Poverty Reduction during the Rural-Urban Transformation:

DOI:
10.1016/j.jpolmod.2017.10.002

Document Version
Accepted author manuscript

Citation for published version (APA):
Imai, K., Gaiha, R., & Garbero, A. (2017). Poverty Reduction during the Rural-Urban Transformation: Rural Development is still more important than Urbanisation. *Journal of Policy Modeling*, *39*(6), 2118-2144. https://doi.org/10.1016/j.jpolmod.2017.10.002

Published in:
Journal of Policy Modeling

Poverty Reduction during the Rural-Urban Transformation: Rural Development is still more important than Urbanisation

Katsushi S. Imai*
School of Social Sciences, University of Manchester, UK and RIEB, Kobe University, Japan

Raghav Gaiha
Global Development Institute, University of Manchester, U.K. & Department of Global Health and Population, Harvard School of Public Health, Boston, MA,02115, USA

Alessandra Garbero
Research and Impact Assessment Division (RIA), Strategy and Knowledge Department, International Fund for Agricultural Development (IFAD), Italy

This version: 10th October 2017

Abstract

Based on cross-country panel datasets, we find that (i) an increase in population share in agriculture is associated with poverty reduction once the longer- term poverty change or the dynamic is taken into account; (ii) rural non-agricultural sector also is poverty reducing in some cases; and (iii) increased population in the mega cities has no role in poverty reduction. In fact, the growth of population in mega cities is "poverty-increasing" in a few cases. Given that a rapid population growth or rural-urban migration is likely to increase poverty, more emphasis should be placed on policies that enhance support for rural agricultural and non-agricultural sectors. If our analysis has any validity, doubts are raised about recent research emphasising the role of secondary towns or urbanisation as the main driver of extreme poverty reduction.

Keywords: Inequality, Poverty, Growth, Agriculture, Non-agriculture
JEL Codes: C20, I15, I39, O13

Corresponding Author:
Katsushi Imai (Dr), Department of Economics, School of Social Sciences, University of Manchester, Arthur Lewis Building, Oxford Road, Manchester M13 9PL, UK; Phone: +44-(0)161-275-4827 ; Fax: +44-(0)161-275-4928 ; E-mail: Katsushi.Imai@manchester.ac.uk

Poverty Reduction during the Rural-Urban Transformation: Rural Development is still more important than Urbanisation [1]

Abstract

Based on cross-country panel datasets, we find that (i) an increase in population share in agriculture is associated with poverty reduction once the longer- term poverty change or the dynamic is taken into account; (ii) rural non-agricultural sector also is poverty reducing in some cases; and (iii) increased population in the mega cities has no role in poverty reduction. In fact, the growth of population in mega cities is "poverty-increasing" in a few cases. Given that a rapid population growth or rural-urban migration is likely to increase poverty, more emphasis should be placed on policies that enhance support for rural agricultural and non-agricultural sectors. If our analysis has any validity, doubts are raised about recent research emphasising the role of secondary towns or urbanisation as the main driver of extreme poverty reduction.

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

JEL Codes: C20, I15, I39, O13

I. Introduction

There has been a lively debate among both policymakers and academics as to whether structural transformation involving the shift from agriculture to manufacturing and services will accelerate economic growth or reduce poverty. This transformation is normally accompanied by an occupational shift from agricultural activities towards more remunerative non-agricultural

[1] This study is funded by IFAD (International Fund for Agricultural Development). The authors are grateful to Paul Winters, Thomas Elhaut and Rui Benfica for their enthusiastic support and guidance throughout this study and for their insistence on highest standards of analytical rigour. They also thank an anonymous external reviewer for IFAD for constructive comments. Gaiha also acknowledges the support and guidance of David Bloom, Harvard School of Public Health. The views expressed are personal and not necessarily of the organisations to which we are affiliated or of IFAD.

activities with a time lag as an economy's heavy dependence on agriculture evolves into greater dependence on non-agricultural sectors. In this process inequality typically increases as poor agricultural workers lack skills necessary for the move to non-agricultural sectors. The structural transformation involves two related, but distinct processes: (i) development of the non-agricultural sector in rural areas and (ii) urbanisation in which workers in rural areas typically migrate and seek employment in the non-agricultural sector in urban areas – including both mega cities and secondary cities or towns. These processes may have different implications for aggregate poverty reduction.

A recent study by Christiaensen and Todo (2014) - CT hereafter - argued that the past empirical literature *either* investigated the role of urbanisation in development or poverty reduction without disaggregating the urban sector into mega cities and secondary cities/towns or suburbs in urban areas, *or* focused on the role of rural non-agricultural sector in poverty reduction. They argued that it is necessary to examine the role of the "missing middle" (the aggregate of secondary towns and rural non-agricultural sector) and of "mega cities" to understand the relation between urbanisation and poverty reduction better. CT's study found that migration out of agriculture into "the missing middle" is *key* to faster poverty reduction than agglomeration in mega cities. Echoing CT, a recent paper by Collier and Dercon (2014) questions the role of smallholders in the development process in the African context, while Imai and et al. (2017) used cross-country panel data and showed that agricultural growth has the greater potential for poverty and inequality reduction over time than non-agricultural growth.

