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Abstract

Drawing upon cross-country panel data for developing countries, the present study examines the role of agricultural growth in reducing inequality and poverty by modelling the dynamic linkage between agricultural and non-agricultural sectors. For this purpose, we have compared the role of agricultural growth and that of non-agricultural growth and have found that agricultural growth is more important in reducing poverty, while the negative effect of agricultural growth on inequality is found in a few models where specific definitions of inequality are adopted. The role of agricultural growth in reducing inequality is, however, undermined by ethnic fractionalisation which tends to make inequality more persistent. Our analysis generally reinforces the case for revival of agriculture in the post-2015 discourse, contrary to the much emphasised roles of rural-urban migration and urbanisation as main drivers of growth and elimination of extreme poverty.

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

JEL Codes: C20, I15, I39, O13

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Does Agricultural Growth Reduce Inequality and Poverty in Developing Countries?

1. Introduction

The main objective of this study is to examine the role of agricultural growth in reducing inequality and poverty using cross-country panel data for developing countries. To achieve this objective, we compare the roles of agricultural growth and non-agricultural growth in poverty and inequality reduction by modelling the linkage between agricultural and non-agricultural sectors. Both poverty headcount ratios and poverty gaps are used as measures of poverty. More broadly, we aim to re-establish the role of agricultural growth - mainly because recent studies by the World Bank (e.g. *The Global Monitoring Report* 2013 (World Bank, 2013)) and others have questioned the primacy of agricultural growth in stimulating overall growth and reduction of poverty.[1] As a persuasive case for stimulating agricultural growth and poverty reduction was made by *World Development Report* 2008 (World Bank, 2007), it is necessary to examine it in light of more recent evidence. Given the goal 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 (2013) and Chandy et al. (2011), among others, that the Millennium Development Goal (MDG) 1A[2] of halving extreme poverty by 2015 was achieved in

[1] In this context Collier and Dercon (2014) have questioned the role of smallholders in African development. Because of the data limitation, the present study focuses on the growth of *overall* agricultural sector growth - rather than the growth originating from smallholders - on poverty and inequality.

[2] 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). This has led to Sustainable Development Goal (SDG) is "By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day" (https://sustainabledevelopment.un.org/sdg1).

2010 – five 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 was expected not to achieve MDG 1A by 2015. It should also be noted that 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 (2013) also 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 remained in extreme poverty in 2015 into those who were in rural and urban areas, respectively. This is crucial for designing appropriate policy interventions for rural and urban areas.

World Bank (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 "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 of those who stay 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).

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 Nations, 2013), addressing inequality is not just a moral imperative but 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 lies 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 equity and poverty. Both poverty and inequality reduction are clearly featured in the Sustainable

[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.8).

Development Goals (SDGs), or the 2030 Agenda for Sustainable Development, which were agreed at United Nations Sustainable Development Summit 2015 in September 2015.

The present study departs from the extant literature in the following ways. First, as an extension of Christiaensen et al. (2011), we will estimate the 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]. 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 of both sectors. 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.[5] Second, we will 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 advantage in obtaining the time-series regression estimate for each country with the shocks common to all the countries. Third, we will estimate the effects of agricultural and non-agricultural growth terms as predictions of the dynamic panel model on inequality and poverty. This focuses on the dynamic role of agricultural growth -in comparison with that of non-agricultural growth - in reducing not

[4] It is referred to as system generalized method of moments (SGMM) estimator which enables us to model the dynamics of agricultural growth and non-agricultural growth over time.
[5] See Christiaensen et al. (2011) and de Janvry and Sadoulet (2010) for more detailed discussions on the linkages between these sectors.

only poverty, but also inequality. We have thus extended Christiaensen et al. (2011) by using different models and more recent data, including the comprehensive data on inequality.

The rest of the paper is structured as follows. After briefly reviewing the literature in Section 2, we summarises the data sources in Section 3. Section 4 elaborates the econometric models we will employ. Regression results are discussed in Section 5. Section 6 offers concluding remarks with policy implications.

2. The Literature Review

Despite the large body of literature demonstrating the role of agricultural growth in overall economic growth and poverty,[6] 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.[7] 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

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

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

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 model 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 agricultural growth (or non-agricultural growth) over time. Their estimation strategy (SGMM) 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.

3. 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, 2013 and 2014 (e.g. World Bank, 2014). 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). We have derived the simple average of four indicators, voice and accountability, political stability and absence of violence, rule of law and control of corruption to capture the overall quality of institutions. While Christiaensen et al. (2011) uses the three year averaged data over the period 1960–2005 for a sample of 85 countries and 588 observations in their main specification (the columns (1) of Table 3 in Christiaensen et al.), the present study covers the period 1969-2010 for 59 countries and 532 observations (Case 1, Table 1). The list of countries is given in Appendix 1. The difference is due to the fact that we have updated the data and have used a different set of explanatory variables.

