation,[23] but for simplicity we will use Case 1 to examine the linkages between agricultural and non-agricultural growth and inequality change in Table 3.

In Panel B of Table 1 based on the annual panel, agricultural growth is significantly associated with non-agricultural growth in all the cases (regardless of whether the country is classified into middle income countries or low income countries) with elasticity ranging from 0.10 to 0.16. The lagged dependent variable is statistically significant only in Cases 11 and 12 (low income countries). Inequality is not associated with non-agricultural growth in the short run. We have tried the interaction of the SSA dummy variable and agricultural growth as in Christiaensen et al. (2011), but it is statistically insignificant as in their paper.

Table 1: Effect of Agricultural Growth on Non-Agricultural Growth Dynamic Panel Regressions (cont.)

Panel B: Based on Annual Panel Data

VARIABLES	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
	Full Sample		Middle Income Countries		Low Income Countries	
D.Log Non Agricultural Value Added per capita (-1)	0.157	0.0107	0.126	0.125	**0.533*** **	**0.545*** **
	(0.0980)	(0.0837)	(0.101)	(0.1000)	**(0.0503)**	**(0.0501)**
D.Log Agricultural Value Added per capita	**0.111*** **	**0.0947***	**0.107*** **	**0.0937*** **	**0.160*** **	**0.139*** **
	(0.0317)	**(0.0524)**	**(0.0315)**	**(0.0345)**	**(0.0273)**	**(0.0275)**
The Share of Mining Sector Income out of GDP (-2)	-0.00081	-2.48E-05	-0.00169	-0.00142	0.00132	0.00108
	(0.00165)	(0.00163)	(0.00194)	(0.00176)	(0.00105)	(0.000902)
D.Log Investment	-	**0.111*** **	-	-	-	-
	-	**(0.0191)**	-	-	-	-
Log Schooling Years (-1)	-	0.0107	-	-	-	-
	-	(0.00707)	-	-	-	-
Log Inequality	-	0.00188	-	-	-	-
	-	(0.00123)	-	-	-	-
D.Log Agricultural Value Added per capita * SSA Dummy	-	-	-	0.0758	-	0.0552
	-	-	-	(0.0618)	-	(0.0605)
Constant	0.0164	-0.0801	0.0162	0.0160	0.0110	0.0108

[23] A possible reason is that a higher (initial) inequality in a poor country might enable wealthier people to invest in high-return and high-risk activities and increase the overall efficiency of the non-farm sector. If the country's wealth is more equally distributed with a majority under the poverty line, such efficient investment may not be easy.

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
	(0.00362)	(0.0614)	(0.00380)	(0.00378)	(0.00531)	(0.00519)
Observations	1,667	1,024	1,289	1,289	366	366
Number of Countries	59	49	44	44	14	14
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)						
Prob > z						
Order 1	0.0005***	0.0424**	0.0012***	0.0012***	0.0164**	0.0159**
2	0.0369**	0.3913	0.1298	0.128	0.1587	0.1517
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)						
	Chi2(1701)	Chi2(1017)	Chi2(1344)	Chi2(1344)	Chi2(470)	Chi2(505)
	1932.03	1434.88	1519.64	1537.38	505.63	532.66
Prob > chi2	0.0001***	0.00***	0.0006***	0.0006***	0.1239	0.1905

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Contrary to Christiaensen et al. (2011) who found that there is no effect from non-agricultural sector to agricultural sector, Table 2 reports positive and significant coefficient estimates of lagged growth in non-agricultural value added in the regression whereby agricultural growth is estimated by using the three-years average panel (Case 1: full sample and Case 3: middle income countries). However, it is negative and significant in Cases 6A and 6B for low income countries. Lagged dependent variable is positive (with significant estimates observed only for low income countries). Mining share is negative for middle income countries and positive and significant for low income countries (in Cases 6A and 6B). Whether the sign reversal manifests mining displacing agriculture in some countries or whether the former helps the latter through positive externalities (e.g. better roads, power supply) needs further investigation. Human capital enhances agricultural growth. Inequality is not associated with agricultural growth dynamically. Precipitation enhances agricultural growth in low income countries.[24]

Table 2: Effect of Non-Agricultural Growth on Agricultural Growth: Dynamic Panel Regressions (Blundell and Bond (1998) SGMM)
Dependant Variable: D.Log Agricultural Value Added per capita
Panel A: Based on 3- Year Average Panel Data

VARIABLES	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6A	Case 6B
	Full Sample		Middle Income Countries		Low Income Countries		

[24] As an extension we have tried the cases with the demographic structure (proxied by population share below 15years and that above 65years) for both agricultural and non-agricultural regressions in Tables 1 and 2. Neither is statistically significant for non-agricultural growth regression, while "population share below 15" is negative and significant in the agricultural growth regression at the 10 percent level, which suggests that higher dependency related to childcare obligations negatively affects agricultural growth.

D.Log Agricultural Value Added Per Capita (-1)	0.0528	0.0313	0.034	0.0338	**0.234****	**0.185***	**0.179***
	(0.0633)	(0.0729)	(0.0587)	(0.0762)	**(0.0954)**	**(0.0959)**	**(0.104)**
D.Log Non-Agricultural Value Added Per Capita (-1) [Endogenous]	**0.111****	0.0483	**0.110***	0.0571	0.0675	**-0.155*****	**-0.179*****
	(0.0497)	(0.0540)	**(0.0596)**	(0.0569)	(0.0852)	**(0.0527)**	**(0.0639)**
The Share of Mining Sector Income in GDP (-2) [Endogenous]	-0.00694	**-0.00735****	-0.00871	-0.00659	0.000451	**0.00752****	**0.0152****
	(0.00523)	**(0.00375)**	(0.00602)	(0.00457)	(0.00590)	**(0.00305)**	**(0.00635)**
Log Schooling Years (-1) [Endogenous]	-	**0.0276****	-	**0.0295****	-	**0.0360*****	**0.0331****
	-	**(0.0126)**	-	**(0.0123)**	-	**(0.0129)**	**(0.0133)**
Log Inequality [Endogenous]	-	0.000327	-	0.00103	-	-0.0024	-0.00207
	-	(0.000991)	-	(0.00112)	-	(0.00146)	(0.00186)
Log Precipitation	-	-	-	-	-	-	**0.0356***
	-	-	-	-	-	-	**(0.0204)**
Constant	0.0258	-0.0303	0.0263	-0.0678	0.0335	0.114	-0.128
	(0.00821)	(0.0508)	(0.0102)	(0.0579)	(0.0109)	(0.0512)	(0.173)
Observations	532	400	414	324	113	71	71
Number of Countries	59	50	44	37	14	12	12
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)							
Prob > z							
Order 1	0.0008***	0.0030***	0.0026***	0.0048***	0.0654*	0.00239**	0.0285**
2	0.0770*	0.4439	0.0820*	0.4279	0.9015	0.9958	0.8563
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)							
	Chi2(316)	Chi2(385)	Chi2(307)	Chi2(329)	Chi2(133)	Chi2(104)	Chi2(103)
	301.88	3969.54	309.89	346.81	134.87	112.82	107.81
Prob > chi2	0.7067	0.2940	0.4431	0.2395	0.4385	0.2608	0.3533

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Panel B of Table 2 reports the results on the effect of non-agricultural growth on agricultural growth using the annual panel data. We have found significant coefficient estimates of the growth in non-agricultural value added per capita in all the cases (Cases 7-12B) with a substantially larger elasticity estimates for low income countries. That is, in the short- run, the effects from non-agricultural sector to agricultural sector are clearly observed. In Case 7 (based on a full sample) the mining share is positive and significant, pointing to positive externalities of mining. Inequality (treated as endogenous) is positively and significantly associated with agricultural growth dynamically. Precipitation is statistically insignificant.

Table 2: Effect of Non-Agricultural Growth on Agricultural Growth: Dynamic Panel Regressions (Blundell and Bond (1998) SGMM) (cont.)
Dependant Variable: D.Log Agricultural Value Added per capita
Panel B: Based on Annual Panel Data

VARIABLES	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12A	Case 12B
	Full Sample		Middle Income Countries		Low Income Countries		
D.Log Agricultural Value Added Per Capita (-1)	**-0.233*** **	**-0.367*** **	**-0.241*** **	**-0.359*** **	**-0.139**	**-0.400*** **	**-0.403*** **
	(0.0778)	**(0.0715)**	**(0.0836)**	**(0.0794)**	**(0.140)**	**(0.123)**	**(0.125)**
D.Log Non-Agricultural Value Added Per Capita (-1) [Endogenous]	**0.101** **	**0.0609**	**0.0806** **	**0.0483**	**0.288*** **	**0.291*** **	**0.284*** **
	(0.0407)	**(0.0492)**	**(0.0382)**	**(0.0483)**	**(0.107)**	**(0.0740)**	**(0.0760)**
The Share of Mining Sector Income in GDP (-2) [Endogenous]	**0.00331***	0.000989	0.00298	-6.49E-05	0.000596	0.000907	0.00219
	(0.00169)	(0.00262)	(0.00201)	(0.00325)	(0.00256)	(0.00161)	(0.00288)
Log Schooling Years (-1) [Endogenous]	-	0.0104	-	0.00559	-	**0.0143** **	**0.0143** **
	-	(0.00652)	-	(0.00841)	-	**(0.00659)**	**(0.00610)**
Log Inequality [Endogenous]	-	**0.00193** **	-	**0.00196***	-	0.000448	0.000433
	-	**(0.000906)**	-	**(0.00101)**	-	(0.00133)	(0.00133)
Log Precipitation	-	-	-	-	-	-	0.00738
	-	-	-	-	-	-	(0.00863)
Constant	0.00422	-0.0921	0.00286	-0.0864	0.00565	-0.0328	-0.0807
	(0.00286)	(0.0432)	(0.00356)	(0.0495)	(0.00388)	(0.0664)	(0.0687)
Observations	1,666	1,025	1,288	856	366	157	157
Number of Countries	59	49	44	37	14	11	11
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)							
Prob > z							
Order 1	0.0001***	0.0022***	0.0002***	0.0043***	0.0045***	0.0529*	0.0516*
2	0.6712	0.2112	0.7643	0.1716	0.1565	0.3292	0.3514
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)							
	Chi2(1700)	Chi2(1039)	Chi2(1343)	Chi2(908)	Chi2(470)	Chi2(259)	Chi2(258)
	1868.46	1143.11	1471.61	1003.07	566.32	220.91	218.95
Prob > chi2	0.0025***	0.013***	0.0078**	0.0149**	0.0015***	0.9585	0.9585

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

2nd Stage: Estimation of Inequality Change (or Poverty) by (predicted) non-agricultural growth and agricultural growth

Based on the estimation results of (1) and (2), we further estimated changes in inequality by predictions of non-agricultural growth and agricultural growth in the second stage. The cases based on the three- year panel are shown in Table 2 where we have used the results predicted by using “Case 2 of Table 1” and “Case 2 of Table 2” (the cases with control variables) and have applied Blundell and Bond’s (1998) SGMM model and country fixed effects. Here our main focus is on the dynamic linkages between (predicted) growth in agricultural and non-agricultural growth and change in inequality over time. It is found by focusing on Case 1 of Table 3 that agricultural growth is negatively and significantly associated with inequality change and its effect is generally larger (that is, more negative) than the effect of non-agricultural growth. That is, if a country experiences a higher level of agricultural growth, the pace of accentuation of inequality is curbed (or the pace of inequality reduction is accelerated) dynamically, *ceteris paribus.* We do not see these effects for non-agricultural growth. This is consistent with the view that if growth is driven by agriculture, it is more "inequality reducing" over time than non-agriculture (Case 1). However, agricultural growth ceases to be statistically significant in Case 2 with a few control variables (education and political stability) and non-agricultural growth becomes significant, while the absolute value of coefficient estimate of the former is still larger than that of the latter.[25] The results based on fixed effect model[26] - in which the persistence effect of inequality change is omitted[27] - are broadly similar to the results based on the SGMM model (Cases 3 and 4). As SGMM is not feasible in disaggregated cases due to the limited sample size, we have disaggregated the results based on fixed effects model (Cases 3 and 4) for middle income countries (Cases 5 and 6) and low income countries (Cases 7 and 8). It is notable that agricultural growth is significant with the larger effect in Cases 7 and 8 for low income countries. For instance, it can be inferred from the result of Case 7 that, if agricultural growth increases by 1%, *the change* in inequality decreases by 61% on average, *ceteris paribus.* This is

[25] The difference between Case 1 and Case 2 of Table 3 (i.e. agricultural growth becomes statistically non-significant, while non-agricultural growth becomes significant in Case 2) appears to be due to the fact that schooling and governance are more highly and positively correlated with agricultural growth (with the coefficient of correlation of 0.625 and 0.404, respectively) than with non-agricultural growth (0.157 and 0.046 respectively).

