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Abstract

Drawing upon cross-country panel data for developing countries, the present study sheds new empirical light on dynamic and long-term linkages among growth in agricultural and non-agricultural sectors, inequality and poverty. Agricultural growth is found to be the most important factor in reducing inequality and poverty. The role of agricultural growth in reducing inequality is undermined by ethnic fractionalisation which tends to make inequality more persistent. 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.

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

JEL Codes: C20, I15, I39, O13

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Dynamic and Long-term Linkages among Growth, Inequality and Poverty in Developing Countries

1. Introduction

The main objective 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 cross-country panel data for developing countries. Both poverty headcount ratios and poverty gaps will be used as measures of poverty. More broadly, we aim to re-establish the role of agricultural growth with cross-country data - mainly because recent studies by the World Bank (e.g. *The Global Monitoring Report* 2013 (World Bank, 2013a)) and others (e.g. Collier and Dercon, 2014) have questioned the primary role of agricultural growth in stimulating overall growth and alleviating poverty. As, in fact, a persuasive case for stimulating agricultural growth and poverty reduction was made by WDR (2008), it is necessary to examine it in light of more recent evidence. Given the primacy of elimination of extreme poverty by 2030, and the lively discourse on the post-2015 development agenda, a careful determination of sectoral growth priorities is imperative.

It is claimed by the World Bank (2013a) and Chandy et al. (2011) that MDG 1A[1] of halving extreme poverty by 2015 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.

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[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).

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.

World Bank (2013a) makes an important contribution to the discourse on MDGs by disaggregating progress into rural and urban components. 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.

World Bank (2013a) 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 "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.[2] 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 in, for instance, a recent study by Collier and Dercon (2014), among several others.

Collier and Dercon (2014) questions the importance assigned to promoting smallholder agriculture as an important pathway out of poverty and refute the argument of *WDR 2008* that stimulating agricultural growth is “vital for stimulating growth in other parts of the economy” and smallholders are at the core of this strategy (World Bank, 2007, p. xiii). Questioning that production and demand linkages are stronger from agriculture than any other sector, so that promoting growth in agriculture has the highest multiplier effects, they point out that the supporting evidence is far weaker than frequently suggested and causality of where growth is originating far from fully

[2] We offer an alternative perspective on the evidence cited in Collier and Dercon (2014), drawn from Tanzania on rural-urban migration and poverty outcomes.

established. Indeed, it is argued that growth dynamics in agriculture typically depend on growth in demand elsewhere in the economy (Gollin, 2010). Besides, importance assigned to agriculture depends on closed economy assumptions that are plausible for landlocked economies in Africa with difficult relations with their neighbours (a case in point is Ethiopia). Another related assertion is that future comparative advantage for natural resource rich or coastal economies is unlikely to imply that agricultural production will have to lead the growth process, let alone that it should be led by smallholders (Gollin, 2010). Furthermore, it would be hard to claim, according to Collier and Dercon (2014), that the current geographical spread of smallholder agriculture and food production is likely to be the optimal spread of agriculture in a globalizing world facing climate change. This is an extraordinary proposition as a prior question is optimal population size of a country.

For instance, recent evidence from Tanzania is cited by Collier and Dercon (2014) in support of promoting rural-urban migration as a means to closing the productivity gap and more rapid reduction in poverty. Collier and Dercon's (2014, p.97) comments on Table 1 in their paper are summarised as follows. First, overall poverty went down from 35 per cent to 27 per cent over the period. But if the survey had been using "standard" techniques, in which only households and individuals were traced in the original village (e.g., by homestead), then poverty declines would have been far lower, from 36 per cent to 32 per cent. Second, the farther someone had gone, the larger was the poverty decline. Those moving out of Kagera experienced the largest declines from 30 per cent to 7 per cent. Third, *ceteris paribus* migrants have 36 per cent higher consumption than similar non-migrants. The improvement in living standards of this previously largely rural- based population living off smallholder agriculture was not simply transmitted back into the smallholder economy—earnings seem to remain lagging with limited poverty reduction for those who did not manage to escape.

What are indeed striking are the low rates of migration to towns, and the small reduction in poverty among those left behind over a long period of 15 years - from 1991 to 2004. So the conclusion of Collier and Dercon (2014) of rural –urban migration as a key driver of reduction of extreme poverty is exaggerated and not tenable on their own evidence. Instead, greater investment in rural areas has the potential of more rapid reduction in poverty.