We argue in this paper that it will be misleading to treat secondary towns and the rural non-agricultural sector as one aggregate sector in analysing the process of poverty reduction because of different locations of these sectors and dynamics between non-agricultural and agricultural sectors in rural areas and between the non-agricultural sector in rural areas and secondary towns[2]. Here we will analyse the rural non-agricultural sector as a separate sector by disaggregating "the missing middle" into the rural non-agricultural sector and secondary towns. We apply econometric estimations to cross-country panel data consisting of developing countries and find that, if the "missing middle" is disaggregated into secondary towns and rural non-agricultural sector, i.e., the whole country is broken down into (i) rural agricultural sector, (ii) rural non-agricultural sector, (iii) secondary towns, and (iv) mega cities, the development of (i) rural agricultural as well as (ii) rural non-agricultural sectors - rather than (iii) secondary small towns - are the most important for acceleration of poverty reduction. It has also been observed that growth in mega cities does not contribute to poverty reduction, or in some cases, *increases* poverty. So the case for urbanisation - especially secondary towns - as the key driver of elimination of extreme poverty put forward by CT rests on a somewhat arbitrary merging of non-agricultural sector in rural areas and secondary towns[3] [4].

In a recent contribution, Cali and Menon (2013) identified and measured the impact of urbanisation on rural poverty in India using NSS and other relevant district data over the years 1983-84, 1993-94 and 1999-2000. They distinguish between the *location* and the economic *linkage* effects. The former entails variation in rural poverty due to the change in residency of some of the rural poor from rural areas to cities. The linkage effects, on the other hand, focus on the impact of urban population growth on rural poverty. There are several *distinct* channels

---

[2] For Illustrative evidence on selected Asian countries, see IFAD (2013).

[3] In another contribution (Christiaensen et al. 2013), a similar argument is developed by combining the evidence from the panel survey in Kagera (Tanzania), and cross-country data analysis. Christiaensen et al. also rely on the merging of rural non-farm activities and secondary towns to restate the case that the "missing middle" is more important than mega cities in reducing poverty with spill over effects on the rural farm economy.

[4] To overcome the limitations of CT, Cali and Menon (2013) identified and measured the impact of urbanisation on rural poverty in India using NSS and other relevant district data over the years 1983-84, 1993-94 and 1999-2000.

through which urban population growth affects poverty in surrounding areas: consumption linkages, rural non-farm employment, remittances, rural land/labour ratios, rural land prices, and consumer prices. Cali and Menon (2013) found that urbanisation has a significant poverty-reducing effect on the surrounding rural areas. An increase in the district's urban population of 200,000 is associated with a reduction in rural poverty in the same district between 1.3 and 2.6 percentage points. Over the entire period in question, urbanisation is associated with a reduction between 13 per cent and 25 per cent of the overall reduction in poverty. But this reduction is not as substantial as due to the state-led rural bank branch expansion which explains approximately half of the overall reduction of rural poverty between 1961 and 2000. However, the contribution of urbanisation to rural poverty reduction is slightly higher than that of another important state rural policy in post-independence India- land reforms, which explain approximately one-tenth of the rural poverty reduction between 1958 and 1992. However, whether these are valid comparisons, given differences in time periods covered and specifications used, is somewhat moot.

Another analysis (Kulkarni et al. 2014), not as detailed as this but based on National Sample Survey (NSS) household data covering the years 1993, 2004, 2009 and 2011, raises doubts about some of these findings. As far as rural poverty is concerned, there are two interesting effects. One is the locational effect captured through the ratio of rural to the urban population. This is positive, implying that the larger the number of rural inhabitants relative to the urban, the higher is the incidence of rural poverty. This is not surprising given that limited access to markets, health and education services constrain livelihood opportunities in rural areas relative to the urban. Evidently, lowering of the rural population will reduce rural poverty but it is not obvious that rural-urban migration is the solution. An additional variable, the difference in urban and rural earnings per capita, has a positive coefficient suggesting that the larger the difference, the higher is the incidence of rural poverty presumably because rural-urban migrants are typically younger, better endowed persons. The larger their number, the higher will be the proportion of poor non-migrant inhabitants in rural areas. However, as the relationship between sectoral population shifts and poverty differs across different countries, there is a need for investigating this using the cross-country panel data.

The rest of the paper is organised as follows. Section II provides a background for the present study by critically reviewing the methodology and findings of Christiaensen and Todo (2014). Section III outlines the data and the econometric methods. The results of various econometric estimations will be presented in Section IV. Section V offers concluding observations and policy implications.