[26] The Hausman test favours fixed effect models over random effects model in all cases. The robust estimates for Fixed-Effects models have been chosen to partly deal with the problem of heteroscedasticity.

[27] Here the application of fixed effects model follows Christiaensen et al.'s (2011) specification for the poverty equation. Since the results of SGMM model tend to be sensitive to its specification, we have also used the fixed effects model as a robustness check. Given the persistence of inequality, our preferred model is the SGMM model.

a substantial effect in terms of pace of inequality change. Such a strong effect is not observed for non-agricultural growth.[28]

Table 3: Effect of Predicted Agricultural/Non-Agricultural Growth on Inequality Change: Dependent Variable: D.Inequality: Based on 3- year average panel

	Blundell and Bond (1998) SGMM (dynamic panel)		**Fixed Effects Model (Robust Estimators)**	
	Case 1	Case 2	Case 3	Case 4
VARIABLES	Full Sample		Full Sample	
D.Inequality (-1)	-0.0527	**-0.150****	-	-
	(0.0666)	**(0.0617)**	-	-
Log Schooling Years [Endogenous]	-	-0.488	-	**-1.026****
	-	(0.307)	-	**(0.411)**
Political Stability [Endogenous]	-	-0.182	-	**-1.898*****
	-	(0.750)	-	**(0.625)**
D.Log Agricultural Value Added per capita [Predicted]	**-29.72***	-15.22	**-25.50***	-29.57
	(17.57)	(29.19)	**(14.98)**	(30.07)
D.Log Non-Agricultural Value Added per capita [Predicted]	-4.091	**-9.945****	-5.065	-4.931
	(3.640)	**(4.493)**	(3.164)	(4.333)
Constant	1.237	4.925	1.164	8.290
	(0.524)	(1.875)	(0.326)	(2.741)
Observations	383	206	414	219
Number of Countries	47	43	49	45
R-squared			0.047	0.118
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)				
Prob > z				
Order 1	0.0003***	0.0160**		
2	0.0629*	0.22		
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)				
	Chi2(114)	Chi2(127)		
	152.22	136.99		
Prob > chi2	0.0097	0.2569		
	Fixed Effects Model (Robust Estimators)		Fixed Effects Model (Robust Estimators)	
VARIABLES	Case 5	Case 6	Case 7	Case 8
	Middle Income Countries		Low Income Countries	
D.Log Agricultural Value Added per capita [Predicted]	-20.39	-10.08	**-61.42***	**-145.0****
	(16.55)	(29.59)	**(31.23)**	**(58.92)**
D.Log Non-Agricultural Value Added per capita	-5.468	-4.784	-2.89	2.878

[28] This reflects our semi-log specification where inequality change (dependent variable) is change in percentages while predicted change in log of agricultural and non-agricultural change is the growth rate of each sector. Inequality change in low income countries is more than 7 times larger than that in middle income countries, resulting in higher coefficient estimates for low income countries. Why the coefficient estimate of agricultural growth gets much larger in Case 8 (-145.0) is not clear, but the coefficient estimate in Case 6 is imprecise as it is not statistically significant. The correlation between agricultural growth and controls (schooling and governance) could be the reason.

[Predicted]				
	(3.455)	(4.321)	(7.363)	(14.27)
Log Schooling Years [Endogenous]		**-1.404*** **		2.976
		(0.427)		(1.845)
Political Stability [Endogenous]		**-2.184*** **		2.48
		(0.653)		(2.676)
Constant	1.001***	10.70***	2.061**	-11.18
	(0.342)	(3.125)	(0.687)	(7.946)
Observations	338	176	71	38
R-squared	0.043	0.146	0.107	0.276
Number of Countries	37	34	11	10

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

In Table 4 we use the annual panel data to estimate the effects of agricultural growth and non-agricultural growth on inequality, which are predicted by using "Case 8 of Table 1" and "Case 8 of Table 2" (the cases with control variables). As in Table 3, we have applied both Blundell and Bond's (1998) SGMM model and fixed-effects model (Cases 1-4). As an extension, we have also applied Pesaran's (2006) common correlated effects mean group (CCEMG) estimator which would enable us to model the country-level heterogeneity in estimating the relationship between inequality change and agricultural/non-agricultural growth and to correct for the cross-sectional correlations of unobservable factors which change over time (Case 6).[29] These two points are recent developments in the panel data econometrics to overcome the limitations of the standard fixed effects model where the country-level heterogeneity is ignored and the unobservable factors are fixed without allowing correlations across different units (or countries). However, the data requirement for the CCEMG model is large as it requires a relatively large *t* (the number of years) and *i* (the number of countries). Another useful feature of CCEMG models is to enable us to derive the coefficient estimate for each country by utilising both time-series variation for the country and the factors common across different countries. This will provide us with the coefficient estimate for each country to show how the linkages between inequality change and

[29] Appendix 1 provides details as well as intuitive explanations of MG and CCEMG models.

agricultural (or non-agricultural) growth differ across countries and then we will apply OLS to estimate the underlying determinants for them by simply regressing the saved coefficient on (more or less) exogenous variables, the results of which are given in Table 6. As a base line of the CCEMG model, the MG (mean group) model (Pesaran and Smith, 1995) is estimated whereby the country-level heterogeneity is modelled without correcting for the cross-sectional correlations of unobservable factors which change over time (Case 5).[30]

Table 4: Effect of Predicted Agricultural/Non-Agricultural Growth on Inequality Change Based on Annual panel

Panel A: Annual Data, Full Sample

VARIABLES	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
	Blundell and Bond (1998)		Fixed Effects Model		MG Estimator	CCEMG estimator
	SGMM (Dynamic Panel		(Robust Estimators)		Pesaran & Smith	Pesaran
					(1995)	(2006)
D.Inequality (-1)	-0.0593*	-0.0772	-	-	-	-
	(0.0351)	(0.108)	-	-	-	-
Log Schooling Years [Endogenous]	-	-0.113	-	0.193	-	-
	-	(0.114)	-	(0.338)	-	-
Political Stability	-	0.0171	-	-0.304	-	-
	-	(0.293)	-	(0.379)	-	-
D.Log Agricultural Value Added per capita [Predicted]	-3.270*	-3.166	-3.947**	-3.817	-3.973**	-6.030**
	(1.730)	(3.005)	(1.808)	(3.069)	(1.992)	(2.646)
D.Log Non-Agricultural Value Added per capita [Predicted]	-11.47***	-14.41**	-9.782***	-15.16**	-10.04**	-11.14**
	(4.354)	(5.985)	(3.133)	(5.911)	(4.182)	(4.695)
Trend [31]	-	-	-	-	-0.00423	-0.0013
	-	-	-	-	(0.00724)	(0.00839)
D.Log Inequality_avg	-	-	-	-	-	0.424**
	-	-	-	-	-	(0.175)
D.Log Agricultural Value Added per capita [Predicted]_avg	-	-	-	-	-	7.117
	-	-	-	-	-	(6.309)
D.Log Non-Agricultural Value Added	-	-	-	-	-	4.449

[30] Technical details of MG and CCEMG models are presented in Appendix 1.
[31] See Appendix 1 for the definition of the trend term.

per capita [Predicted]_avg						
	-	-	-	-	-	(9.730)
Constant	0.360	1.328	0.331	-1.169	0.613	0.14
	(0.113)	(0.853)	(0.0791)	(2.656)	(0.280)	(0.342)
Observations	849	360	932	384	927	927
Number of Countries	45	40	49	42	45	45
R-squared			0.014	0.023		
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)						
Prob > z						
Order 1	0.0005***	0.0180***	-	-	-	-
2	0.8820	0.5317	-	-	-	-
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)						
	Chi2(764)	Chi2(331)				
	863.50	334.89	-	-	-	-
Prob > chi2	0.0070***	0.4376	-	-	-	-

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

In case where annual data are used (Panel A, Table 4), agricultural growth tends to reduce accentuation of inequality, as suggested by the negative and significant coefficients for (predicted) agricultural growth. The range of coefficient estimates (-3.27 to -3.97) in Cases 1-5 is much smaller than that based on three-year panel data reflecting the difference in the data structure. If agricultural growth increases by 1%, *the change* in inequality decreases by 3.3% on average, *ceteris paribus* (Case 1). Recalling the fact that we have the (time-series) average in agricultural growth, the estimate in Case 6 has changed to -6.0. It has also been found (by the coefficient estimate for "D.Log Non-Agricultural Value Added per capita") that the effect of non-agricultural sector growth in reducing the inequality change is much larger (with the estimates ranging from -14.4 to -9.8). If we disaggregate the results into sub-periods, before and after 2000, we find that (i) non-agricultural growth tends to reduce inequality change before and after 2000 with the larger magnitude after 2000, and (ii) agricultural growth does not significantly reduce the inequality change before 2000, but it does significantly after 2000 in case of the robust fixed effects model (Panels B and C, Table 4).

While there is some variation in the magnitude of the effect, we can conclude that both agricultural sector and non-agricultural sector growth reduce accentuation of inequality or accelerate the inequality reduction. If we go by the longer-term effect using the three- year average panel, we can conclude that this effect is much larger for the agricultural sector than for the non-agricultural sector, which confirms the central role of agricultural growth in inequality reduction.

Table 4: Effect of Predicted Agricultural/Non-Agricultural Growth on Inequality Change Based on Annual panel (cont.)

Panel B: Annual Data, Before 2000

VARIABLES	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
	Blundell and Bond (1998) SGMM (Dynamic Panel		Fixed Effects Model (Robust Estimators)		MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)
D.Inequality (-1)	-0.0579	-0.092	-	-	-	-
	(0.0465)	(0.250)	-	-	-	-
Log Schooling Years [Endogenous]	-	**-0.388****	-	0.11	-	-
	-	**(0.188)**	-	(0.594)	-	-
Political Stability	-	0.0618	-	0.557	-	-
	-	(0.917)	-	(0.912)	-	-
D.Log Agricultural Value Added per capita [Predicted]	-1.539	1.796	-2.18	1.101	-2.497	-6.266
	(1.940)	(4.139)	(1.838)	(3.662)	(3.596)	(4.332)
D.Log Non-Agricultural Value Added per capita [Predicted]	**-7.968***	-8.341	**-6.666****	-9.607	-7.829	-9.684
	(4.779)	(8.713)	**(3.037)**	(7.927)	(5.012)	(6.091)
Trend	-	-	-	-	0.00264	0.00258
	-	-	-	-	(0.0170)	(0.0200)
D.Log Inequality_avg	-	-	-	-	-	**0.739*****
	-	-	-	-	-	**(0.228)**
D.Log Agricultural Value Added per capita [Predicted]_avg	-	-	-	-	-	-3.296
	-	-	-	-	-	(8.719)
D.Log Non-Agricultural Value Added per capita [Predicted]_avg	-	-	-	-	-	-11.17
	-	-	-	-	-	(18.38)
Constant	0.292	3.025	0.279	-0.422	-0.0817	-0.0922
	(0.108)	(1.338)	(0.0668)	(4.164)	(0.418)	(0.572)
Observations	632	143	667	152	623	623
Number of Countries	43	36	43	38	38	38
R-squared			0.006	0.027		
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)						
Prob > z						
Order 1	0.0002***	0.0512*	-	-	-	-
2	0.8820	0.8015	-	-	-	-

Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)						
	Chi2(551)	Chi2(107)				
	647.13	113.95	-	-	-	-
Prob > chi2	0.0029***	0.3047	-	-	-	-

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Table 4: Effect of Predicted Agricultural/Non-Agricultural Growth on Inequality Change Based on Annual panel (cont.)