Another major issue glossed over by Collier and Dercon (2014) is the source of demand and smallholders' advantage in responding to it in a context of globalisation. If agriculture is incompletely tradable, growth in food production can help lower the domestic price of consumption goods and raise real incomes, which benefits the urban poor, landless rural workers, and the many net-buyers among smallholders. With increasing tradability of agriculture, productivity gains in agriculture are transmitted increasingly less via lower food prices, and increasingly more through higher employment and wages. Growth offers a multiplicity of pathways out of poverty depending on the sector where growth occurs and on the structure of production, in particular, asset distribution among producers and the labour intensity of production (de Janvry and Sadoulet, 2010). If agriculture remains neglected, labour, credit and land markets are imperfect, and the rural infrastructure is weak, then labour productivity will remain low and the gap in productivity vis-à-vis non-agriculture will remain large. The demise of smallholders in a context of globalisation is likely to be poverty increasing under such conditions. The evidence of lower profitability of smallholders - while the inverse size-productivity relation is largely intact - points to potential gains from policies guaranteeing easier access to markets for those smallholders (Fan et al. 2013).

As the food price surge in 2007-08 and again in 2010-11, and a continuing rise in the price of food suggests, the demand pressure to produce more food is likely to continue. This is in part reinforced by growing biofuel demand necessitating alternative uses of crops such as corn and acreage. So the demand for food will grow not just from within an economy but also from outside. What is also missing is the dietary transition that is underway (e.g. switch away from cereals towards fruits and vegetables, dairy products, meat, and edible oil) and associated with it emergence of high value chains that could enhance returns to smallholders conditional upon producers' associations and buyers helping them to upgrade the quality of their produce market it better (e.g. through contract farming).[3] The argument in favour of promoting smallholders because of its

[3] One of the main reasons emphasised by Collier and Dercon (2014) for the imminent demise of smallholders/small farmers is their lack of competiveness. Swinnen et al. (2010) offers a strong rebuttal on the basis of their own evidence from different regions and for different commodities, and evidence culled from other studies. An important contribution of this study is the elaboration of conditions under which smallholders have integrated into these high value chains and in disposing of certain misconceptions about their exclusion. Two contributory factors are: (i) the growth of demand for high value products in local markets, and (ii) increased exports of high-value commodities to high-income countries. Domestic consumption of high-value crops such as fruits and vegetables in developing countries increased by 200 per cent in the period 1980-2005, while consumption of cereals stagnated, while high-value food exports from developing countries increased by more than 300 per cent in the period 1980-2005 and now constitute more than 40 per cent of total developing country agri-food exports (World Bank, 2007). High-value food exports have promoted rural income mobility and poverty reduction among smallholder producers in these countries. The shift towards high-value agriculture is also accompanied by a significant transformation of the agri-food sector (Swinnen et al. 2010). This restructuring or "modernization" of the supply chain includes (i) the increasing number and stringency of food standards - both public and private - for quality and safety; (ii) a shift from a fragmented sector to consolidation in the chain (mostly at the level of processing, distribution and/or retail); (iii) a shift from spot market transactions in traditional wholesale markets to increasing levels of vertical coordination in the supply chain. These structural changes have important implications for the participation of small farmers and the distribution of the benefits.

poverty impact thus remains, even if nested within an overall growth strategy that makes agriculture important but not the key sector. Collier and Dercon (2014) point out that (i) productivity per worker outside agriculture is twice the productivity per worker in agriculture across all developing countries[4], (ii) agriculture is not the sector that most effectively will reduce poverty given a very low labour productivity, and (iii) the large gaps also suggest that the process of labour movement from activities with lower productivity to higher productivity is inadequate. So the most intuitive process of closing this gap would be to encourage more (labour) resources into the high return activities, taking away from the low return resources, as a means of bringing down this gap. Hence attention must shift to a process of *releasing* labour via migration. Growth in the rest of the economy can induce this movement, but it is also important to get labour markets further integrated so that labour productivity gains elsewhere are transmitted across the economy into the rural sector. But for the reasons stated and the evidence furnished on the competitiveness of smallholders in high value chains, shifting dietary preferences and persistence of poverty in rural areas, this conclusion is suspect.

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 (United

[4] In a rebuttal of an earlier comment by Collier (2008), Byerlee and de Janvry (2009) show that smallholders are in fact efficient commercial farmers under favourable circumstances. In India, for example, cereal yields are now 2.6 times as large as they were in the 1960s, with nearly 90 percent of the country's farmland controlled by farmers with less than 2.5 acres. Asia's smallholders now consume over half the world's fertilizers. Africa reflects governments' and donors' consistent bias against smallholders’ agriculture. When given the opportunity, smallholders in Africa have proved to be just as responsive to new technologies as their Asian counterparts (e.g. the adoption of hybrid maize in much of southern Africa, the dairy revolution in East Africa, and the increased production of cocoa, cassava, and cotton in West Africa). In contrast, large-scale farming in Africa frequently suffered from failed starts.