II. Background: Review of Christiaensen and Todo (2014)

In some countries, the structural transformation involves rapid agglomeration in mega cities (as in South Korea and the Philippines), while in others there is diversification out of agriculture into the rural non-farm economy and secondary towns (Taiwan and Thailand). So a testable hypothesis is whether different patterns of rural-urban transformation are associated with different rates of economic growth and poverty reduction. To do so, CT classify the population of each country according to their occupation and location: (i) those living in rural areas and engaged in agriculture; (ii) those living in megacities (1 million or more persons) and employed in industry and services; and (iii) those living in rural areas and secondary cities and employed outside agriculture - especially rural non-farm activities - on the grounds that the latter draw inputs through secondary cities. This is referred to as the “missing middle”. CT’s empirical investigation is based on 206 poverty spells across 51 countries from different regions during 1980-2004.

The empirical findings of CT suggest that migration out of agriculture into rural nonfarm activities and secondary towns is associated with a reduction of poverty, while no statistically significant effect on the rate of poverty reduction was found from agglomeration in mega cities. Further exploration of the channels indicates that rural diversification and secondary town expansion yield on average more inclusive growth patterns. In contrast, mega-city agglomeration yields faster income growth, but also comes with higher income inequality, which appears to offset its potential impact on overall poverty. While no causality is purported as such, these empirical regularities are robust to a series of definitional issues and competing hypotheses. It is noted, however, that natural population increase has more to do with urbanisation than migration under some circumstances (Jedwab et al., 2016). [5]

CT have shown that urban increase contributes to explaining why the cities of the developing world grew so fast post-1960, and why many of these cities may be highly congested today. They have reported several policy implications. First, any urban population growth slowdown (for example, through enhanced family planning programmes) could contribute to increasing the urban capital-labour ratio and prevent congestion effects from kicking in. Second, better urban planning could help mitigate the negative externalities of high urban fertility rates on urban

[5] Using an extensive historical dataset on urbanisation and the urban demographic transition, Jedwab et al. (2016) show that (i) rapid urban growth in 33 developing countries during 1960-2010 was driven mostly by natural increase, and not by migration; (ii) many of the cities in these countries could be classified as "mushroom cities", as fertility remains high while mortality has fallen, leading to high urban rates of natural increase; and (iii) fast urban growth, and urban natural increase, in particular, are associated with congested cities which limit agglomeration economies. One policy option is to invest more in the cities. But this could further fuel migration, and not investing in them could make matters worse. Alternatively, more could be invested in rural areas of these countries to slowdown excessive migration and relieve the already congested cities. This policy choice is reinforced by our empirical analysis.

resources. While investing in these cities could further fuel migration, not investing in them could reduce future welfare, since they will continue to grow. Fertility remains high in many developing cities, especially in Africa, and takes time to drop. An important question then becomes which urban planning policies should be adopted, given minimal fiscal resources and weak institutions.

The authors aim to capture an "income level effect" that shifts the income distribution of each sector to the right and reduces poverty. Following Ravallion (2002), it is assumed that an increase in the population share of a sector may change its income distribution (holding average income constant), referred to as the "income distributional effect". If the distribution becomes less equal, the concentration may change the poverty level. To separate these effects, the authors used a simplified specification as follows.

$$\frac{dP}{P} = \beta_u \frac{ds_u}{s_u} + \beta_N \frac{ds_N}{s_N} + \gamma \frac{dy}{y} \qquad (1)$$

Here P is a decomposable poverty measure (a sum of weighted poverty measure in each of the three sectors, with s_u denoting share of urban metropolitan population, s_N denoting share of rural non-farm and small towns' population, and s_A representing the share of agricultural population). Instead of sectoral incomes required for the complete decomposition, the average income of each country is used, raising questions about the unbiasedness of the sectoral and income effects. So the total change in poverty is attributed to total changes in the urban and the missing middle population shares and per capita income (specifically, GDP per worker). In order to allow for country-specific and global year-specific effects, equation (1) is augmented as specified below.

$$\frac{dP_{it}}{P_{it}} = \beta_u \frac{ds_{uit}}{s_{uit}} + \beta_N \frac{ds_{Nit}}{s_{Nit}} + \gamma \frac{dy_{it}}{y_{it}} + \vartheta_i + \varepsilon_{it} \qquad (2)$$

where $\vartheta_i$denotes a country -specific effect. Equation (2) is estimated using OLS with a correction for heteroscedasticity. By testing whether β_u=β_N, inferences are drawn about whether poverty reducing effects of movements out of agriculture into the missing middle and large cities differ.