We will adopt three kinds of inequality measures. First, 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 - derived from the relationship between UTIP-UNIDO, other conditioning variables, and the World Bank's Deininger and Squire data set. This is taken from the University of Texas Inequality Project (http://utip.gov.utexas.edu/data.html). Herzer and Vollmer (2012) selected 46 countries for the period 1970-2008 to minimise the problem of missing observations given that they apply the panel co-integration method. The EHII dataset 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). Besides, we have further expanded the EHII data on inequality by supplementing them with the World Bank data (World Bank, 2014) on inequality (the Gini Index) on the PovcalNet, by estimating the EHII data on inequality by the World Bank data (World Bank 2014) using Ordinary Least Squares and replacing the missing observations by the 'out-of-sample' predictions. With this method, we have managed to cover 119 countries, including 49 countries[8] in the first set of analyses.[9] 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)). While the UTIP-UNIDO dataset on pay inequality is based on global pay inequality data, Galbraith and Kum (2005) have shown that this is highly correlated with the Deininger and Squire's (1996) Gini measure of inequality and it is thus reasonable to assume that the EHII dataset is one of the best data sources for inequality analyses of developing countries in terms of its coverage of countries. In our case coefficient of correlation between the EHII data on inequality and the Gini coefficient is 0.723. However, the limitation of the EHII dataset should be noted as it does not cover self-employment data or the agricultural wage data and may be a poor proxy for inequality of low income countries relying on agricultural sectors. Second, given the limitations of the EHII dataset, we will also use the World Bank's Gini index. While this is widely used, a major limitation of the Gini index in our study context is that the coverage of countries/years is highly limited. We cannot thus apply Pesaran's CCEMG model. Third, we will also use the 'raw' EHII data of inequality without aforementioned adjustment. In this case the coverage of years/countries is also limited. Although

[8] The number of countries varies from 40 to 49 depending on which specification we use for the inequality estimation.
[9] Descriptive statistics are found in Appendix 2.

each indicator has its own limitations, we will apply these three measures in our empirical analyses.

4. 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 (3- year averages, that is, from 1969-72, 73-75,…, 2008-2010)[10], $\Delta Y^{NA}{}_{it}$ is the first difference in log of 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 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 log of investment[11], and log of schooling years (first lag). While we will examine the effects of predicted agricultural and non-agricultural growth on inequality in the second stage, we will

[10] Our use of 3 years average panel data follows Christiaensen et al. (2011). We have also used annual panel data. Our discussions are mainly based on the results of 3 years average panel as the results based on annual panel data tend to be influenced by business cycle and short-term fluctuations or shocks, which may not have an immediate impact on inequality or poverty. However, we will also report the results based on the annual data set selectively, as it would enable us to explore the time-series association between agricultural or non-agricultural growth and inequality based on Pesaran's (2006) common correlated effects mean group estimator. This will be discussed later in this section.

[11] Here investment is based on the estimates of physical capital formation in World Development Indicators 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.

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 (e.g. 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[12 13], 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 instrumental 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 is used in the present study. This estimator is useful to address the

[12] 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.

[13] 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 justify 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 over-identifying restrictions are valid in some cases (i.e., Cases 1, 3, 4, 5 and 6 of Table 1, Case 5 of Table 3, and Cases 1 and 7 of Table 4) and the results in these cases should be interpreted with caution. Over-identifying restrictions are deemed valid in other cases (i.e., Case 2 of Table 1, all the cases of Table 2, Cases 1, 2, 3, 4, and 6 of Table 3, and Cases 2 and 8 of Table 4). Using different specifications (e.g. including external instruments, treating $\boldsymbol{Z}_{it}$ as exogenous) does not overcome this difficulty.

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 $\boldsymbol{Z}_{it}$.[14] We have included precipitation.[15]

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

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

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

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

[14] 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 World Development Indicators 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.

[15] The case with precipitation is shown only for low income countries because it yielded insignificant or counter-intuitive results in other cases. Including precipitation will not change the results significantly.

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. The equation is estimated by the fixed effects model with the robust estimator for the Gini coefficient due to small sample size.