Panel C: Annual Data, After 2000

VARIABLES	Case 13	Case 14	Case 15	Case 16	Case 17	Case 18
	Blundell and Bond (1998)		Fixed Effects Model		MG Estimator	CCEMG estimator
	SGMM (Dynamic Panel		(Robust Estimators)		Pesaran& Smith	Pesaran
					(1995)	(2006)
D.Inequality (-1)	**-0.130***	-0.125	-	-	-	-
	(0.0675)	(0.0768)	-	-	-	-
Log Schooling Years	-	-0.0233	-	0.582	-	-
	-	(0.142)	-	(0.998)	-	-
Political Stability	-	-0.145	-	-0.805	-	-
	-	(0.391)	-	(0.660)	-	-
D.Log Agricultural Value Added per capita [Predicted]	-4.919	-4.969	**-7.556***	**-9.166***	-4.764	-5.706
	(3.652)	(4.243)	**(4.204)**	**(5.015)**	(4.966)	(3.706)
D.Log Non-Agricultural Value Added per capita [Predicted]	**-17.97****	**-17.55****	**-14.47***	-16.95	**-19.66*****	-12.63
	(7.884)	**(8.084)**	**(8.409)**	(10.14)	**(7.292)**	(14.02)
Trend	-	-	-	-	0.0357	**0.0881***
	-	-	-	-	(0.0226)	**(0.0460)**
D.Log Inequality_avg	-	-	-	-	-	0.69
	-	-	-	-	-	(0.442)
D.Log Agricultural Value Added per capita [Predicted]_avg	-	-	-	-	-	-3.447
	-	-	-	-	-	(11.53)
D.Log Non-Agricultural Value Added per capita [Predicted]_avg	-	-	-	-	-	42.23
	-	-	-	-	-	(31.36)
Constant	0.536	0.676	0.451	-4.512	-1.122	-4.501
	(0.299)	(1.192)	(0.275)	(8.441)	(1.141)	(2.616)
Observations	217	217	265	232	255	255
Number of Countries	37	37	45	40	28	28
R-squared			0.028	0.05		
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)						
Prob > z						
Order 1	0.0435**	0.0488**	-	-	-	-
2	0.0840*	0.0937*	-	-	-	-
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)						
	Chi2(210)	Chi2(219)				
	225.04	227.43	-	-	-	-
Prob > chi2	0.2268	0.3338	-	-	-	-

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Appendix 2 lists the country-level coefficient estimates based on the CCEMG model (Case 6, Table 4). We have checked what sort of factors have high statistical associations with these coefficient estimates representing the linkages between inequality change and growth in agricultural or non-agricultural sector by running a simple OLS (Ordinary Least Squares). The results are given in Table 5. There were not many statistically significant cases found in these regressions. However, we can summarise the results as follows.

(i) If a country is more ethnically fractionalised,[32] it tends to have a higher (i.e., more positive or less negative) value in the coefficient indicating the effect of agricultural growth on inequality change. This implies that the role of agricultural sector reducing accentuation of inequality is likely to be undermined by ethnic fractionalisation which tends to make (economic) inequality more persistent.

(ii) There is some regional diversity in the linkages between the agricultural or non-agricultural growth and inequality change. For instance, the countries in Sub-Saharan Africa tend to experience slower changes in improvement in equality as a result of

Table 5: Underlying Determinants of Relationships between Agricultural Growth (or Non-Agricultural Growth) and Inequality Change

[OLS results for the saved coef. estimates and t-values (based on the country-level regression results shown in Case 6, CCEMG estimator (Pesaran (2006)) on the Effect of (predicted) Agricultural/Non-Agricultural Growth on Inequality Change)]

	Case 1	Case 2	Case 3	Case 4
VARIABLES	Coef. of Agricultural Growth	t value of Agricultural Growth	Coef. of Non-agricultural Growth	t value of Non-agricultural Growth
Institution	13	0.5	17.06	0.607
	(10.63)	(1.015)	(18.02)	(0.998)

[32]The index of ethnic fractionalisation is based on Alesina et al. (2003) and indicates the degree of fractionalisation of ethnic groups where the definition of ethnicity involves a combination of racial and linguistic characteristics. A high value implies that the country consists of different ethnic groups, while a low value indicates homogeneous ethnic composition.

Ethnic Fractionalisation	**28.43***	0.58	31.45	0.818
	(16.56)	(1.582)	(28.08)	(1.555)
Inequality	-1.769	-0.0491	-3.411	-0.0397
	(1.313)	(0.125)	(2.226)	(0.123)
MENA	15.71	0.383	**37.34***	0.393
	(12.97)	(1.239)	**(21.99)**	(1.218)
SSA	**27.28****	1.079	44.30*	-0.0139
	(13.34)	(1.274)	(22.61)	(1.252)
LAC	20.37	2.131	34.89	0.85
	(13.41)	(1.281)	(22.73)	(1.259)
EAP	-0.891	-0.203	-15.63	-1.37
	(12.20)	(1.166)	(20.69)	(1.146)
SA	**28.18***	0.797	40.65	0.563
	(15.87)	(1.515)	(26.90)	(1.490)
Constant	44.22	0.966	102.1	0.883
	(48.93)	(4.674)	(82.95)	(4.594)
Observations	41	41	41	41
R-squared	0.286	0.19	0.311	0.151

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

growth in both agricultural and non-agricultural sectors. South Asian countries also tend to have slow changes as a result of agricultural growth.

Inequality index used in the analysis for Tables 3 and 4 captures overall economic inequality of a country. It would be also useful to see how agricultural growth or non-agricultural growth affects poverty (defined by the poverty headcount ratio or the poverty gap) (in level), following Christiaensen et al. (2011)[33].

Table 6 reports the results on the effect of agricultural or non-agricultural growth on poverty headcount ratio or poverty gap - for a full sample of countries (Panel A), middle income countries (Panel B) and low income countries (Panel C). Following Christiansen et al. (2011), we apply the country-fixed effects model[34] and use only predicted values of agricultural or non-

[33] If we use the first difference in poverty, the number of observations will be reduced significantly due to missing observations.
[34] The Hausman test results favour fixed effects model over random effects model.

agricultural growth (based on Case 2 in Table 1 and Case 2 in Table 2) without adding further control variables.[35]

Table 6: Effect of Predicted Agricultural/Non-Agricultural Growth on Poverty: Based on 3 -year panel, country fixed effects estimation

Panel A: Full Sample

VARIABLES	Case 1	Case 2	Case 3	Case 4
	Poverty Head Count US$1.25	Poverty Gap US$1.25	Poverty Head Count US$2.00	Poverty Gap US$2.00
	Full Sample		Full Sample	
D.Log Agricultural Value Added per capita [Predicted]	**-28.97*** **	**-25.77*** **	**-19.86*** **	**-23.60*** **
	(10.60)	**(7.529)**	**(7.298)**	**(6.448)**
D.Log Non-Agricultural Value Added per capita [Predicted]	-1.151	-0.638	-0.578	-1.616
	(1.841)	(1.360)	(1.350)	(1.454)
Constant	2.372	1.223	3.189	2.294
	(0.283)	(0.186)	(0.195)	(0.185)
Observations	234	227	234	232
R-squared	0.165	0.182	0.13	0.234
Number of Countries	45	45	45	45

Panel B: Middle Income Countries

VARIABLES	Case 5	Case 6	Case 7	Case 8
	Poverty Head Count US$1.25	Poverty Gap US$1.25	Poverty Head Count US$2.00	Poverty Gap US$2.00
	Middle Income Countries		Middle Income Countries	
D.Log Agricultural Value Added per capita [Predicted]	**-30.95** **	**-25.36*** **	**-21.81** **	**-24.98*** **
	(12.40)	**(8.398)**	**(8.567)**	**(7.446)**
D.Log Non-Agricultural Value Added per capita [Predicted]	-0.822	-0.318	-0.339	-1.449
	(2.008)	(1.459)	(1.469)	(1.572)
Constant	2.031	0.848	2.960	2.008
	(0.325)	(0.206)	(0.225)	(0.209)
Observations	193	186	193	191
R-squared	0.156	0.161	0.126	0.226
Number of Countries	35	35	35	35

Panel C: Low Income Countries

VARIABLES	Case 9	Case 10	Case 11	Case 12
	Poverty Head Count US$1.25	Poverty Gap US$1.25	Poverty Head Count US$2.00	Poverty Gap US$2.00
	Low Income		Low Income	

[35] The cases of poverty regressions with further control variables (following Imai et al. 2010) will be shown in Section IV. Adding further control variables is difficult in the regressions in Table 6 as we use a restricted sample with disaggregated sectoral data available in this section. Christiansen et al. (2011) did not add control variables either in their poverty regressions.

	Countries		Countries	
D.Log Agricultural Value Added per capita [Predicted]	-19.59	**-30.94***	-10.36	-18.96
	(13.27)	**(16.13)**	(8.842)	(11.81)
D.Log Non-Agricultural Value Added per capita [Predicted]	-3.611	-3.588	-2.071	-2.343
	(2.203)	(2.990)	(1.124)	(1.585)
Constant	4.354	3.401	4.607	3.950
	(0.263)	(0.320)	(0.190)	(0.253)
Observations	39	39	39	39
R-squared	0.472	0.448	0.453	0.466
Number of Countries	9	9	9	9

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

Table 6 shows that agricultural growth has a stronger and significant effect in reducing both poverty headcount ratio and poverty gap regardless of whether the US$1.25 a day poverty line or the US 2.00 a day poverty line is adopted, while there is no statistically significant effect of non-agricultural growth. The pattern of the results is unchanged if we restrict the sample only to middle income countries where agricultural growth is found to reduce poverty regardless of which definition is used. On the other hand, in the case of low income countries with the caveat that this is based on a small number of observations, we find a statistically significant coefficient estimate for agricultural growth only in Case 10 for poverty gap based on US$1.25 line. Poverty reducing effects of agricultural growth are weaker in terms of their magnitude for low income countries than for middle income countries. Non-agricultural growth is negative and statistically insignificant for both middle and low income countries, with the coefficient estimates larger for the latter. Broadly consistent with Christiaensen et al. (2011), we confirm that agricultural growth has a stronger poverty-reducing effect than non-agricultural growth.

Section II analyses in detail whether agricultural growth or non-agricultural growth impacts inequality and poverty after taking account of the dynamic linkages between the agricultural and the non-agricultural sectors over time. The analyses draw upon both dynamic and static panel models using the annual data as well as the three-year averages.