Nations, 2013), addressing inequality is not just a moral imperative but also a necessity for sustainable development[5]. 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 present study departs from the extant literature in the following two ways. First, as an extension of Christiaensen et al. (2011), we 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)[6]. We will 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 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.[7] In the first stage, we will estimate these dynamic

[5] 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).
[6] 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.
[7] See Christiaensen et al. (2011) and de Janvry and Sadoulet (2010) for more detailed discussions on the linkages between these sectors.

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.[8] 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 of 41 countries in the period 1970-2010. As an extension, we will also apply Pesaran's (2006) common correlated effects mean group (CCEMG) estimator to take account of the cross-country dependence of error terms. This model has an additional advantage to derive the time-series regression results for each country with the shocks common to all the countries.

The rest of the paper is structured as follows. Section 2 summarises the data sources and elaborates the econometric models we will employ. Regression results will be summarised in Section 3. The final section offers concluding remarks with policy implications.

[8] 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.

2. Data and Econometric Models

Despite the large body of literature demonstrating the role of agricultural growth in overall economic growth and poverty,[9] rigorous empirical analyses of the role of growth in *both* 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.[10] 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 (p.8). Using the household panel data 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 (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

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

[10] Haggblade et al. (2007) give evidence on multiplier effects of agricultural sector using an input-output model for developing countries.

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

2.1. Data

The data for the first set of analyses of the effects of agricultural and non-agricultural growth on inequality or poverty in Section 2 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 for the period 1970-2008 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 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 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 (e.g. incomplete credit and insurance markets in the latter). We have thus constructed an unbalanced panel data for inequality based on the EHII data covering a larger number of countries (86 countries) for a longer period (1970-2008). Beside, we have further expanded the EHII data on inequality by extending them with the World Bank data (World Bank, 2013b) on inequality (the Gini Index) on the PovcalNet, by estimating the EHII data on inequality by the World Bank data (World Bank 2013b) using Ordinary Least Squares and replacing the missing observations by the predicted values. With this method, we have managed to cover 119 countries, which include 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)). 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 period 1960 - 2006. GARCH (1, 1) method has been applied to capture the uncertainty of export commodities.

2.2. Econometric Models

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 respectively[11]), $\Delta Y^{NA}{}_{it}$ 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[12], 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

[11] 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.

[12] Here investment is based on the estimates 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.

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 social and cultural factors) and ε_{it} is an error term, independent, and identically distributed (or *i.i.d.*).

As an alternative to the standard first differencing approach[13] [14], 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. Here 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 (SGMM) 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

[13] 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). 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. It should also be noted that, as Hayakawa (2007) has shown by simulations for various cases (e.g. n=50), the possible biases for small sample are smaller with the SGMM estimator than with the GMM first-difference estimator. We have thus adopted the SGMM estimator to minimise the biases.

[14] 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. Considering 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.

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 $\boldsymbol{Z}_{it}$.[15] We have also included precipitation.[16]

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

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), in the second stage, we further estimated changes in inequality by non-agricultural growth and agricultural growth which were predicted in the second stage.

$$\Delta I_{it} = \gamma_0 + \gamma_1 \Delta I_{it-1} + \gamma_2 \widehat{\Delta Y^{A}}_{it} + \gamma_3 \widehat{\Delta Y^{NA}}_{it} + \boldsymbol{Z'}_{it} \cdot \gamma_4 + \eta'_i + \varepsilon'_{it} \tag{3}$$

where ΔI_{it} is the first difference of the inequality measure, based on the EHII data, which is estimated by its first lag, the predicted values of agricultural and non-agricultural

[15] 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 the proxy.

[16] 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).

growth ($\widehat{\Delta Y^A}_{it}$ and $\widehat{\Delta Y^{NA}}$) as well as a vector of endogenous variables, $\boldsymbol{Z'}_{it}$, such as, log of schooling years and political stability which is taken from the World Bank's World Governance Indicators. This is estimated by the Blundell-Bond system GMM estimator with the finite-sample correction. As an extension, the equation is estimated by the fixed effects model with the robust estimator for the full sample as well as for the middle or low income countries.[17]

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. 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* (number of years) and *i* (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 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. As a

[17] Estimating system GMM is not feasible for sub-samples as the number of observations becomes too small.

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.

$$P_{it} = \gamma'_0 + \gamma'_1 \widehat{\Delta Y^A}_{it} + \gamma'_2 \widehat{\Delta Y^{NA}}_{it} + \boldsymbol{Z}'_{it} \cdot {}'\gamma_3 + \eta''_i + \varepsilon''_{it} \qquad (4)$$

Finally, poverty head count ratio or poverty gap based on either US$1.25 or US$2 poverty line is estimated by $\widehat{\Delta Y^A}_{it}$ and $\widehat{\Delta Y^{NA}}_{it}$ using the robust fixed effects model to examine the relationship between agricultural or non-agricultural growth and poverty. Because the international poverty data are available only for a limited number of years, we are unable to take the first difference of poverty, or to estimate the dynamic panel model with lagged dependent variables.