Given that the specification in equation (2) is highly simplified, neither the income effect nor the sectoral income distributional effects can be accepted at face value. Apart from the nomenclature difficulties (e.g. why were rural non-farm activities bundled together with small towns?), it is misleading to attribute the entire change in the share of the missing middle ($\frac{ds_{Nit}}{s_{Nit}}$) to movement out of agriculture as there is also a *natural* increase in the population of small/secondary cities (Jedwab et al., 2016). Besides, there is migration out of small cities into metropolitan ones. Furthermore, although attributing the coefficient to both rural non-farm and small towns is statistically valid, farm and non-farm activities in rural areas have a different dynamic than between the latter and small towns. This is because, for example, many farm households divide their time between farm and the non-farm employment and use the latter to cope with seasonal or temporary risks (IFAD, 2013), while the link between the small towns and farm activities has more to do with value chains, rather than occupational choices. In this sense, rural non-farm activities merit consideration as a sub-sector in their own right. Finally, the change in the share of the missing middle ($\frac{ds_{Nit}}{s_{Nit}}$) or of the urban metropolitan ($\frac{ds_u}{s_u}$) is likely to be endogenous to the change in poverty because of the opposite direction of causality. For instance, if the share of population that is undernourished or less productive in the labour market decreases, there may be more incentives for urban-to-rural migration.) As we will discuss later, the present study attempts to take into account the endogeneity problem by applying the dynamic panel model. With these caveats in mind, we will briefly summarise the main results of CT.

Controlling for overall growth in the economy, diversification into the rural non-farm population and small/secondary towns is associated with poverty reduction at both \$1 and \$2 per day headcount ratios, while agglomeration in the mega cities is not (as in Table 3 in CT). These effects are in addition to the poverty reducing effect of overall growth (per worker). Recall that rural diversification is not measured explicitly. If quadratic terms of change in sectoral population shares are included (Table 4 in CT), there is no effect of mega cities on poverty while that of the missing middle is robust, with a strong poverty reducing effect that declines with the migration rate to this sector. As another robustness check, CT examined the effects of (share weighted) agricultural and non-agricultural growth rates (Table 5). Growth originating in agriculture is more poverty reducing than growth originating outside agriculture, while the advantage of agricultural growth over non-agricultural growth disappeared for \$2 per day poverty. The conclusion that "Agricultural growth appears not to be driving the results" (p. 6) appears to be false, as in Columns (1), (2), and (4), it has a significant *negative* coefficient. CT in fact make a stronger assertion that "….part of the poverty reducing powers of agricultural growth appear to derive from its interactions with the rural non-farm sector and secondary towns (with the effects likely going in both directions), as agriculture seems to lose most of its edge over non-agriculture in reducing poverty after inclusion of the expansion rate of the rural non-farm and small town populations" (p.8). There are a few caveats. First, out of the two specifications in which sectoral shares are combined with agricultural and non-agricultural growth rates, in Column (4) of Table 5, both agricultural growth rate and share of the missing middle have significant negative coefficients. On the result that the coefficient of the latter is larger in (absolute) terms, it is surmised that if the rural non-farm sector share were excluded, the gap could reduce or disappear. It is also noted that any interaction effect between the missing middle share and agriculture may not be captured when the two terms appear additively. In Columns (5) and (6) of Table 5 where the dynamic specification is applied, growth rates of agriculture and non-agriculture are omitted and replaced by initial poverty rate which has a significant negative coefficient. While CT interpret this as a lack of poverty-induced migration, a more straightforward interpretation would be that the higher the initial poverty rate, the lower is the poverty change[6]. Two additional results have been reported by CT in Tables 7 and 8, that is, (i) mega cities accelerate growth through agglomeration economies but without any role for agriculture; and (ii) the former also aggravates inequality. CT conclude that agglomeration in mega cities is on average associated with faster growth and higher income inequality, while diversification into rural non-farm and secondary towns typically facilitates a more inclusive but a slower growth process and, when rapid poverty reduction is the primary objective, more attention should be given to fostering rural diversification and secondary town development. As we will discuss below, however, more emphasis should be given to the role of rural infrastructure fostering agricultural sector growth.

III. Data and Methodology

Data

Christiaensen and Todo (2014) (CT) use the Word Bank's World Development Indicators (WDI) and POVCAL data to construct the poverty estimates. They also used the data of the United

[6] Ravallion (2012) argues that the initial poverty rate matters to the subsequent rate of poverty reduction through two distinct channels, namely, the growth rate in mean consumption, and the elasticity of poverty to the mean. There is an adverse direct effect of poverty on growth, such that countries with a higher initial incidence of poverty tend to experience a lower rate of growth, controlling for the initial mean. Additionally, a high poverty rate makes it harder to achieve any given proportionate impact on poverty through growth in the mean. Thus the two "poverty effects" work against the mean convergence effect, leaving little or no correlation between the initial incidence of poverty and the subsequent rate of progress against poverty.