First, we generally observe strong growth linkages between agricultural and non-agricultural sectors. In the analyses focusing on the short-term effects based on the annual panel, strong effects are observed from agricultural sector to non-agricultural sector as well as from the latter to the former regardless of whether the country belongs to middle income or low income countries. Such linkages are found in the full sample as well as in the sub-sample of middle income countries when the three- year average panel is used.

Second, agricultural growth is found to reduce accentuation of inequality, or accelerate inequality reduction in the full sample as well as in the sub-sample of low income countries when the three-year average panel is used. While such inequality reducing effects of agricultural growth are found in the short-run based on the annual panel, non-agricultural growth tends to reduce inequality faster in the short run. The degree of ethnic fractionalisation is key to explaining the magnitude of negative linkages between agricultural/non-agricultural growth and inequality changes.

Third, agricultural growth reduces poverty - both poverty gaps and headcount ratios - in both middle income and low income countries.

While the recent work by Collier and Dercon (2013) questions the role of smallholders in development process, our analyses clearly show that agricultural growth has the greater potential for poverty and inequality reduction over time than non-agricultural growth. Indeed, Collier and Dercon's emphatic rejection of smallholders not only rests on shaky empirical foundation but could also slow poverty and inequality reduction[36].

[36] For a different interpretation of the evidence and gaps in their arguments, see Gaiha (2014).

III. The long-term relationship between inequality and economic growth (or agricultural growth)

In the last section, we have examined how agricultural growth and non-agricultural growth are dynamically interlinked, and then how agricultural or non-agricultural growth influences inequality or poverty over time. For instance, we have found in Tables 3 and 4 that both agricultural growth and non-agricultural growth tend to accelerate inequality reduction over time. However, it is not clear how inequality influences economic growth over time and how this effect is different among different countries. This section addresses how inequality will affect economic growth or agricultural growth and controls for institutional qualities of countries in some cases. We will also address how the inequality-growth relationship differs among different countries and analyse the underlying determinants of this relationship.

There is a complex bi-directional causal relationship between inequality and economic growth, or its components, such as agricultural or non-agricultural growth. The empirical and theoretical literature of pro-poor growth mainly focuses on how the benefit of overall economic growth will be distributed across different income groups of the country by comparing the growth rate of the poor and the overall growth (e.g. Ravallion and Chen, 2003). For instance, if the growth is urban-biased, the benefit of the country may not trickle down to the rural area as in the case of recent China, particularly the migration is restricted by policy factors (e.g. strict restrictions in migrants' registrations with urban Hukou). However, inequality itself will dynamically curb the overall economic growth. For instance, inequality implies inequalities in access to productive assets resulting in under-utilisation of the productive potential of the poor and this negative effect will be augmented by the imperfect credit market where the poor cannot invest in capital (Jalilian and Kirkpatrick, 2005). As the market failure is greater for the poor, the higher share of the poor or higher inequality in the initial period will curb the economic growth (Ravallion, 2001). However, whether inequality dampens growth is specific to a country's institutional context and will have to be investigated empirically.

Section III draws on Herzer and Vollmer's (2012) seminal paper on the inequality - growth relationship. They used heterogeneous panel cointegration techniques and estimated the long-run effect of income inequality on per-capita income for 46 countries - 28 high income countries and 18 developing countries (i.e. middle or low income countries) over the period 1970–1995. They found that inequality based on the EHII data has a negative long-run effect on income.

As our panel data are inevitably unbalanced, we use Pesaran's (2006) method which assumes stationarity of the data. Using Pesaran's (2006) method for panel data, we have estimated the effect of inequality on GDP per capita for each country. This is in line with Herzer and Morrissey (2013) who estimated the effect of foreign aid on GDP per capita for each country[37]. Section III supplements the analyses in Section II by investigating the relationship between the *overall* growth and inequality covering a larger number of countries.

In Section III, we have tried two cases for the inequality-income relations: (i) the parsimonious specification where log GDP per capita is estimated only by log investment and by inequality, following Herzer and Vollmer (2012) and Herzer and Morrissey (2013), and (ii) the specification with a few more explanatory variables to control for country specific factors, such as population growth, inflation, intensity of conflict, and the country's vulnerability (proxied by price uncertainty of export commodities captured by GARCH (1, 1) model)[38]. We have applied

[37] They used the between-dimension group-mean panel DOLS estimator (Pedroni, 2000, 2001) and then identified which factors (e.g. religious tension, law and order, government size) influenced the aid-growth relationship at the country level.

[38] Export price uncertainly is likely to negatively affect both economic growth and poverty reduction outcomes. For instance, if the country is dependent on agricultural sector as many developing countries are, the uncertainty or shocks will make many agricultural households credit constrained and deter them from investing risky agricultural investment with high returns (Dercon and Christiaensen, 2011). The theory of real options also predicts that non-

Pesaran's (2006) common correlated effects mean group (CCEMG) estimator which takes into account the cross-sectional correlations of unobservables as well as Pesaran and Smith (1995) mean group (MG) estimator which is similar to Pesaran (2006), but does not consider the cross-sectional correlations of unobservables. In these two models, the country level estimates of the effect of inequality on log GDP per capita can be derived in addition to the panel estimates.[39, 40] Besides, we have extended the above models to examine the relationship between inequality and agricultural value added per worker. In this model, we have dropped log of total investment and examined the relationship between agricultural value added per worker and inequality.

Table 7 gives a set of results for the parsimonious specification. Here log GDP per capita is estimated by log of investment and inequality (based on the extended inequality data covering 119 countries[41]). Panel A of Table 7 gives the regression results for the full sample for 1970-2008 (annual data) based on Pesaran & Smith's (1995) MG Estimator, and Pesaran's (2006) CCEMG estimator. Panels B and C show the results for the sample before and after 2000,

Table 7 Long-term relationship between inequality and overall income -Parsimonious Specification: Effect of Inequality on log GDP per capita (Dependent Variable: Log of GDP per capita) based on Annual Panel

	A. A Full Sample		**B. Before 2000**		**C. After 2000**	
VARIABLES	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)
Log Investment	**0.164*** **	**0.104*** **	**0.145*** **	**0.128*** **	0.0679	0.027
	(0.0491)	**(0.0331)**	**(0.0206)**	**(0.0240)**	(0.0872)	(0.0248)
Inequality	**-0.0152***	-0.00633	**-0.0082*** **	**-0.00769*** **	**-0.0436*** **	-0.00819
	(0.00819)	(0.00516)	**(0.00262)**	**(0.00235)**	**(0.0143)**	(0.0104)
Trend	**0.0222*** **	**0.0195*** **	**0.0127*** **	**0.0112*** **	**0.0280*** **	**0.0229*** **
	(0.00258)	**(0.00285)**	**(0.00260)**	**(0.00266)**	**(0.00280)**	**(0.00253)**
Log GDP per capita_avg	-	0.00351	-	-0.0274	-	0.0638

agricultural investment tends to be postponed under the macro-uncertainty – including export price uncertainty - which would have a negative impact on economic growth (e.g. Dixit and Pindyck, 1994).

[39] Technical details of CCEMG model and MG model are given in Appendix 1.

[40] As baseline estimates, we have also tried fixed effects and random effects models. The results are broadly similar to those based on the MG estimator. These will be furnished on request.

[41] We have also run the same regression using the raw data on inequality covering 86 countries. The results are broadly similar and will be furnished on request.

	-	(0.0888)	-	(0.0277)	-	(0.0615)
Log Investment_avg	-	0.0862	-	**0.0982*** **	-	**0.0605** **
	-	(0.0707)	-	**(0.0364)**	-	**(0.0253)**
Inequality_avg	-	**-0.0507*** **	-	**-0.0115** **	-	**-0.100*** **
	-	**(0.0126)**	-	**(0.00505)**	-	**(0.0204)**
Constant	6.291	8.510	6.560	7.010	7.590	8.260
	(0.357)	(1.111)	(0.184)	(0.462)	(0.779)	(0.577)
Observations	3,360	3,360	1,649	1,649	1,664	1,664
R-squared						
Number of Countries	119	119	80	80	119	119

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

respectively. Investment has a positive effect on GDP per capita income in the long run, but it ceases to be significant after 2000 in most cases (except Case C)[42]. Consistent with Herzer and Vollmer's (2012) study, based on a sample of 28 developed countries and 18 developing countries, our study based on a much larger sample of 119 developing countries confirms that the long-term effect of inequality on GDP per capita is negative and significant except in a few cases. In these cases (i.e., the second column of Panel A, and the second column of Panel C based on CCEMG estimator), the cross-country average term of inequality is negative and statistically significant, while the inequality at the country level is negative but not significant. This implies that the long-term negative effect of inequality on log GDP per capita was statistically associated with the common trend of inequality across different countries (i.e. "Inequality_avg")[43], rather than the trend specific to individual countries.

Table 8 reports the results based on the specification with other control variables, such as Log Population Growth, Log Inflation, Conflict Intensity and GARCH (1,1) measure of uncertainty in export price. The coefficient estimate of inequality is statistically insignificant in all the cases. In case of CCEMG model (the second column of Panels A, B and C), the negative effect of

[42] The reason for lack of significance is not clear, but it could be due to the small sample size.

[43] In Pesaran's (2006) model, inclusion of trend of inequality is meant to control for the unobserved common factors and the relationships between common factors of all explanatory variables and a dependent variable does not have to be causal. We will thus refrain from making any causal interpretations here.

inequality is through the common trend in inequality across countries, rather than through individual country trend.

Table 8 Long-term relationship between inequality and overall income -Full specification with control variables: Effect of Inequality on log GDP per capita (Dependent Variable: Log of GDP per capita) based on Annual Panel

	A Full Sample		B. Before 2000		C. After 2000	
VARIABLES	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)
Log Investment	**0.0971****	0.0951	**0.113*****	0.0379	**0.0971****	0.0951
	(0.0462)	(0.0627)	**(0.0275)**	(0.0761)	**(0.0462)**	(0.0627)
Inequality	0.00193	-0.00562	-0.00392	-0.00876	0.00193	-0.00562
	(0.00437)	(0.00498)	(0.00375)	(0.00631)	(0.00437)	(0.00498)
Log Population Growth	0.236	-0.025	-0.136	-0.423	0.236	-0.025
	(1.488)	(0.0321)	(1.089)	(0.553)	(1.488)	(0.0321)
Log Inflation	0.00299	0.00893	0.000313	-0.00449	0.00299	0.00893
	(0.00933)	(0.00958)	(0.00594)	(0.00955)	(0.00933)	(0.00958)
Conflict Intensity	0.00347	0.00186	-0.0128	-0.00629	0.00347	0.00186
	(0.00266)	(0.00210)	(0.0172)	(0.0171)	(0.00266)	(0.00210)
GARCH (1,1) Export Price	0.44	0.122	-0.435	-4.316	0.44	0.122
	(0.414)	(0.0910)	(0.358)	(3.800)	(0.414)	(0.0910)
Trend	**0.0519*****	**0.0368*****	**0.0169*****	-0.00667	**0.0519*****	**0.0368*****
	(0.00893)	**(0.00631)**	**(0.00539)**	(0.0132)	**(0.00893)**	**(0.00631)**
Log GDP per capita_avg	-	0.14	-	0.204	-	0.14
	-	(0.223)	-	(0.131)	-	(0.223)
Log Investment_avg	-	-0.0355	-	-0.142	-	-0.0355
	-	(0.126)	-	(0.137)	-	(0.126)
Log Population Growth_avg	-	0.0973	-	-1.946	-	0.0973
	-	(0.0973)	-	(2.702)	-	(0.0973)
Log Inflation_avg	-	0.0308	-	-0.0248	-	0.0308
	-	(0.0219)	-	(0.0245)	-	(0.0219)
Conflict Intensity_avg	-	-0.0209	-	0.194	-	-0.0209
	-	(0.205)	-	(0.144)	-	(0.205)
GARCH (1,1) Export Price_avg	-	-0.0245	-	1.095	-	-0.0245
	-	(0.0245)	-	(0.860)	-	(0.0245)
Inequality_avg	-	**-0.0330****	-	**-0.0370****	-	**-0.0330****
	-	**(0.0136)**	-	**(0.0184)**	-	**(0.0136)**
Constant	4.42	6.239	6.719	13.71	4.42	6.239
	(3.774)	(1.213)	(2.533)	(6.107)	(3.774)	(1.213)
Observations	336	336	1,259	1,259	336	336
R-squared	-	-				
Number of Countries	35	35	66	66	35	35

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

As an extension, we have tried the case where income inequality is instrumented by Gini of land distribution, or land Gini. However, there is not enough time-series variation in land Gini and thus it cannot be used as an instrument for the Fixed Effects 2SLS where first-differencing is involved. Thus land Gini is interacted with the lagged value in inequality and their interaction as well as lagged inequality have been used as additional instruments on the assumption that the impact of income inequality affects differently the future income inequality according to the level of inequality in land distribution because (i) land distributions tend to be more stable than income distributions over time, and (ii) the impact of current income on future income at different distributional points is likely to be different depending on how much land the household owns. However, as income inequality is also persistent, this instrumenting strategy is admittedly not ideal and the results will have to be interpreted with caution. Our dataset does not have better instruments.