While the determinants of inequality or its changes have been analysed theoretically as well as empirically in the macro and development economics literature, there is no single consensus, as far as we aware, as to what sort of models should be used for inequality or its change. The earlier theoretical literature draws upon Kuznets's (1955, 1963) hypothesis of the inverted U relation between inequality and GDP per capita. Under the hypothesis, at the initial stage of development, inequality increases as GDP per capita increases, for instance, as (i) the rural-urban inequality gap as well as (ii) the inequality within the urban sector increases. This is caused by rural-to-urban migration as urban areas are industrialised, while urban wage workers' pay rise does not match the increase in profits of capital owners. While the agricultural sector features low per capita income and relatively little inequality within the sector (Barro, 2000), in the process of development, the inequality within rural sector may increase while the agricultural sector reduces its size, in which only a subset of households are likely to benefit from mechanisation and/or rural-to-urban migration. Under these circumstances, both agricultural and non-agricultural growth is likely to increase inequality at the early stage of development. However, inequality is supposed to decrease after a significant number of people benefit from industrialization.[16] More recently, Acemoglu and Robinson (2002) proposed a political economy

[16] While the empirical literature on Kuznets hypothesis typically tests signs of a square and a cube of GDP per capita to examine the inverted U relationship between inequality and GDP per capita, we do not include these terms as this is not our primary objective. In most specifications, squared agricultural and non-agricultural terms are found to be statistically insignificant.

model of the Kuznets Curve where they emphasised the role of political stability and democratisation, leading to institutional changes and thus redistribution. In Barro's (2000) specification for inequality, he controlled for not only log GDP per capita, but also schooling and political and institutional indices. On the other hand, Bourguignon and Morrisson (1998) modelled the inequality being determined by the relative labour productivity of non-agricultural and agricultural sectors. Our empirical specification draws upon Bourguignon and Morrisson (1998) as well as Barro (2000), but we have adopted a simplified version as Equation (3) guided by the data availability.[17]

As an extension, we have also applied Pesaran's (2006) common correlated effects mean group (CCEMG) estimator. This estimator enables us to model the country-level heterogeneity in estimating the relationship between inequality change and agricultural/non-agricultural growth. It also corrects for the cross-sectional correlations of unobservable factors that 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) and we have thus applied this model only for the annual panel data in the case we use the expanded EHII data on inequality. Another useful feature of CCEMG model 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 provides us with the coefficient estimate for each country to

[17] Ideally, we should model the effect of sectoral growth on sectoral inequality, that is, inequality within agricultural or non-agricultural sector (or rural or urban sector) in Equation (3). However, we use an aggregate inequality of the country (I_{it}) as such data are not available.

show how the linkages between inequality change and agricultural (or non-agricultural) growth differ across countries. We then apply OLS to estimate the underlying determinants for them by simply regressing the saved coefficient on exogenous variables. 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 that 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.

5. Econometric Results

Tables 1 and 2 report the estimation results of equations (1) and (2) for three-year average panel for three cases – (i) a full sample, (ii) middle income countries and (iii) low income countries.[18] For each case, two sets of results are shown. The first case is the parsimonious case with only 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

[18] If we use the annual panel, we find that (i) agricultural growth is significantly associated with non-agricultural growth in all the cases with elasticity ranging from 0.10 to 0.16; (ii) the lagged dependent variable is statistically significant only for low income countries; and (iii) inequality is not associated with non-agricultural growth. These results will be furnished on request.

industry (the second lag)[19]. Additional explanatory variables, such as log of schooling years or log of investment, are added in the second case.

[Table 1 to be inserted]

. Table 1 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 to the middle income category, the nature of agriculture typically changes from subsistence-oriented farming to more commercialised and market farming and it has a closer linkage with non-agricultural sector. The elasticity estimates of non-agricultural growth rate with respect to agricultural growth rate range 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) would 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.[20]

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, investment growth, schooling years,

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

[20] This may be because we have used a more recent sample comprising a different set of countries. We have tried the same regressions by restricting them to the period before 2005. Consistent with Christiaensen et al. (2011), the coefficient of agricultural growth on non-agricultural growth becomes statistically insignificant in all cases.

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.[21] We will use Case 2 to examine the linkages between agricultural and non-agricultural growth and inequality change in Table 3.[22]

In Table 2 we estimate the effect of non-agricultural growth on agricultural growth. Table 2 reports positive and significant coefficient estimates of lagged growth in non-agricultural value added on growth of agricultural value added in Case 1 based on a full sample and Case 3 for middle income countries.[23] However, it is negative and significant in Cases 6A and 6B for low income countries. A lagged dependent variable is positive with significant estimates observed only for low income countries. The share of mining sector is negative for the full sample, with the coefficient estimate significant only in Case 2. This result could be related to the large literature on the Dutch Disease where, for instance, Nigerian cocoa farmers uprooted cacao plants following the petroleum boom in the 1970s (Roemer, 1985). It is, however, positive and significant for low income countries (in Cases 6A and 6B) and negative and insignificant for middle income countries. The positive effect could reflect positive externalities from the mining sector to agricultural sector (e.g. better roads, power supply), while the negative effect could be due to displacement of the agricultural sector by the mining sector. Human capital enhances

[21] 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. Overall, at the earlier stage of development, rural society is homogeneous with less degree of inequality, but inequality will expand as the country grows at certain threshold (Kuznets, 1955, 1963).