Nations' World Urbanization Prospects (UNWUP) to derive the share of the population living in cities with one million or more. To compute the share of people in agriculture, CT used the WDI and FAOSTAT. The present study will extend CT in the following three ways. First, we will treat the rural non-agricultural sector as a separate sector by disaggregating "the missing middle" into the rural-non-agricultural sector and secondary towns. To do so we have used the share of people in agricultural sector available from FAOSTAT in 2013 and have derived the approximate share of population in rural non-agricultural sector as the difference between the share of rural population in the total population (calculated based on World Development Indicator (WDI) in 2013) and the share of population in the agricultural sector in the total population (taken from FAOSTAT 2013). Here we assume that all the agricultural population lives in rural areas as agricultural activities are predominantly rural, that is, those in urban suburbs are rarely found in developing countries.[7] This will further reduce the sample size, as we will see later, but as we have argued in the previous section, it is crucial to treat rural non-agricultural sector separately from small or secondary towns in urban areas because these sectors differ in location and intersectoral dynamics. Definitions of other variables follow CT. For instance, the share of the population in mega cities is defined as the population share living in cities with a population of more than one million and is based on the United Nations' World Urbanization Prospects (UNWUP). Real GDP per capita is taken from WDI 2013. We have used the World Bank's POVCAL data as well as WDI 2013 to update the international poverty estimates, that is, poverty headcounts and poverty gaps based on US$1.25 and US$2 (PPP).

[7] In some countries (e.g. Latin American or Sub-Saharan African countries) agricultural population is found in urban areas. The few cases where the total agricultural population is larger than the total rural population are omitted. However, we do not argue that the role of agriculture in urban areas is not important. For instance, the number of medium-scale investor farmers has risen significantly in urban areas in some Sub-Saharan African countries (Jayne et al., 2016). Another limitation is that the classification we use is based on the main occupation and ignores the secondary occupation. So we do not consider the agricultural activities conducted by rural non-farming households or by those in small towns.

Secondly, we have updated the data coverage to 2010. We have thus covered the period 1980-2010, while CT covered the period 1980-2004. However, as we have imposed further restrictions on the dataset by (i) calculating the approximate share of population in rural non-agricultural sector, (ii) dropping the cases where the share of agricultural population exceeds that of rural population and (iii) further dropping a few cases showing data inconsistencies (e.g. the cases where the sum of the share of rural population and the share of mega city population exceeds one, that is, the share of small cities is negative). Admittedly, our approach suffers from a few limitations. First of all, we ignore the cases where the urban agricultural sector is substantial, typically, Latin American countries and thus the number of observation is smaller than in CT. We have covered 44 countries and 129 country-years for the unbalanced panel (for Level-Level regressions). Another limitation is related to the procedure for dividing the economy into the four sectors. As CT derived "the missing middle" (= [rural non-agricultural sector] + [small or secondary towns]) as the residual sector (= 1- [agricultural sector] – [mega cities]), we have derived "the small or secondary towns" as the residual sector (= 1- [rural sector (=rural agricultural sector + rural non-agricultural sector)] – [mega cities]). Hence the residual sector is likely to suffer from measurement errors. The details of the data, namely, descriptive statistics and the list of countries/years with the corresponding data, are shown in Appendix 1. In Appendix 2 we have summarised the regional changes of sectoral population shares over the period 2000-2010. It is observed that the shares of rural-non agriculture and of secondary towns have increased over the years, while the share of agricultural population and that of mega cities population have marginally decreased. The increase of the rural non-agricultural sector is due to the rapid increase of this sector in Middle East & North Africa as well as East Asia & the Pacific, while the increase in secondary towns seems to be due to the increase in this sector in Sub-

Saharan Africa, Latin America, and East Asia and the Pacific. It is noted that the agricultural population share in all the regions (except South Asia with only one observation in 2000) and the population share of mega cities has increased (except Sub-Saharan Africa). [8]

Finally, we use different specifications in the following ways. First, CT estimated the approximate annual rate of change of poverty, defined as the average annual change of poverty between the initial year (for which the data are available for each country) and the survey year (for which the data are available for that country); and similarly annual change of sectoral population share for "the missing middle" and the mega cities between the initial year and the survey year (as defined on p.4 of CT). It is not clear that in the case where there are more than two data points for a country (e.g. 1992, 1997, 2000), why the initial year (1992) is used as the base year for them (1997 and 2000). The base year should be the previous data point (e.g. 1992 for 1997 and 1997 for 2000). While the number of observations is reduced, we have taken a more standard method of calculating the annual change, that is, by taking the first difference of log poverty or log sectoral population by using the difference operator for the panel data as well as estimating the level equations. That is, we have estimated *either* the level of poverty headcount *or* changes (both in logarithm) by *either* the level of sectoral population shares *or* their changes (both in logarithm), focusing on three cases of regression, namely "Level (dependent variable)-Level (explanatory variables)", "first difference (FD)-Level" and "FD-FD", using 3-year average data.[9] As FD in log denotes the approximate value of growth rate (e.g. $\frac{dP_{it}}{P_{it}}$ or $\frac{ds_{uit}}{s_{uit}}$), econometric models for equation (2) should be specified as "FD (in log)-FD (in log)" to estimate how changes in e.g. urban metropolitan population share are associated with changes

[8] These regional patterns should not be generalised due to the small number of observations in each region.