Table 9 Long-term relationship between inequality and overall income -Full specification with control variables: Effect of Inequality on log GDP per capita (Dependent Variable: Log of GDP per capita) based on Annual Panel, Instrumental Variable Regression where Inequality is treated as an endogenous variable

VARIABLES	Case 1	Case 2	Case 3
	FE 2SLS	RE 2SLS	RE 2SLS
[Second Stage]			
Inequality	**-0.0315*** **	**-0.0418*** **	**1.109** **
[Endogenous]	**(0.00470)**	**(0.0151)**	**(0.472)**
Log Investment	**0.141*** **	**-0.568*** **	**-3.079** **
	(0.0292)	**(0.214)**	**(1.516)**
Log Population Growth	0.287	**-9.735*** **	**-51.34*** **
	(0.371)	**(1.032)**	**(17.62)**
Log Inflation	0.0037	**0.0773** **	**-0.0862**
	(0.00472)	**(0.0350)**	**(0.184)**
Conflict Intensity	**0.0300** **	-0.11	**-1.386** **
	(0.0143)	(0.0882)	**(0.677)**
GARCH (1,1) Export Price	**-0.824** **	**5.679*** **	3.321
	(0.332)	**(1.887)**	(9.716)
Constant	7.783	32.22	78.87
	(0.815)	(2.271)	(22.39)
Observations	263	263	302
Number of countries	17	17	17
[First Stage]			

(Instruments)			
Inequality (-1)	**0.397***	**0.845*****	-
	(0.220)	**(0.136)**	-
Land Gini*Inequality(-1)	0.485	0.0697	-
	(0.324).	(0.210).	-
Land Gini	-	-3.191	**4.348****
		(10.072).	**(2.51).**
Specification tests for Case 1	Hausman Test: Ho: difference in coefficients not systematic chi2(33) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 261.06 Prob>chi2 = 0.0000 In Favour of FE Sargan statistic (overidentification test of all instruments): 0.118 Chi-sq(1) P-val = 0.73 Weak identification test Ho: equation is weakly identified Cragg-Donald Wald F-statistic 116.82		

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold.

The results are shown in Table 9. In Cases 1 and 2, the identification relies on lagged inequality, rather than land distribution or its interaction term. The Hausman specification test favours the fixed effects model over the random effects model. The Sargan-Hansen test for overidentifying restrictions is based on the null hypothesis that the instruments are valid instruments, that is, uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. In our case, the Sargan statistic is not statistically significant and this implies the validity of our instruments in Case 1, satisfying the exclusion restrictions. In Case 3 (RE-2SLS) the land Gini is positive and significant in the first stage.

It is not easy to draw a conclusion because inequality is negative and significant in Case 1 and Case 2 and positive and significant in Case 3. However, if we go by the Hausman specification test and Sargan test, we could choose Case 1 (FE-2SLS) over Case 2. In that case, it is safe to conclude, based on Case 1, that inequality is negatively and significantly associated with log GDP per capita after taking account of the issue of endogeneity.

In Table 10, we have tried the same set of estimations by replacing conflict intensity with the aggregate institutional quality, as a simple average of political stability, rule of law, control of conflict and voice and accountability, as in Imai et al. (2010) for the entire period. Breaking the sample into sub-periods was not possible due to the insufficient number of observations. We have also tried the panel instrumental variable (IV) estimations by using Population Density in 1500 (in log) and European's Settler's Mortality Rate (in log) as instruments. Consistent with Imai et al. (2010), the institutional quality is positive and statistically significant only in the fixed or random effect estimations where it is not instrumented for both definitions of inequality. Institution is not statistically significant in either MG model or CCEMG model. The results of other variables are more or less consistent with those in Table 8.

Table 10 Long-term relationship between inequality and overall income –with Institution: Effect of Inequality on log GDP per capita (Dependent Variable: Log of GDP per capita) based on Annual Panel

VARIABLES	Fixed Effects	Random Effects	IV Fixed Effects	IV Random Effects	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)
Log Investment	0.0718	**0.0761***	**0.104*****	-0.291	**0.147*****	0.0709
	(0.0441)	**(0.0436)**	**(0.0301)**	(0.614)	**(0.0275)**	(0.0584)
Inequality	-0.00503	**-0.00554***	0.00164	0.002	-0.00255	-0.0051
	(0.00303)	**(0.00306)**	(0.00149)	(0.00892)	(0.00415)	(0.00778)
Log Population Growth	**0.423****	0.326*	-	-3.442	**2.166***	4.022
	(0.211)	(0.188)	-	(5.242)	**(1.284)**	(4.035)
Log Inflation	0.00134	0.00158	0.00289	0.0324	0.00780**	0.00903
	(0.00383)	(0.00382)	(0.00257)	(0.0466)	(0.00382)	(0.0106)
Institutional Quality	**0.162*****	**0.203*****	0.162	2.862	0.045	-0.000414
	(0.0394)	**(0.0378)**	(0.139)	(4.101)	(0.0361)	(0.133)
GARCH (1,1) Export Price	**0.655*****	**0.646*****	0.16	2.333	0.0206	-0.469
	(0.239)	**(0.240)**	(0.214)	(3.460)	(0.185)	(0.375)
Trend	-	-	-	-	**0.0458*****	0.0371
	-	-	-	-	**(0.00579)**	(0.0280)
Log GDP per	-	-	-	-	-	0.245
capita_avg	-	-	-	-	-	(0.393)
Log Investment_avg	-	-	-	-	-	0.288
	-	-	-	-	-	(0.330)

Log Population	-	-	-	-	-	0.674
Growth_avg	-	-	-	-	-	(0.599)
Log Inflation_avg	-	-	-	-	-	-0.0692
	-	-	-	-	-	(0.0688)
Institutional Quality_avg	-	-	-	-	-	-0.138
	-	-	-	-	-	(0.359)
GARCH (1,1) Export Price_avg	-	-	-	-	-	-0.628
	-	-	-	-	-	(0.430)
Inequality Full_avg	-	-	-	-	-	**-0.0611***
	-	-	-	-	-	**(0.0324)**
Constant	6.234	6.147	7.221	16.48	0.506	-4.486
	(0.476)	(0.441)	(0.121)	(14.62)	(3.122)	(8.094)
Observations	814	814	386	386	626	626
R-squared	0.756					
Number of Countries	103	103	49	49	51	51

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Significant coef. estimates and t values are shown in bold.

Appendix 3 shows a part of the regression results at the country level only for inequality measures for the full sample in Table 8 (the second column where the Pesaran's (2006) CCEMG estimator has been applied). Coefficient estimates and t-values in Appendix 3 for inequality will be further regressed on a few possible determinants in Table 12. Here equations (1), (2) and (3) will be estimated by the CCEMG model whereby the coefficient estimate for each explanatory variable in the vector x_{it} - including inequality - will be computed for each country, *i*. Then the coefficient estimate as well as *t* value will be saved for all the countries. These saved coefficient estimates and *t* values are further estimated by (relatively) exogenous factors in Table 11, as in Herzer and Morrissey (2013).[44]

Table 11 presents the determinants of the long term inequality-growth relationship based on the saved coefficient estimates at the country level. Our findings are:

(1) Institutional quality is negative and significant in Case 1 where better institutional quality tends to weaken the negative association between inequality and GDP per capita. If there is any causality from inequality to the economic growth, then our result implies that even in a country with a larger degree of income inequality, the dampening effect of inequality on economic growth will weaken due to the country's better institutions.

(2) Higher price of export commodities (excluding oil, gold and food) or higher levels of inflation tends to strengthen the negative inequality-growth relationship (Cases 2 and 3). This implies that if a country has higher prices or inflation, high inequality tends to get magnified.

[44] It is noted that equations (A1)-(A3) in Appendix 3 are based on general forms where f_t and g_t can be non-stationary and y_{it} and x_{it} can be co-integrated. In this context, x_{it} should not contain too many variables, and the saved coefficient estimates and *t* values represent the long-term relationship between y_{it} and x_{it} (Eberhardt 2011), which would allow us to further estimate the saved coefficient estimates and *t* values by other factors in Table 11.

(3) Access to water is negative and significant in Case 4. That is, better infrastructure tends to weaken the negative linkage between inequality and growth.

(4) Belonging to low income countries is positively and significantly associated with the inequality-growth relationship, as observed in Case 6. This implies that if a country is classified into the low income category, the negative inequality-growth linkage tends to be stronger.

Table 11 Underlying Determinants of the Long-term Inequality-Income Relationship:
Using OLS for the saved coefficient estimates (based on Pesaran's (2006) CCEMG Estimator, Case A in Table 7 Long-term relationship between inequality and growth -Parsimonious Specification)

VARIABLES	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6*	Case 7*
Institutional Quality	__-0.09*__	-	-	-	-	-	-
	__(0.05)__	-	-	-	-	-	-
Price of Export Commodities (excluding oil, gold, food)	-	__0.0021***__	-	-	-	-	__0.0022***__
	-	__(0.0007)__	-	-	-	-	__(0.0008)__
Inflation	-	-	__0.0012***__	-	-	__0.0012***__	-
	-	-	__(0.00026)__	-	-	__(0.00025)__	-
Water access	-	-	-	__-0.00331*__	-	-0.0014	-0.00058
	-	-	-	__(0.00182)__	-	(0.00206)	(0.00089)
Conflict Intensity	-	-	-	-	-	0.0557	0.0143
	-	-	-	-	-	(0.114)	(0.0510)
Low income	-	-	-	-	__0.163**__	__0.134*__	-0.0151
	-	-	-	-	__(0.0680)__	__(0.0781)__	(0.0358)
Constant	-0.025	-0.229	-0.053	0.270	-0.0411	0.125	-0.181
	(0.039)	(0.0730)	(0.0332)	(0.145)	(0.0394)	(0.189)	(0.115)
Observations	119	109	119	117	119	117	107
R-squared	0.025	0.081	0.161	0.028	0.047	0.249	0.088

Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.Significant coef.estimates and t values are shown in bold.
In Cases 6 and 7, the share of agricultural land in total has been included as another control variable, but it is not statistically significant in either Case 6 or Case 7.