[22] The choice of Case 2 is guided by the specification test results showing that there is no second order serial correlation and that over-identifying restrictions are valid.

[23] These results will be unchanged if we run the same regression using the sample before 2005.

agricultural growth. Inequality is not associated with agricultural growth dynamically. Precipitation enhances agricultural growth in low income countries.[24] It can be inferred through the comparison of Case 1 of Table 1 and Case 1 of Table 2 that agricultural growth generates spillovers (0.22) twice as large as those of non-agricultural growth (0.11).

[Table 2 to be inserted]

Using Case 2 (a full sample with control variables) of Tables 1 and 2, we have obtained predicted values of agricultural and non-agricultural growth. We have then applied Blundell and Bond's (1998) SGMM model where a dependent variable is the change in inequality. Three panels (Cases 1-2, 3-4 and 5-6) in Table 3 report the results based on the expanded EHII data on inequality covering the largest number and years of countries, the Gini coefficient, and the raw EHII data on inequality, respectively. Here our main focus is on the dynamic linkages between growth in agricultural and non-agricultural sectors and change in inequality over time.

Reflecting the differences in coverage of countries as well as in definition of inequality, the results vary in these three panels. In Case 1 of Table 3, agricultural growth is negatively and significantly associated with inequality change and its (absolute) effect is generally larger than that 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

[24] When we use the annual panel data, we find significant coefficient estimates of growth of non-agricultural value added per capita in all the cases, with a larger coefficient estimate for low income countries. Based on a full sample, we find that the mining share is positive and significant. Inequality (treated endogenous) is positively and significantly associated with agricultural growth dynamically. Precipitation is statistically insignificant.

ceases to be statistically significant in Case 2 with a few control variables (education and political stability) and non-agricultural growth becomes statistically significant.[25]

[Table 3 to be inserted]

In Cases 3 and 4 of Table 3, neither agricultural nor non-agricultural growth is significant in which the change in the Gini coefficient is a dependent variable. We observe a strong persistence in the change in the Gini coefficient in Cases 3 and 4. So in these cases agricultural and non-agricultural growth do not affect inequality changes. In Cases 5 and 6, the raw EHII data are used for the measure of inequality and the dynamic model is applied. In these cases agricultural growth is not statistically significant, while non-agricultural growth is negative and significant in Case 6 where schooling and political stability are added as control variables. This is consistent with the inequality reducing effect of non-agricultural growth which we have found in Case 2. While the results vary depending on the specifications, agricultural growth has an inequality-reducing effect in the case without controlling for schooling years and political stability. Once we control for these variables, non-agricultural sector has some inequality-reducing effect.

In Table 4 we use the annual panel data to estimate the effects of agricultural growth and non-agricultural growth on inequality. Three measures of inequality are used as a dependent variable in three panels - the first difference in inequality based on the expanded EHII data (Cases 1-4), the Gini coefficient (Cases 5-6), and inequality based on the raw EHII data (Cases 7-8). In cases where the expanded EHID data are used, we have applied both Blundell and Bond’s (1998)

[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).

SGMM model and MG estimator (Pesaran and Smith, 1995) and CCEMG estimator (Pesaran, 2006) to take account of the cross-country dependence of error terms. On the contrary, only fixed effects model is applied for Cases 5 and 6 in which the change in the Gini is estimated as this is a highly unbalanced panel. In Cases 7 and 8 with the raw EHII data of inequality, only SGMM model is applied.

When the expanded EHII data on inequality are used, we find that agricultural growth tends to reduce accentuation of inequality, as suggested by the negative and significant coefficients of (predicted) agricultural growth in Cases 1, 3, 5 and 6. 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. Using a semi-log specification, the coefficient estimate of agricultural (or non-agricultural) growth captures how many percentage points will be changed in response to a one percentage point increase in agricultural (or non-agricultural) growth in a year in Table 4, while the same calculation applies to the three year period in Table 3. If agricultural growth increases by 1%, *the change* in inequality decreases by 3.3% on average, *ceteris paribus* (Case 1 of Table 4). 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). This is consistent with Bourguignon and Morrisson who show that an increase in relative labour productivity (non-agriculture/agriculture) tends to increase inequality (or ratio of share of top 20% to bottom 60%).