[9] A few cases of "0", have been replaced by a small positive value (e.g. 0.01) in converting them to log. The cases of "FD-Level" are not presented as no meaningful results were obtained.

in the poverty ratio where the positive (negative) and significant coefficient estimate implies that, if the growth rate of urban population increases, the growth rate of poverty rate increases (decreases) (i.e. the poverty rate increase will be accelerated (decelerated)). In the meantime, it would be meaningful to estimate the Level-Level regression (as in CT) (in which e.g. the positive coefficient estimate implies that if the urban population increases, the poverty rate tends to increase) or the FD-Level regression (in which the positive coefficient estimate implies that if the urban population increases, the change in poverty rate tends to increase).

Methodology

As we have noted earlier, as an extension of CT, we have estimated three sets of models based on "Level-Level", "FD-Level" or "FD-FD" specification for the 3-year average panel data and "Level-Level" specification for the annual panel data.[10] We mainly adopt the robust fixed or random effects estimator given that the data are relatively small and unbalanced.[11] We also use the robust Arellano-Bover (1995) /Blundell-Bond (1998) linear dynamic panel estimator in the case where the "Level-Level" specification is applied to the annual panel data. We have taken the log of the share of agricultural population in the total population (or its change), the log of the share of non-agricultural population (or its change) and the log of the share of mega city population (or its change) as explanatory variables to explain a dependent variable (defined for 4 different cases, *either* the log of poverty headcount ratio *or* the log of poverty gap, based on US$1.25 *or* US$2 poverty line). Either the change or the level of log GDP per capita is used as a control variable.

[10] Taking the first difference of the annual panel dataset will make the sample size very small as it is highly unbalanced.
[11] The choice between fixed and random effects is guided by the Hausman specification tests.

Fixed-Effects Model

Case A: The “FD-FD” regression (for the 3-year average panel)

$$dlogP_{it} = \beta_0 + \beta_A dlogS_{Ait} + \beta_{NA} dlogS_{NAit} + \beta_U dlogS_{Uit} + \gamma dlogGDPpc_{it} + \boldsymbol{X}\delta + \mu_i + e_{it} \quad (3)$$

where i denotes country, t denotes time, $dlogP_{it}$ is the growth rate of poverty headcount or poverty gap for the US$1.25 (or US$2) a day poverty line ,), $dlogS_{Ait}$ is the first difference of log of the share of population in rural agricultural sector, $dlogS_{NAit}$ is the first difference of log of the share of population in rural non-agricultural sector, and $dlogS_{Uit}$ is the first difference of log of the share of population in mega cities (with the the population more than one million). $dlogGDPpc_{it}$ is the growth rate of GDP per capita. $\boldsymbol{X}$ is a vector of the control variables (e.g. conflict intensity and the institutional quality of the country). In our case, we have tried the cases with and without the intensity of conflict and the aggregate level of institutional quality. Conflict intensity, taking the value ranging from 0 to 2, shows how intense internal or external conflicts- including armed conflicts- were in a particular country and year. The data were obtained from CSCW and Uppsala Conflict Data Programme (UCDP) at the Department of Peace and Conflict Research, Uppsala University. The institutional quality is a simple average of 4 different World Bank's Governance Indicators, political stability, rule of law, control of conflict and voice and accountability (Imai et al., 2010). μ_i is the unobservable fixed effect specific to each country, and e_{it} is the error term, independent and identically distributed (*i.i.d.*). This is a specification where the growth rate of poverty is estimated by the growth rate of population in each sector. For instance, the positive coefficient estimate for β_U implies that if the mega city population grows at a higher rate, poverty headcount ratio also grows at a higher rate. We have used the Huber-White robust estimator in all the cases.

Case B: The "FD-Level" regression (for the 3-year average panel)

$$dlogP_{it} = \beta'_0 + \beta'_A logS_{Ait} + \beta'_{NA} logS_{NAit} + \beta'_U logS_{Uit} + \gamma' logGDPpc_{it} + \boldsymbol{X}\delta' + \mu'_i + e'_{it} \quad (4)$$

Equation (4) is same as equation (3) except that the right hand side variables are in levels, rather than in first differences. This is a specification where the rate of change in poverty is estimated by the level of the share of the population in each sector. For instance, the positive coefficient estimate for β_U implies that if the mega city population increases, poverty headcount ratio rises at a higher rate.