3. Econometric Results

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)[18]. Additional explanatory variables, such as log of schooling years or log of investment, are added in the second case.

[18] Inclusion of mining share follows Christiaensen et al. (2011).

[Table 1 to be inserted]

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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 the 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-agricultural growth as reflected in the positive coefficient estimate of the lagged dependent variable and 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,[19] 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 as middle income country or low income country) 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 interaction of the SSA dummy variable and agricultural growth, but it is statistically insignificant, as in their paper.

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

[19] 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.

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.[20]

[Table 2 to be inserted]

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 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.

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 sectors and change in inequality

[20] As an extension we have tried the cases with the demographic structure (proxied by population share below 15 years and that above 65 years) 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.

over time. Focusing on Case 1 of Table 3, 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.[21] The results based on the fixed effect model[22] - in which the persistent effect of inequality change is omitted[23] - 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.

[21] 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).

[22] The Hausman test favours fixed effect model 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.

[23] 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.

For instance, it can be inferred from Case 7 that, if agricultural growth increases by 1%, *the change* in inequality decreases by 61% on average, *ceteris paribus.* This is a substantial effect in terms of pace of inequality change. Such a strong effect is not observed for non-agricultural growth.[24]

[Table 3 to be inserted]

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).

[Table 4 to be inserted]

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

[24] This reflects our semi-log specification where inequality change (dependent variable) is change in percentage points 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.

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. Indeed, 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 so, 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.

Using 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) (Table 5). First, if a country is more ethnically fractionalised,[25] it tends to

[25]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.

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 agriculture in reducing accentuation of inequality is likely to be undermined by ethnic fractionalisation which tends to make (economic) inequality more persistent. Second, 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 growth in both agricultural and non-agricultural sectors. South Asian countries also tend to have slow changes as a result of agricultural growth.

[Table 5 to be inserted]

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)[26]. 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[27] and use only predicted values of agricultural or non-agricultural

[26] If we use the first difference in poverty, the number of observations will be reduced significantly due to missing observations.

[27] The Hausman test results favour fixed effects model over random effects model.

growth (based on Case 2 in Table 1 and Case 2 in Table 2) without adding further control variables.[28]

[Table 6 to be inserted]

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.

[28] 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. Neither did Christiansen et al. (2011) in their poverty regressions.

4. Concluding Observations

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. Using econometric models, we have analysed 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 annual data as well as three-year averages. The main findings are summarised below from a policy perspective.

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. ~~S~~uch 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. That is, the role of agricultural sector reducing accentuation of inequality is likely to be undermined by ethnic fractionalisation which tends to make inequality more persistent.

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

Recent research has questioned the key roles of agricultural growth and of smallholders in particular. We are sceptical of these views as we find them ill-informed and potentially misleading.

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. Agricultural sector 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 to 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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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						
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(14 3)
	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**

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)	(0.0018)	(0.00105)	(0.00090 2)
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
	(0.00362)	(0.0614)	(0.00380)	(0.0038)	(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.

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		
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

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)	(0.0033)	(0.00256)	(0.00161)	(0.00288)
Log Schooling Years (-1) [Endogenous]	-	0.0104	-	0.00559	-	**0.0143****	**0.0143****

	-	(0.00652)	-	(0.0084)	-	**(0.00659)**	**(0.00610)**
Log Inequality [Endogenous]	-	**0.00193****	-	**0.00196***	-	0.000448	0.000433
	-	**(0.000906)**	-	**(0.001)**	-	(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***	0.004***	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.

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 [Predicted]	-5.468	-4.784	-2.89	2.878
	(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.

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) SGMM (Dynamic Panel		Fixed Effects Model (Robust Estimators)		MG Estimator Pesaran & Smith (1995)	CCEMG estimator Pesaran (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	-	-	-	-	-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 per capita [Predicted]_avg	-	-	-	-	-	4.449
	-	-	-	-	-	(9.730)
Constant	0.360	1.328	0.331	-1.169	0.613	0.14
	(0.113)	(0.853)	(0.079)	(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	-	-	-	-

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	-	-	-	-

Panel C: Annual Data, After 2000

VARIABLES	Case 13	Case 14	Case 15	Case 16	Case 17	Case 18
	Blundell and Bond (1998) SGMM (Dynamic Panel		Fixed Effects Model (Robust Estimators)		MG Estimator Pesaran& Smith (1995)	CCEMG estimator Pesaran (2006)
D.Inequality (-1)	**-0.130***	-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.

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)
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.

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 Countries		Low Income 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.