[Table 4 to be inserted]

However, when we estimate the first difference in Gini coefficient by fixed-effects model (Cases 5 and 6), neither agricultural or non-agricultural growth is statistically significant. In Cases 7 and 8 where the raw EHII data on inequality are used, we do not find any negative and significant coefficient estimate as we did in Cases 1-2. In Cases 7 and 8 with the dynamic model, signs of coefficient estimates of agricultural and non-agricultural growth are negative, but statistically insignificant.[26] While the results vary depending on the specifications, if we rely on the results based on the expanded EHII data on inequality, we can conclude that both agricultural and non-agricultural growth accelerate inequality reduction over time.

Given the variation of signs of agricultural and non-agricultural growth terms in Tables 3 and 4, it is difficult to derive a single conclusion about the effects of sectoral growth on inequality. However, if we rely on the results of the dynamic panel model in Table 3 based on three years average data where the model adjusts for short-term fluctuations and measurement errors as well as takes account of the endogeneity of sectoral growth, we can conclude that agricultural agricultural growth has some inequality reducing effect (Case 1 of Table 3). We have also found that non-agricultural growth accelerates inequality reduction once we control for schooling years and political stability.

Using the country-level coefficient estimates based on the CCEMG model based on the expanded EHII data on inequality (Case 4, Table 4), we have checked which factors are associated with the country-level estimates of the effect of agricultural or non-agricultural

[26] It is conjectured that instability of agricultural growth, which is, for instance, affected by weather conditions – would make the impact of agricultural growth on inequality weaker in the short run because a part of income fluctuations may be well insured by both the rich and the poor (e.g. Townsend, 1994). In the medium run, this attenuating effect may be less relevant and the inequality reducing effect of each sector is more accurately estimated. It is noted that the coefficient of variation of annual growth (there-year average growth) is 22.2 (8.5) for agricultural sector and 5.0 (3.0) for non-agricultural sector. Our main conclusion is thus derived by (follows from) the results of three-year average panel data.

growth on inequality change by running a simple OLS (Ordinary Least Squares) (Table 5). Appendix 3 reports the country-level coefficient estimates and z values on the CCEMG model.

[Table 5 to be inserted]

In Cases 1-4 of Table 5 where the expanded data on inequality are used, we find several statistically significant coefficient estimates. First, if a country is more ethnically fractionalised,[27] 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 changes. 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. This is understandable because if the country consists of different ethnic groups, typically with a few ethnic minority groups which may be excluded from development process of agriculture (e.g. mechanisation), agricultural growth may have little impact on inequality over time, other factors being unchanged. Second, in Case 1, there is some regional diversity in the linkages between agricultural or non-agricultural growth and inequality change. For instance, 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. Countries in Middle East and North Africa have tended to experience slower changes in improvement in equality as a result of growth in non-agricultural sectors. This could

[27] 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.

be due to the higher share of resource dependency (e.g. oil) in many countries in these regions where corruption may perpetuate inequality (e.g. Gupta, et al., 2002).

Inequality index used in the analysis for Tables 3 and 4 reasonably captures overall economic inequality of a country (Galbraith and Kum, 2005). However, given the aforementioned limitation of our inequality measure, it would be also useful to see how agricultural growth or non-agricultural growth affects poverty, which is defined by the poverty headcount ratio or the poverty gap, following Christiaensen et al. (2011).[28] 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 Christiaensen et al. (2011), we apply the country-fixed effects model[29] and use only predicted values of agricultural or non-agricultural growth (based on Case 2 in Table 1 and Case 2 in Table 2) without adding further control variables.[30]

[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 on either poverty headcount or poverty gap. The pattern of the results is broadly unchanged if we restrict the sample only to middle income countries where agricultural

[28] If we generate the first differences in poverty, the number of observations will be reduced significantly due to missing observations. So we use these poverty indices in levels, rather than first differences.
[29] The Hausman test results favour fixed effects model over random effects model.
[30] 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. Nor did Christiaensen et al. (2011) in their poverty regressions. It should also be noted that use of other cases (Case 1 of Tables 1 and 2) will not change the results significantly.

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 of agricultural growth only in Case 10 on 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. We confirm that agricultural growth has a stronger poverty-reducing effect than non-agricultural growth. This is consistent with Table 6 of Christiaensen et al. (2011, p.248) which shows a stronger poverty reducing effect at the US$1 threshold, but not Table 7 (p.249) in which while agricultural and non-agricultural growth significantly reduce US$2 poverty, the effect of non-farm sector growth becomes more prominent as its effect is larger than that of agricultural growth in 4 out of 8 cases and statistically significant in all cases. A similar pattern, however, is found in Case 11 where non-agricultural growth is statistically significant, while agricultural growth is not.