Table 12 reports regression results on the long-run relationship between inequality and agricultural value added per capita. Because the results vary with the model/periods, it is not easy to derive a single conclusion. However, if we confine to our preferred case of (CCEMG estimator - based on the most general specification), we can conclude that there is an overall negative and significant long-term association between inequality and agricultural growth for the entire sample (based on the second column of Table 12). [45]

Table 12 Long-term relationship between inequality and agricultural income: Effect of Inequality on log Agriucltural Value Added per capita (Dependent Variable: Log of Agricultural Value Added per capita) based on Annual Panel

VARIABLES	MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)
Inequality	**-0.0102*** **	**-0.00700*** **
	(0.00217)	**(0.00233)**
Trend	**0.0190*** **	**0.0180*** **
	(0.00249)	**(0.00286)**
logagripw_avg	-	**0.0553* **
	-	**(0.0324)**
inequality_avg	-	-
	-	-
Inequality_avg	-	**-0.0120** **
	-	**(0.00573)**
Constant	6.680	6.902
	(0.156)	(0.380)
Observations	1,595	1,595
R-squared		
Number of Countries	90	90

Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.Significant coef.estimates and t values are shown in bold.

We can conclude that in the longer term, log GDP per capita is negatively associated with inequality regardless of the specifications – including the general specification based on CCEMG estimator which takes into account the country's heterogeneity and the cross-sectional correlations of unobservable factors changing over time. The conclusion holds once we take account of the endogeneity associated with inequality by using the IV model. We have also found that the country's macro institutions tend to weaken the negative relation between inequality and GDP per capita.

[45] This significant relationship will disappear once the sample is disaggregated into the two sub-periods.

IV. The dynamic relationship among poverty, income inequality, and income growth

In Section IV, we will further investigate how poverty, income inequality, and income (or GDP per capita) are linked over time by using the model that takes into account other macro variables which influence them, such as trade openness, conflicts, institution, or vulnerability. Following Imai et al. (2010), the poverty gap (or headcount ratio based on US$1.25or US$2.00 a day) is estimated by 3SLS applied to the following system equations. Here, time fixed effects are taken into account by year dummy variables. Regional effects are also incorporated. As in Imai et al. (2010), all regressions are weighted by the total population of each country to take account of the effect of the country size on the coefficient estimate.

The poverty equation is specified as given below:

$$P_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 G_{it} + \beta_3 I_{it} + \beta_4 E_{it} + \boldsymbol{T_t}\beta_5 + \boldsymbol{D_i}\beta_6 + e^1{}_{it} \qquad (3)$$

where $P_{it}$is poverty gap or head count ratio (based on US$1.25-a-day poverty line adjusted by PPP in 2005). Y_i is log of GDP per capita in t for i^{-th} country. G_i is an inequality measure. I_{it} denotes conflict intensity. In one case, conflict intensity is replaced by institutional quality. $E_{it}$is the price of export commodities excluding oil, gold and food. $\boldsymbol{T_t}$is a vector of year dummy variables to capture the time effects and $\boldsymbol{D_i}$is a set of dummy variables to capture the regional fixed effects for six regions (namely, South Asia; East or South East Asia and the Pacific; Sub-Saharan Africa; Middle East & North Africa; Latin America & the Caribbean; Central Asia & East Europe – where Middle East & North Africa is the reference case). e_{it} is an error term.

The income equation is specified as:

$$Y_{it} = \delta_0 + \delta_1 I_{it} + \delta_2 O_{it-1} + L_{it-1}\delta_3 + \delta_4 G_{it-1} + T_t\delta_5 + D_i\delta_6 + e^2{}_{it} \qquad (4)$$

Here Y_{it}, log of GDP per capita, is estimated by, I_{it}, O_{it}, a measure of openness in terms of log of share of imports and exports in GDP, L_{it}, log of lagged agricultural value added per worker, and G_{it-1}, lagged inequality as well as $T_t$and$\boldsymbol{D_i}$.

Openness equation is estimated by the instrument, log of inverse of the physical isolation index (McArthur and Sachs, 2002).

$$O_{it} = \theta_0 + \theta_1 S_{it-1} + \boldsymbol{T_t}\theta_4 + \boldsymbol{D_i}\theta_5 + e^3{}_{it} \qquad (5)$$

The inequality equation is estimated by the instrument, Gini of land distribution ($G_{-LAND\ it}$) as well as the lagged value of log of GDP per capita, which has been inserted to capture the feedback effect of growth on inequality and instrumented poverty.

$$G_{it} = \vartheta_0 + \vartheta_1 G_{-LAND\ it} + \vartheta_2 Y_{it-1} \quad + \vartheta_3 P_{it} + \boldsymbol{T_t}\vartheta_4 \quad + \boldsymbol{D_i}\vartheta_5 \ + e^4{}_{it} \qquad (6)$$

Tables 13 and 14 report the results of 3SLS for two sets of cases - the cases with conflict and those with institutions. We have weighted regressions by country's population. The results are broadly consistent with those in earlier sections. In Case 1 (Case2) of Panel A in Table 13, poverty gap, based on US$1.25 (US$2), are estimated, while in Panel B (Cases 3 and 4), poverty gap is replaced by poverty headcount ratio. Table 14 shows the results based on the same specifications for Table 13 except that conflict intensity is replaced by macro-level institutional quality. Only key results are summarised below.

Table 13 Determinants of the Long-term relation among Inequality, Poverty and Income Relationship based on 3SLS (with Conflict Intensity)
Panel A (Poverty Gap)

	Case 1: 3SLS for Poverty Gap (US$1.25)				**Case 2: 3SLS for Poverty Gap (US$2.00)**			
Conflict	Exogenous				Exogenous			
Inequality	Endogenous				Endogenous			
Openness	Endogenous				Endogenous			
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Poverty	Log GDP per capita	Inequality	Log Trade Share	poverty	Log GDP per capita	inequality	Log Trade Share
Conflict Intensity	**0.150****	**-0.0945****	-	-	0.0684	**-0.0900***	-	-

	(0.0763)	**(0.0464)**	-	-	(0.0469)	**(0.0461)**	-	-
Log Agricultural Value Added Per Worker (-1)	-	**0.311*****	-	-	-	**0.264*****	-	-
	-	**(0.102)**	-	-	-	**(0.102)**	-	-
Log Trade Share (-1)	-	**-2.207*****	-	-	-	**-2.248*****	-	-
	-	**(0.258)**	-	-	-	**(0.259)**	-	-
Export Price (excl. oil, food and gold)	**0.0151****	**0.00851***	-	-	**0.00659***	**0.00983***	-	-
	(0.00602)	**(0.00510)**	-	-	**(0.00368)**	**(0.00509)**	-	-
Inequality (-1)	**0.0451****	**-0.0372****	-	-	**0.0255****	**-0.0390*****	-	-
	(0.0211)	**(0.0149)**	-	-	**(0.0129)**	**(0.0149)**	-	-
Log GDP per capita (-1)	**-0.716*****	-	**-6.752*****	-	**-0.576*****	-	**-5.795*****	-
	(0.163)	-	**(0.954)**	-	**(0.0990)**	-	**(1.074)**	-
Log Poverty Gap US$1.25	-	-	**-1.385****	-	-	-	-	-
	-	-	**(0.566)**	-	-	-	-	-
Gini in Land Distribution	-	-	**41.85*****	-	-	-	**39.91*****	-
	-	-	**(6.232)**	-	-	-	**(5.969)**	-
Log [the inverse of physical isolation index] (-1)	-	-	-	**0.122***	-	-	-	**0.129***
	-	-	-	**(0.0700)**	-	-	-	**(0.0697)**
Log Poverty Gap US$2.00	-	-	-	-	-	-	-0.763	-
	-	-	-	-	-	-	(1.157)	-
Constant	0	0	67.83	3.718	3.746	15.55	0	4.337
	(0)	(0)	(5.728)	(0.303)	(1.168)	(1.541)	(0)	(0.333)
Observations	117	117	117	117	118	118	118	118
R-squared	0.775	0.724	0.553	0.808	0.899	0.715	0.632	0.808

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Significant coef.estimates and t values are shown in bold. Regional dummy variables have been included in the regressions, but not shown in the table.

Panel B (Poverty Headcount Ratio)

	Case 3: 3SLS for Poverty Headcount (US$1.25)				**Case 4: 3SLS for Poverty Head Count (US$2.00)**			
Conflict	Exogenous				Exogenous			
Inequality	Endogenous				Endogenous			
Openness	Endogenous				Endogenous			
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
VARIABLES	poverty	Log GDP per capita	inequality	Log Trade Share	poverty	Log GDP per capita	inequality	Log Trade Share
Conflict Intensity	0.0808	**-0.0891***	-	-	0.0138	0	-	-
	(0.0591)	**(0.0461)**	-	-	(0.0325)	(0.0463)	-	-
Log Agricultural Value Added Per Worker (-1)	-	**0.269*****	-	-	-	**0.226****	-	-
	-	**(0.102)**	-	-	-	**(0.103)**	-	-
Log Trade Share (-1)	-	**-2.263*****	-	-	-	**-2.296*****	-	-
	-	**(0.259)**	-	-	-	**(0.261)**	-	-
Export Price (excl. oil, food and gold)	0.00707	**0.0100****	-	-	-0.000293	**0.0110****	-	-
	(0.00464)	**(0.00509)**	-	-	(0.00255)	**(0.00512)**	-	-
Inequality (-1)	**0.0405****	**-0.0394*****	-	-	0.0170*	**-0.0383****	-	-

	(0.0162)	(0.0149)	-	-	(0.00923)	(0.0149)	-	-
Log GDP per capita (-1)	-0.687***	-	-5.742***	-	-0.479***	-	-1.658	-
	(0.125)	-	(1.082)	-	(0.0736)	-	(1.287)	-
Gini in Land Distribution	-	-	39.96***	-	-	-	39.27***	-
	-	-	(6.079)	-	-	-	(6.395)	-
Log [inverse of physical isolation index] (-1)	-	-	-	0.126*	-	-	-	0.130*
	-	-	-	(0.0697)	-	-	-	(0.0699)
Log Poverty Headcount US$1.25	-	-	-0.565	-	-	-	-	-
	-	-	(0.894)	-	-	-	-	-
Log Poverty Headcount US$2.00	-	-	-	-	-	-	6.605***	-
	-	-	-	-	-	-	(2.258)	-
Constant	3.244	15.58	0	4.334	5.947	15.90	12.54	4.338
	(1.471)	(1.541)	(0)	(0.333)	(0.846)	(1.547)	(17.17)	(0.333)
Observations	118	118	118	118	118	118	118	118
R-squared	0.888	0.712	0.634	0.808	0.94	0.704	0.553	0.808

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Significant coef.estimates and t values are shown in bold. Regional dummy variables have been included in the regressions, but not shown in the table.