Case C: The "Level-Level" regression (for the 3-year average panel and the annual panel)

$$logP_{it} = \beta''_0 + \beta''_A logS_{Ait} + \beta''_{NA} logS_{NAit} + \beta''_U logS_{Uit} + \gamma'' logGDPpc_{it} + \boldsymbol{X}\delta'' + \mu''_i + \varepsilon''_{it} \quad (5)$$

Equation (5) is same as equation (3) except that variables in both left and right hand sides are defined in levels. This is a specification where poverty is estimated by the level of the share of the population in each sector. For instance, the positive coefficient estimate for β_U implies that if the mega city population increases, poverty headcount ratio is likely to increase.

Dynamic Panel **(**for the 3-year average panel and the annual panel)

As an alternative to the fixed-effects model[12], we can use the lagged differences of all explanatory variables as instruments for the level equation and combine the difference equation and the level equation in a system whereby the panel estimators use instrument variables, based on previous realisations of the explanatory variables as the internal instruments, using 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 $(\Delta dlogP_{it-1} - \Delta dlogP_{it-2})$ and $(\varepsilon_{it} - \varepsilon_{it-1})$ (Baltagi, 2005, Chapter 8). Assuming that ε_{it} is not serially correlated and that the regressors in $\boldsymbol{X}_{it}$ are weakly exogenous, the generalized method-of-moments (GMM) first difference estimator (e.g. Arellano and Bond, 1991) can be used.

Blundell-Bond (1998) system GMM estimator based on additional moment conditions. Such a system gives consistent results under the assumptions that there is no second order serial correlation and the instruments are uncorrelated with the error terms. The Blundell-Bond System GMM (SGMM) estimator is used, as in the previous study. A disadvantage is that the number of observations is reduced and thus the results have to be interpreted cautiously. We will use the robust estimator based on Windmeijer's (2005) WC robust estimator. The results have to be interpreted with caution because of the small sample.

Quantile Regression **(**for the annual panel)

To reflect the heterogeneous effect of changes in sectoral share on poverty according to the level of poverty, we have also estimated the fixed-effect quantile regression based on Canay (2011) to estimate equation (5) for the annual panel. This approach consists of two steps. In the first step, we estimate equation (5) by a household fixed-effect panel specification to obtain standard within estimators ($\hat{\mu}"_i$). This is used to get rid of fixed effects in $logP_{it}$ by calculating $\widetilde{logP_{it}} = logP_{it} - \hat{\mu}"_i$. In the second step, we use a standard linear quantile regression and estimate the λth quantile function (i.e. 10%, 25%, 50%, 75%, 90%) conditional on explanatory variables.[13]

IV. Results

In this section, we will report and discuss the econometric results for the models presented in the previous section.[14] Table 1 shows the results of econometric models for equations (1)-(3) for the

[13] See Canay (2011) and You et al. (2016) for more details.

[14] We have used CT's data and have applied both robust fixed estimator and robust Arellano-Bover/Blundell-Bond linear dynamic panel estimator to take account of the endogeneity of the sectoral population shares or their changes. Here we have treated "the missing middle" as a sum of rural non-

3-year average panel data (Cases 1-4 for “FD-FD”, Cases 5-8 for “FD-Level” and Cases 9-12 for “Level-Level” specifications). In cases where the “FD-FD” specification is used, the rate of change in the share of the agricultural population is found to be negatively and significantly associated with the rate of the change in poverty, regardless of the definitions of poverty in Cases 1-4. For instance, in the case where the country reduces the population share in the agricultural sector and the overall poverty also decreases, the faster decline in agricultural population leads to the slower poverty reduction. On the contrary, the slower decline in agricultural population share leads to the faster poverty reduction. For example, if the rate of change in the agricultural population decreases by 10%, the rate of change in poverty headcount based on $1.25 increases by 18%, other things being equal (Case 1). This result is robust to the use of other definitions of poverty (Cases 2-4). The results imply that rapid decline in agricultural population - for instance, as a result of rural-to-urban migration - may dampen the overall poverty reduction in the country. It is noted that the rate of change in the population share in the rural non-agricultural sector is also negatively associated with the rate of change in poverty (which is statistically significant in Cases 1, 2 and 4), but the size of the coefficient estimate is much smaller. The population share of mega cities is not statistically significant. The growth of GDP per capita does not significantly influence the rate of change in poverty.

(Table 1 to be inserted)

When we use the “FD-LEVEL” specification, we find that the increase of the population share in the mega cities leads to an acceleration of increase in poverty, regardless of the definitions of poverty. For instance, a 10% increase in the population share in the mega cities is

agricultural sector small or secondary towns, while all the other aspects are identical. We have obtained results broadly consistent with CT, while the magnitude of coefficient estimates is different reflecting the different specifications for the model. The results are provided in Appendix 3. It was also noted that even without the recent data (2005-2010) in the results do not change significantly.

associated with 0.7% increase in the rate of change of poverty headcount ratio based on $1.25 or $2. The population share in the agricultural sector is negative and significant only for poverty headcount based on $2 and insignificant otherwise. The share of the population in the rural non-agricultural sector is negative and significant for the poverty headcount ratios based on $1.25 and $2. Overall, one can conclude that the shift of population to mega cities, or the population increase in mega cities, increases poverty. In Cases 5-8 where the "Level-Level" specification is applied to the 3-year average panel, we do not find any statistically significant coefficient for sectoral population shares. This is partly because the log of GDP per capita is negative and highly significant.