6. 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 agricultural growth, inequality and poverty in developing countries. Using econometric models, we have analysed in detail whether agricultural growth impacts inequality and poverty after taking account of the dynamic linkages between the agricultural and the non-agricultural sectors over time. To understand the relative role of agricultural sector, we have compared the effect of agricultural growth and that of non-agricultural growth on inequality and poverty. The analyses draw upon both dynamic and static panel models using three-year averages covering the period 1969-2010. This is supplemented by the annual panel data for the same period. The main findings are summarised below from a policy perspective.

First, we generally observe strong growth linkages between agricultural and non-agricultural sectors for all developing countries (full sample) and middle income countries. Lagged agricultural growth - which is treated as an endogenous variable in the model - tends to promote non-agricultural growth, while lagged (endogenous) non-agricultural growth also tends to enhance agricultural growth. We, however, have found that agricultural growth generates spillovers twice as large as those of non-agricultural growth.

Second, in the case where the expanded EHII data are used, agricultural growth is found to reduce accentuation of inequality, or accelerate inequality reduction. 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. In this case, the degree of ethnic fractionalisation is key to explaining the magnitude of negative linkages between agricultural/non-agricultural growth and inequality changes in the short term. 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. However, once we use the Gini coefficient or the inequality based on raw EHII data - which reflects wage inequality in manufacturing sector -, these relationships are no longer observed. There is no clear relationship between sectoral growth and changes in Gini coefficient in either the short or the medium term. When we use raw EHII data of inequality, we observe an inequality reducing effect of non-agricultural growth in the medium run.

Third, agricultural growth reduces poverty - both headcount ratios and poverty gaps - in both middle income and low income countries. Such poverty reducing effects are not clearly observed for non-agricultural growth. Our results thus reinforce the role of *overall* agricultural sector in promoting overall economic growth and reducing poverty.

The World Bank recently strongly endorsed the case for promoting rural-urban migration and concomitant shift of resources towards efficient urbanisation, as reported in *Global Monitoring Report 2013, Monitoring the MDGs* (World Bank, 2013). However, this claim has been robustly rejected by our analysis that reinforces the case for revival of agriculture. Our conclusion - based on sophisticated econometric modelling and updated data - is consistent with the World Bank's earlier position supporting the role of agricultural sector in reducing poverty (e.g. *World Development Report 2008* (World Bank, 2007))[31].

Agricultural sector continues to have strong linkages with the non-agricultural sector and has substantial potential for reducing inequality and poverty. More seriously, if our analysis has any validity, 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 and eliminate worst forms of deprivation in the post-2015 scenario.

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[31] World Bank (2007) concludes that '(I)n the 21st century, agriculture continues to be a fundamental instrument for sustainable development and poverty reduction' (p.1).

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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 (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(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**

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 (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

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

	Based on the expanded EHII data on inequality		**Based on Gini**		**Based on the raw EHII data on inequality**	
	Blundell and Bond (1998) SGMM (dynamic panel)					
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
VARIABLES	Full Sample		Full Sample		Full Sample	
D.Inequality (-1)	-0.0527	**-0.150****	**0.820*****	**0.643*****	**0.786*****	**0.770*****
	(0.0666)	**(0.0617)**	**(0.0706)**	**(0.107)**	**(0.0928)**	**(0.0579)**
Log Schooling Years [Endogenous]	-	-0.488	-	-0.745	-	-0.475**
	-	(0.307)	-	(0.577)	-	(0.196)
Political Stability [Endogenous]	-	-0.182	-	0.275	-	-0.199
	-	(0.75)	-	(0.868)	-	(0.736)
D.Log Agricultural Value Added per capita [Predicted]	**-29.72***	-15.22	-36.51	45.32	-2.254	20.79
	(17.57)	(29.19)	(34.47)	(48.15)	(18.60)	(21.10)
D.Log Non-Agricultural Value Added per capita [Predicted]	-4.091	**-9.945****	4.254	-7.677	-4.556	**-9.546*****
	(3.64)	**(4.493)**	(7.977)	(7.807)	(3.707)	**(2.171)**
Constant	1.237	4.925	8.34	19.33	10.25**	13.86***
	(0.524)	(1.875)	(2.887)	(6.484)	(4.324)	(3.174)
Observations	383	206	167	129	278	129
Number of Countries	47	43	42	39	42	38
R-squared						
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)						
Prob > z						
Order 1	0.0003***	0.0160**	0.0022***	0.0064***	0.0719*	0.0218**
2	0.0629*	0.22	0.911	0.6842	0.2411	0.4516
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)						
	Chi2(114)	Chi2(127)	Chi2(46)	Chi2(79)	Chi2(107)	Chi2(85)
	152.22	136.99	47.47	76.64	163.29***	94.20
Prob > chi2	0.0097	0.2569	0.4172	0.5543	0.0004	0.2319