Table 14 Determinants of the Long-term relationship among Inequality, Poverty and Income (with Institution) (Poverty Gap)

Panel A (Poverty Gap)

	Case 1: 3SLS for Poverty Gap (US$1.25)			Case 2: 3SLS for Poverty Gap (US$2.00)		
Conflict	Exogenous			Exogenous		
Inequality	Endogenous			Endogenous		
Openness	Exogenous			Exogenous		
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
	(1)	(2)	(3)	(5)	(6)	(7)
VARIABLES	Poverty	Log GDP per capita	Inequality	Poverty	Log GDP per capita	Inequality
Institutional Quality	-0.952***	0.552***	-	-0.520***	0.550***	-
	(0.229)	(0.0378)	-	(0.122)	(0.0376)	-
Log Agricultural Value Added Per Worker (-1)	-	0.414***	-	-	0.402***	-
	-	(0.0461)	-	-	(0.0463)	-
Log Trade Share (-1)	-	-0.181***	-	-	-0.189***	-
	-	(0.0355)	-	-	(0.0359)	-
Export Price (excl. oil, food and gold)	0.00328	0.00215	-	0.00211	0.00237	-
	(0.00725)	(0.00177)	-	(0.00385)	(0.00176)	-
Inequality (-1)	0.0617**	-0.0109*	-	0.0258**	-0.0118**	-
	(0.0248)	(0.00568)	-	(0.0132)	(0.00565)	-
Log GDP per capita (-1)	0.378	-	-7.535***	-0.169	-	-9.567***
	(0.318)	-	(1.440)	(0.173)	-	(1.741)
Log Poverty Gap US$1.25	-	-	-2.975***	-	-	-

	-	-	**(0.702)**	-	-	-
Gini in Land Distribution	-	-	**43.11*** **	-	-	**41.58*** **
	-	-	**(8.256)**	-	-	**(8.128)**
Log Poverty Gap US$2.00	-	-	-	-	-	**-5.756*** **
	-	-	-	-	-	**(1.381)**
Constant	-7.450	5.316	73.77	1.029	0	101.0
	(2.963)	(0.525)	(8.963)	(1.601)	(0)	(13.36)
Observations	75	75	75	76	76	76
R-squared	0.625	0.99	0.327	0.855	0.99	0.287

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Significant coef.estimates and t values are shown in bold.Regional dummy variables have been included in the regressions, but not shown in the table.

Panel B (Poverty Headcount Ratio)

	Case 3: 3SLS for Poverty Headcount (US$1.25)			**Case 4: 3SLS for Poverty Head Count (US$2.00)**		
Conflict	Exogenous			Exogenous		
Inequality	Endogenous			Endogenous		
Openness	Exogenous			Exogenous		
Regional Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	poverty	Log GDP per capita	inequality	Poverty	Log GDP per capita	Inequality
Institutional	**-0.674*** **	**0.551*** **	-	**-0.331*** **	**0.546*** **	-
Quality	**(0.156)**	**(0.0376)**	-	**(0.0760)**	**(0.0377)**	-
Log Agricultural Value Added Per Worker (-1)	-	**0.407*** **	-	-	**0.388*** **	-
	-	**(0.0461)**	-	-	**(0.0471)**	-
Log Trade Share (-1)	-	**-0.186*** **	-	-	**-0.198*** **	-
	-	**(0.0357)**	-	-	**(0.0370)**	-
Export Price (excl. oil, food and gold)	0.00163	0.00226	-	0.000972	0.00258	-
	(0.00495)	(0.00176)	-	(0.00236)	(0.00177)	-
Inequality (-1)	**0.0423** **	**-0.0113** **	-	0.0129	**-0.0129** **	-
	(0.0169)	**(0.00565)**	-	(0.00808)	**(0.00568)**	-
Log GDP per capita (-1)	-0.131	-	**-9.363*** **	**-0.375*** **	-	**-11.61*** **
	(0.221)	-	**(1.761)**	**(0.109)**	-	**(2.330)**
Gini in Land Distribution	-	-	**43.31*** **	-	-	**40.63*** **
	-	-	**(8.267)**	-	-	**(8.023)**
Log Poverty Headcount US$1.25	-	-	**-4.386*** **	-	-	-
	-	-	**(1.054)**	-	-	-
Log Poverty Headcount US$2.00	-	-	-	-	-	**-8.814*** **
	-	-	-	-	-	**(2.457)**
Constant	0	0	93.49	5.032	0	135.8
	(0)	(0)	(11.97)	(1.003)	(0)	(23.28)
Observations	76	76	76	76	76	76

R-squared	0.839	0.99	0.293	0.947	0.99	0.297

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Significant coef.estimates and t values are shown in bold. Regional dummy variables have been included in the regressions, but not shown in the table.

First, conflict intensity is found to be positively and significantly associated with poverty gap (US$1.25) (Case 1, Table 13), while the coefficient of macro institutional quality is negative and significant in all cases in Table 14. As expected, conflicts tend to hamper economic growth (Cases 1-3, Table 13) and better macro institutions promote growth (Cases 1-4, Table 14). In all cases in Tables 13 and 14, the lagged agricultural value added per capita tends to be associated with higher GDP per capita. Counterintuitively, the effect of trade share on GDP per capita is negative and significant, as in Imai et al. (2010). Whether the IV estimation of trade share could be better is subject to further investigation. Besides, in the absence of good quality institutions the potential positive effect of trade is largely undermined in all cases in Tables 13-14.

Consistent with Section III, higher degree of inequality is associated with lower levels of GDP per capita and higher levels of poverty with significant coefficient estimates in all cases in Tables 13-14 (except for poverty in Case 4 of Table 14). Lagged GDP per capita - which has been inserted in the inequality equation to capture the bi-causal relationship between inequality and income growth - is negatively and significantly associated with inequality in the current period. The bi-causal relationship between poverty and inequality has also been examined. The coefficient of poverty is negative and significant in the inequality equation, while lagged inequality has been found to be positive and significant in the poverty equation. The former is counterintuitive, but it should be noted that this negative relationship is conditional on (i) the positive association between lagged inequality and poverty (or GDP per capita) in the poverty equation, (ii) the negative correlation between GDP per capita and inequality in the income equation, and (iii) the positive correlation between land Gini and inequality in the inequality equation. If we estimate the inequality equation separately with the same covariates, poverty is found to be positively and significantly associated with inequality. The inverse of physical isolation index, as expected, has a positive and significant association with trade share, our proxy for the trade openness.

To summarise the key findings from Table 13 and 14:

(1) Higher income (log of GDP per capita) decreases poverty gap and poverty headcount ratio (these results are consistent with those in Section II).

(2) Conflict intensity has a negative effect on income.

(3) Institutions have a positive effect on income.

(4) Agricultural sector (proxised by lagged agricultural value added per worker) is important for economic growth.

(5) Higher price of export commodities tends to be related to higher level of poverty and lower level of income.

(6) Inequality has a negative and significant effect on income (which is consistent with the results in Section III). There is also a negative feedback effect from lagged income to inequality. That is, lagged income has a negative association with inequality.

(7) Instrumented lagged inequality increases poverty gap. However, instrumented poverty gap decreases inequality (after controlling for the strong positive effect of land Gini (an instrument) on inequality).

V. Concluding Observations

Our analysis points to a drastic shift away from rural-urban migration and urbanisation as main drivers of growth and elimination of extreme poverty, and towards revival of agriculture in the post-2015 policy agenda.

Drawing upon cross-country panel data for developing countries, the present study sheds new empirical light on the dynamic and long-term linkages among growth, inequality and poverty in developing countries. The main findings are summarised below from a policy perspective.

First, agricultural growth is found to be the most important factor in reducing inequality and poverty - measured in terms of poverty headcount ratio and poverty gap. This involves both direct effects of agricultural growth on poverty or inequality and the indirect effect realised through non-agricultural sector growth. In general, the strong growth linkages between agricultural sector and non-agricultural sector are significant regardless of whether annual panel or three -year average panel is used.

Second, there is an overall significant and negative association between inequality and GDP per capita regardless of the specification, a relationship that has remained neglected in the recent literature *despite* growing concern about rising inequality. Similarly, much has been written about institutional reform but not backed with rigorous empirical research. Our finding therefore that better institutional quality weakens the negative association between inequality and GDP per capita is of considerable significance. Indeed, if there is any causality from inequality to economic growth, even in a country with a larger degree of income inequality, the dampening effect of inequality on economic growth will weaken if institutional quality is better.

Third, policies designed to prevent conflicts and their disruptive effects and violence, to stabilise commodity prices, and promote better institutions (proxied by the aggregate indicator of institutional quality encompassing rule of low, political stability, control of conflict, voice and accountability) are likely to accelerate growth and reduce poverty significantly.

Overemphatic endorsements of promoting rural-urban migration and concomitant shift of resources towards efficient urbanisation are robustly rejected by our analysis which reinforces the case for revival of agriculture. It continues to have strong linkages with the non-agricultural sector and has substantial potential for reducing inequality and poverty. More seriously, the lop-sided shift of emphasis to urbanisation rests on not just shaky empirical foundations but could mislead policy makers and donors. Those left behind in rural areas - especially the poor - deserve better and more resources to augment labour productivity in agriculture which on our evidence would speed up overall growth, curb rising inequality and eliminate worst forms of deprivation in the post-2015 scenario. It is conjectured that this may even be more cost-effective than the urbanisation strategy.

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Appendix 1: Technical Details of MG and CCEMG models

The main purpose of both MG (Mean Group) and CCEMG (Common Correlated Effects Mean Group) estimators is to model explicitly the country-level heterogeneity in estimating the relationship between the agricultural/non-agricultural growth and inequality change in case of Section II, or between the inequality and the log of GDP per capita in case of Section III. Appendix 1 provides a few intuitive explanations as well as technical details.

The well-known attractiveness of the static panel data model using the fixed-effects estimator – for instance, using the cross-country panel regression - is to take account of the county-fixed effects as an unobservable term. This unobservable term could include the country's specific shocks or the cultural/social factor (not captured by the observable data). However, in the fixed effects model, the unobservable term is fixed over time and there is no correlation among the unobservable terms. Given that the cultural factor could change and the idiosyncratic shock could be influenced by the common shock, this may be an unrealistic assumption. CCEMG model aims to relax these assumptions. Also, both MG and CCEMG estimators enable us to derive the estimate at the country level after taking account of the panel feature of the model (and cross-sectional dependence of unobservables in case of CCEMG model).

The MG model or CCEMG model can be laid out as follows.[46] [47] Let us assume the following simple model for i=1,..., N (or 119) (countries), t=1 (for the year 1970),..., 29 (for 2008) (years), and T is the maximum number in t (that is, 29).

$y_{it} = x_{it}\, b^1{}_i + b^2{}_i\, t/T + u_{it}$ (A1)

$u_{it} = a_i^1 + \lambda_i f_t + \varepsilon_{it}$ (A2)

[46]The presentation is based on Eberhardt (2011).

[47] The following specification corresponds to the model we use in Section III, but this can be extended to the model in Section II straight forwardly.

$x_{it} = a_i^2 + \lambda_i f_t + \gamma_i g_t + e_{it}$ (A3)

where y_{it} is log GDP per capita for the i^{th} country in year, t, and x_{it} is a vector of explanatory variables, namely, log of investment and inequality.[48] $b^1{}_i$ is the country-specific coefficient estimates of x_{it} and u_{it} consist of the unobservables and the error terms e_{it}. t/T is the trend term specific to each country and $b^2{}_i$ is the country-specific coefficient.The unobservables in (A2) are made up of standard country-specific fixed effects a_i^1, which capture time-invariant heterogeneity across groups, as well as an unobserved common factor f_t with heterogeneous factor loadings λ_i, which captures time-variant heterogeneity and cross-section dependence. g_t is also meant to capture time-variant unobserved common factor associated with x_{it} where $\gamma_i g_t$ as a whole is a residual term in the heterogeneous component $(\lambda_i f_t + \gamma_i g_t)$ in the equation (A3). In this setting, the factors f_t and g_t are not limited to linear evolution over time and they can be nonlinear and nonstationary and y_{it} and x_{it} can be cointegrated.

Both MG and CCEMG estimators follow the common methodologies 1 and 2 with differences explained below.

1. Estimate N country-specific ordinary least-squares regressions.
2. Average the estimated coefficients across countries.

The Pesaran and Smith (1995) MG estimator does not concern itself with cross-section dependence and assumes away $\lambda_i f_t$ or models these unobservables with a linear trend. Thus (A1) is estimated for each country i, including an intercept to capture fixed effects and a linear trend to capture time-variant unobservables. The estimated coefficients b_i are averaged across countries.