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

	Based on the expanded EHII data on inequality				Based on Gini Coefficient		Based on the raw EHII data on inequality	
VARIABLES	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
	Blundell and Bond (1998) SGMM (Dynamic Panel		MG Estimator	Pesaran & Smith	Fixed Effects Model (Robust Estimators)		Blundell and Bond (1998) SGMM (Dynamic Panel	
D.Inequality (-1)	**-0.0593* *[1]**	-0.0772	-	-	-	-	0.743*** [1]	0.676***
	(0.0351)	(0.108)	-	-	-	-	(0.107)	(0.0794)
Log Schooling Years [Endogenous]	-	-0.113	-	-	-	-		-0.280***
	-	(0.114)	-	-	-	-		(0.0949)
Political Stability	-	0.0171	-	-	-	-		-0.567**
	-	(0.293)	-	-	-	-		(0.259)
D.Log Agricultural Value Added per capita [Predicted] *2	**-3.270***	-3.166	**-3.973****	**-6.030****	-0.144	-0.854	-0.511	-1.897
	(1.730)	(3.005)	**(1.992)**	**(2.646)**	(5.042)	(0.590)	(1.695)	(1.445)
D.Log Non-Agricultural Value Added per capita [Predicted] *2	**-11.47*****	**-14.41****	**-10.04****	**-11.14****	0.976	0.423	-0.0422	-5.023
	(4.354)	**(5.985)**	**(4.182)**	**(4.695)**	(18.16)	(0.780)	(5.855)	(3.904)
Trend	-	-	-0.00423	-0.0013	-	3.685	-	-
	-	-	(0.00724)	(0.00839)	-	(3.265)	-	-
D.Log Inequality_avg	-	-	-	**0.424****	-	15.84	-	-
	-	-	-	**(0.175)**	-	(15.04)	-	-
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	0.613	0.14	-	-	11.54	16.71***
	(0.113)	(0.853)	(0.280)	(0.342)	-	-	(4.668)	(3.654)
Observations	849	360	927	927	338	216	791	301
Number of Countries	45	40	45	45	48	41	42	36
R-squared					41.72	48.33		
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)								
Prob > z								
Order 1	0.0005***	0.0180***	-	-	-	-	0.0017***	0.0127***
2	0.8820	0.5317	-	-	-	-	0.2065	0.4276
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)								
	Chi2(764)	Chi2(331)					Chi2(713)	Chi2(271)
	863.50	334.89	-	-	-	-	984.460	330.00
Prob > chi2	0.0070***	0.4376	-	-	-	-	0.0000***	0.0028

Notes: 1. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Statistically significant coefficient estimates are shown in bold. 2. Agricultural growth and non-agricultural growth are estimated by the Blundell and Bond (1998) SGMM model using annual panel data where the specification is same as Case 2 (with control variables) of Tables 1 and 2.

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

	Based on the expanded EHII data on inequality			
	Case 1	Case 2	Case 3	Case 4
VARIABLES	Coef. of Agricultural Growth	z value of Agricultural Growth	Coef. of Non-agricultural Growth	z value of Non-agricultural Growth
Institution	13	0.5	17.06	0.607
	(10.63)	(1.015)	(18.02)	(0.998)
ethinic	**28.43***	0.58	31.45	0.818
	(16.56)	(1.582)	(28.08)	(1.555)
inequality_D	-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

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.

Appendix 1: A List of countries included in the base case (Case 2, Table 1 and 2)
Albania, Algeria, Argentina, Bangladesh, Bolivia, Brazil, Bulgaria, Cameroon, Chile, China, Colombia, Congo, Rep., Cote d'Ivoire, Ecuador, Egypt, Arab Rep., Gabon, Guatemala, Hungary, India, Indonesia, Iran, Islamic Rep., Jordan, Kazakhstan, Kyrgyz Republic, Lithuania, Malaysia, Mauritania, Mexico, Moldova, Morocco, Pakistan, Peru, Philippines, Poland, Romania, Russian Federation, Senegal, Serbia, Slovak Republic, Slovenia, South Africa, Sudan, Tajikistan, Thailand, Tunisia, Ukraine, Vietnam, Yemen, Rep.

Appendix 2: Descriptive Statistics (3 year average)

Variable		Mean	Std. Dev.	Min	Max	Observations
Log agricultural value	overall	4.522191	3.528402	-14.31253	6.508571	N = 400
Added per capita	between		2.832785	-14.25602	6.205418	n = 50
	within		0.1558084	3.927754	5.064494	T = 8
log non agricultural	overall	6.396096	3.972115	-14.26882	9.725732	N = 400
value added per capita	between		3.261406	-14.00379	9.543673	n = 50
	within		0.3189024	4.79499	7.975028	T = 8
log share of mining	overall	0.6489725	2.200495	-7.736457	4.60517	N = 393
sector	between		2.470386	-7.341874	4.60517	n = 49
	within		0.7346914	-2.297781	6.016172	T = 8.02041
log average schooling	overall	1.64029	0.5785531	-0.0544562	2.46232	N = 408
Years	between		0.5572342	0.3357747	2.441865	n = 50
	within		0.2778844	0.6884905	2.329862	T = 8.16
Inequality measure [*1]	overall	44.93206	5.86294	26.10158	56.32093	N = 285
	between		5.206041	33.52282	53.96552	n = 42
	within		2.842125	31.66142	51.97356	T = 6.78571
Log poverty head count	overall	1.388775	2.209113	-4.60517	4.431055	N = 234
ratio (based on US$1.25)	between		2.103891	-3.69173	4.069453	n = 45
	within		0.9697695	-3.631829	4.875062	T = 5.2
Log poverty head count	overall	2.530772	1.773186	-4.60517	4.583027	N = 234
ratio (based on US$2.00)	between		1.799346	-3.066161	4.460227	n = 45
	within		0.7233758	-1.4441	5.213912	T = 5.2
Log poverty gap	overall	0.3851648	1.924393	-4.055864	3.670206	N = 227
(based on US$1.25)	between		1.838318	-3.290796	2.874465	n = 45
	within		0.7717002	-2.221556	2.801716	T = 5.04444

Log poverty gap	overall	1.445092	1.846722	-4.60517	4.082103	N =	232
(based on US$1.25)	between		1.843677	-3.613397	3.676857	n =	45
	within		0.7269117	-1.945267	3.921741	T = 5.15556	

Note: [1]. Inequality measure is 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).

Appendix 3: Relationship between agricultural or non-agricultural growth and inequality at Country level: based on Pesaran's (2006) CCEMG Estimator

	Based on the expanded EHII data on inequality			
Country	Based on Pesaran (2006)	Based on Pesaran (2006)	Based on Pesaran (2006)	Based on Pesaran (2006)
Albania	-63.30	-1.38	-136.82	-1.58
Algeria	3.58	0.35	23.04	0.63
Argentina	6.91	0.88	-24.99	-3.73
Bangladesh	-1.24	-0.07	**29.31**	**2.07**
Bolivia	7.83	0.46	8.54	0.61
Brazil	-3.65	-0.4	**24.52**	**2.14**
Bulgaria	-1.52	-0.21	-9.23	-0.69
Cameroon	18.87	1.24	-25.04	-1.17
Chile	**32.27**	**1.73**	-1.64	-0.1
China	-16.68	-0.44	-29.75	-0.58
Colombia	-1.49	-0.28	-11.92	-1.58
Congo, Rep.	11.08	0.15	-21.14	-0.86
Cote d'Ivoire	-3.75	-0.15	57.34	1.14
Ecuador	-9.20	-0.6	-21.43	-1.35
Egypt, Arab Rep.	-14.04	-0.63	-2.87	-0.21
Guatemala	-19.03	-0.52	0.91	0.05
Hungary	**-13.29**	**-2.67**	**-27.89**	**-2.53**
India	-3.15	-0.56	-5.96	-0.69
Indonesia	-12.88	-0.48	-14.80	-1.05
Iran, Islamic Rep.	3.17	0.16	-4.87	-0.54
Jordan	**-11.96**	**-3.08**	-12.72	-1.24
Kyrgyz Republic	3.93	0.32	1.34	0.1
Lithuania	-27.56	-0.92	6.15	0.34
Malaysia	-9.53	-1.02	**-32.03**	**-1.7**
Mauritania	**-30.95**	**-3.55**	**-35.05**	**-4.06**
Mexico	**9.22**	**9.23**	**13.29**	**6.5**
Moldova	-6.44	-1.08	-16.12	-0.88
Pakistan	-4.43	-0.76	**-48.72**	**-2.27**
Peru	-65.37	-1.06	-57.74	-0.42
Philippines	-48.97	-1.46	-78.21	-2.32
Poland	-4.49	-0.25	11.24	0.92
Romania	-38.51	-1.36	-54.79	-0.89
Russian Federation	2.75	0.34	0.64	0.03
Senegal	1.86	0.18	-2.91	-0.2
Serbia	-6.49	-0.31	-0.98	-0.03
Slovenia	-4.68	-0.55	14.78	0.81
South Africa	**31.37**	**1.9**	55.12	1.16
Thailand	**-26.96**	**-2.02**	**-75.37**	**-1.82**
Tunisia	-40.40	-0.6	-29.31	-0.43
Ukraine	-14.78	-0.86	-13.30	-0.28
Vietnam	**-22.45**	**-1.61**	**-75.08**	**-3.99**