[48] In the context of our econometric specification in Section II, y_{it} is inequality for the i^{th} country in year, t, and x_{it} is a vector of explanatory variables, namely, predicted terms of agricultural growth and non-agricultural growth.

On the other hand, the Pesaran (2006) CCEMG estimator allows for the empirical setup as laid out in (A1), (A2), and (A3). The empirical setup induces cross-section dependence and time-variant unobservables with heterogeneous impact across panel members, and problems of identification. The CCEMG model introduces the cross-section averages of the dependent and independent variables, $\bar{y}_t$ and $\bar{x}_t$, as additional regressors. The combination of $\bar{y}_t$ and $\bar{x}_t$ can account for the unobserved common factor f_t. Given the country-specific estimation, the heterogeneous impact (λ_i) is also given. The coefficients b_i are averaged across panel members. The CCEMG model takes the general form to consider cross-section dependence and time-variant unobservables with heterogeneous impact across panel members. However, it is assumed that in both MG and CCEMG (as well as fixed or random effects models) x_{it} is exogenous and we have thus estimated the panel instrumental variable (IV) model to address the endogeneity of inequality as well as institution in the model.

Because of the above settings of the model, in the context of this study, we can interpret the coefficient estimate for $b^1{}_i$ as the long term effect of x_{it} (inequality) on y_{it} (log of GDP per capita)[49] after taking account of (i) the time variant country's observables, and (ii) their interdependence across countries, and we focus only on $b^1{}_i$ in Section III. The main reason for applying CCEMG model in this paper is to derive the country level estimates of $b^1{}_i$ (as summarised in Appendix 2 and Appendix 3) after taking account of the common shocks, the country's differential response to common shocks (through the unobservable term) and the correlation among different responses, as an extension of the fixed effects model. We have then estimated the saved coefficient for $b^1{}_i$ or $\hat{b}^1{}_i$ for each country by some exogenous variables to see what sort of underlying factors would be correlated with the long- term relationship between

[49] In the context of Section II, we can interpret the coefficient estimate for $b^1{}_i$ as the long term effect of x_{it} (agricultural growth or non-agricultural growth) on y_{it} (change in inequality).

inequality and log of GDP per capita in Section III. This is not feasible with the standard static panel data approach, such as, fixed-effects or random effects model. [50]

Appendix 2: Relationship between agricultural or non-agricultural growth and inequality at Country level:based on Pesaran's (2006) CCEMG Estimator

	Country level coef. Estimate for the effect of predicted agricultural growth on inequality based on Pesaran (2006)	Country level t value for agricultural growth predicted agricultural growth on inequality based on Pesaran (2006)	Country level coef. Estimate for non-agricultural growth predicted non-agricultural growth on inequality based on Pesaran (2006)	Country level t value for non-agricultural growth predicted non-agricultural growth on inequality based on Pesaran (2006)
Albania	-63.29816	-1.38	-136.8157	-1.58
Algeria	3.582947	0.35	23.03751	0.63
Argentina	6.910185	0.88	-24.99267	-3.73
Bangladesh	-1.235037	-0.07	**29.31191**	**2.07**
Bolivia	7.825085	0.46	8.53896	0.61
Brazil	-3.652458	-0.4	**24.52468**	**2.14**
Bulgaria	-1.519614	-0.21	-9.225243	-0.69
Cameroon	18.87179	1.24	-25.03898	-1.17
Chile	**32.26959**	**1.73**	-1.637774	-0.1
China	-16.67909	-0.44	-29.75108	-0.58
Colombia	-1.488674	-0.28	-11.9226	-1.58
Congo, Rep.	11.08399	0.15	-21.14319	-0.86
Cote d'Ivoire	-3.750939	-0.15	57.34062	1.14
Ecuador	-9.201074	-0.6	-21.43253	-1.35
Egypt, Arab Rep.	-14.04027	-0.63	-2.87126	-0.21
Guatemala	-19.0317	-0.52	0.9144737	0.05
Hungary	**-13.29332**	**-2.67**	**-27.88665**	**-2.53**
India	-3.148784	-0.56	-5.96426	-0.69
Indonesia	-12.88498	-0.48	-14.80075	-1.05
Iran, Islamic Rep.	3.165309	0.16	-4.870389	-0.54
Jordan	**-11.95975**	**-3.08**	-12.71548	-1.24
Kyrgyz Republic	3.925209	0.32	1.342802	0.1
Lithuania	-27.5554	-0.92	6.147157	0.34
Malaysia	-9.53069	-1.02	**-32.03053**	**-1.7**
Mauritania	**-30.94634**	**-3.55**	**-35.05415**	**-4.06**
Mexico	**9.22422**	**9.23**	**13.29457**	**6.5**
Moldova	-6.436534	-1.08	-16.11591	-0.88
Pakistan	-4.430034	-0.76	**-48.72128**	**-2.27**
Peru	-65.36517	-1.06	-57.7382	-0.42
Philippines	-48.97319	-1.46	-78.21306	-2.32
Poland	-4.490306	-0.25	11.23592	0.92
Romania	-38.50922	-1.36	-54.79224	-0.89
Russian Federation	2.745336	0.34	0.6410077	0.03
Senegal	1.86316	0.18	-2.905575	-0.2
Serbia	-6.493667	-0.31	-0.9833378	-0.03
Slovenia	-4.677016	-0.55	14.77735	0.81

[50] Agricultural growth (or non-agricultural growth) and change in inequality in Section II.

South Africa	**31.36529**	**1.9**	55.12179	1.16
Thailand	**-26.9646**	**-2.02**	**-75.36897**	**-1.82**
Tunisia	-40.39556	-0.6	-29.31271	-0.43
Ukraine	-14.78166	-0.86	-13.29963	-0.28
Vietnam	**-22.45493**	**-1.61**	**-75.08415**	**-3.99**

Appendix 3 Inequality-Growth Relationship at Country level:based on Pesaran's (2006) CCEMG Estimator

Code	Country	coef_ineqd	tvalue_ineqd
1	Albania	-0.0088694	-3.31
2	Algeria	-0.0141526	-1
3	Angola	-0.0093809	-5.50E+04
4	Argentina	-0.0815859	-0.83
5	Armenia	0.0062734	0.89
6	Azerbaijan	-0.0118798	-1.39
7	Bangladesh	-0.0540867	-6.32
8	Belarus	0.0077529	0.2
9	Belize	0.0252448	0.51
10	Benin	0.1505211	8.80E+05
11	Bhutan	0.0388615	84412.77
12	Bolivia	-0.0514961	-4.89
13	Botswana	0.0435418	1.82
14	Brazil	0.0377963	1.93
15	Bulgaria	-0.0219889	-5.15
16	Burkina Faso	0.1044985	3.01
17	Burundi	0.1250423	4.17
18	Cambodia	0.0137127	6.52
19	Cameroon	0.0109249	2.07
20	Cape Verde	0	.
21	Central African Republic	-0.0403763	-3.59
22	Chad	0.4150496	2.10E+06
23	Chile	0.0036912	0.31
24	China	0.0158977	1.8
25	Colombia	-0.0075456	-0.73
26	Comoros	-0.0916214	-1.40E+06
27	Congo, Dem. Rep.	2.830062	5.00E+06
28	Congo, Rep.	-0.0880854	-2.93
29	Costa Rica	-0.0320816	-3.11
30	Cote d'Ivoire	-0.0137867	-1.59
31	Croatia	0.0339566	2.33
32	Czech Republic	-0.1042133	-10.53
33	Djibouti	-0.1743998	-1.20E+06
34	Ecuador	-0.0298906	-3.62
35	Egypt, Arab Rep.	-0.0024561	-0.8
36	El Salvador	-0.026584	-1.78
37	Estonia	-0.0457049	-4.18
38	Ethiopia	-0.109186	-3.48
39	Fiji	-0.0089919	-2.44
40	Gabon	0.0285315	0.54
41	Gambia, The	-0.0354041	-1.49
42	Georgia	-0.0171702	-1.41
43	Ghana	0.0275377	1.08
44	Guatemala	-0.0231876	-4.63
45	Guinea-Bissau	0.6854733	4.60E+05
46	Guinea	0.0006238	295.99

47	Guyana	0.0947276	62918.25
48	Haiti	-2.043867	-4.80E+04
49	Honduras	-0.0009072	-0.08
50	Hungary	-0.0395907	-3.58
51	India	-0.0449429	-8.17
52	Indonesia	0.0036456	0.29
53	Iran, Islamic Rep.	0.0261951	3.31
54	Iraq	0	.
55	Jamaica	-0.0028698	-0.35
56	Jordan	-0.0031337	-0.22
57	Kazakhstan	-0.0093078	-1.1
58	Kenya	0.0327996	1.54
59	Kyrgyz Republic	-0.0416496	-1.68
60	Lao PDR	0.3548072	2.00E+05
61	Latvia	-0.0567362	-6.64
62	Lesotho	-0.0199414	-2.56
63	Liberia	0.8647814	9.30E+05
64	Lithuania	-0.010567	-0.35
65	Madagascar	0.0572703	3.86
66	Malawi	-0.0586818	-6.22
67	Malaysia	-0.1677679	-6.88
68	Mali	-0.1256478	-4.50E+04
69	Mauritania	0.0233587	4.81
70	Mexico	0.0021599	0.08
71	Micronesia, Fed. Sts.	0	.
72	Moldova	-0.2576331	-1.58
73	Montenegro	0.075174	1.10E+05
74	Morocco	-0.0247796	-4.1
75	Mozambique	0.0167694	1.44
76	Namibia	0.1083704	1.10E+05
77	Nepal	0.0175517	0.82
78	Nicaragua	-0.118659	-2.57
79	Nigeria	-0.1151736	-5.40E+04
80	Niger	-0.6942689	-2.10E+04
81	Pakistan	-0.0005959	-0.25
82	Panama	-0.0078368	-0.94
83	Papua New Guinea	-0.0257283	-2.81
84	Paraguay	-0.02167	-1.32
85	Peru	-0.0144109	-1.86
86	Philippines	-0.0046607	-0.71
87	Poland	0.0564584	3.35
88	Romania	-0.0148153	-2.81
89	Russian Federation	-0.0196015	-1.11
90	Rwanda	-0.0089214	-0.5
91	Sao Tome and Principe	-0.1151736	-5.40E+04
92	Senegal	-0.0154116	-2.99
93	Serbia	0.0631042	0.84
94	Seychelles	0.0785366	2.11
95	Sierra Leone	0.5932819	2.00E+06
96	Slovak Republic	-0.0160093	-0.62
97	Slovenia	-0.1115548	-4.46
98	South Africa	0.1353692	3.78
99	Sri Lanka	-0.0020487	-0.25
100	St. Lucia	-0.2551016	-3.80E+05
101	Sudan	-0.0103549	-3.60E+04
102	Suriname	-0.0287039	-1.61
103	Swaziland	0.0313359	1.69

104	Syrian Arab Republic	-0.0390181	-3.26
105	Tajikistan	0.1289471	1.34
106	Tanzania	0.1164974	8.60E+05
107	Thailand	-0.0396426	-2.59
108	Timor-Leste	0	.
109	Togo	-0.0329159	-5.9
110	Trinidad and Tobago	0.039321	2.14
111	Tunisia	0.0102017	2.11
112	Turkmenistan	-0.1724302	-3.80E+04
113	Uganda	0.0154914	2.14
114	Ukraine	0.0182904	0.96
115	Uruguay	0.0155952	0.71
116	Venezuela, RB	-0.0038391	-0.49
117	Vietnam	0.0954324	7.25
118	Yemen, Rep.	-0.1424227	-3.68
119	Zambia	-0.01916	-0.61