To further investigate the relationships between sectoral population shares and poverty, we have estimated the linear dynamic panel estimator based on the 3-year average panel data. The results are presented in Table 2. The dependent variable is the headcount ratio based on either $1.25 or $2.00 poverty line. The population shares are either in current values (Cases 1 and 2) or lagged values. First, the first lag of poverty is statistically significant in Cases 2, 3 and 4. Second, while the agricultural population share is statistically insignificant, the rural non-agricultural share is negative and significant in Case 3 where the poverty headcount based on $2.00 is estimated by the lagged population shares. The population share in mega cities is positive and significant in Cases 1 and 3 based on the current population shares.

In sum, when our estimations are based on the 3-year average panel, the increase in rural population - in the agricultural sector in particular and in the rural non-agricultural sector to a smaller extent – accelerates poverty reduction. Overall, increase in population share in mega cities is positively associated with an increase in national poverty.

(Table 2 to be inserted)

Next, the annual panel data are used to estimate the effect of sectoral population shares (in levels) on poverty headcount or poverty gap (in levels).[15] In the case where the dependent variable is the poverty headcount ratio based on $1.25, the population share in mega cities is positive and significant with or without conflict intensity. We have also found that the higher conflict intensity tends to increase poverty headcount or poverty gap. Interestingly, if we break down the estimation into the two periods, before and after 2000, the share of the agricultural population is negative and significant before 2000, while it is statistically insignificant after 2000. This implies that decrease in the agricultural population share (e.g. rapid migration from agricultural households from rural areas to towns or cities) tended to increase poverty till 2000. In other cases, the population shares are mostly statistically insignificant.

The results of fixed-effects quantile regressions - which are based on the annual panel and on the poverty head count of $1.25 - are presented in Table 3. It should be noted that the poverty elasticity of GDP per capita is negative and significant regardless of the percentiles, but the elasticity is lower for the higher level of poverty. This implies that the poverty-reducing effect of income growth is limited if the country's poverty level is high.

(Table 3 to be inserted)

An interesting result is obtained on the coefficient estimates of the log of the population share in the agricultural sector. At the 10% percentile point in the distribution of poverty headcount based on $1.25 (e.g. in the upper or lower middle countries which had already reduced extreme poverty), the increase in the share of agricultural population tends to increase poverty, while the increase in the share of population in mega cities is associated with poverty reduction. However, at the 90% percentile point in the distribution of poverty headcount based on $1.25 (e.g. in low income countries with a higher level of poverty), the increase in the share of agricultural

[15] A full set of results will be provided on request.

population decreases poverty. Here, given that the coefficient estimates for the shares of agricultural population, rural non-agricultural population and mega cities are negative and significant, the increase in the share of urban small towns is likely to increase poverty. At 50% and 75%, the increase in the share of the population in rural non-agricultural sector tends to reduce poverty.

In Table 4 we have estimated the effects of sectoral population shares on poverty headcount ratio based on $1.25 or $2.00 using Arellano-Bover/Blundell-Bond linear dynamic panel estimator. The results of the current population shares are presented in Cases 1 and 3, while those of the lagged population shares are presented in Cases 2 and 4. It is found that (i) the increase in the share of agricultural population tends to reduce poverty regardless of the definitions of poverty; (ii) the increase in the share of population in rural non-agricultural sector also tends to reduce poverty, but the size of the effect of the rural non-agricultural population share is smaller than that of the agricultural population share; and (iii) the increase in the share of population in mega cities tends to increase poverty.

(Table 4 to be inserted)

The pattern of the results on the effects of population compositions in different sectors differs according to which econometric model or specification is adopted, or whether the 3-year average panel data or the annual panel data are used. However, we can conclude that the population share in the rural agricultural sector is negatively associated with poverty in some cases (e.g. when we apply the "FD-FD" specification and the static panel model to the 3-year average panel; when the "LEVEL-LEVEL" specification is applied to the headcount based on $1.25 before 2000 or at the high percentile (90%); when the dynamic panel is used for the annual data). In some cases, rural non-agricultural sector is also poverty reducing (e.g. when the "FD-FD" specification and the static panel model are used for the 3-year average panel; when the dynamic panel is used for the annual data). Overall, the absolute magnitude of the poverty reducing effect is larger with the population or its changes in the agricultural sector than with the rural non-agricultural sector. Also, in some cases, the share of the population in mega cities tends to *increase* poverty (e.g. the FE-LEVEL specification for the 3-year average panel; the dynamic panel for the annual panel), though at the low and high percentiles its coefficient estimates are found to be negative and significant in the fixed-effects quantile regressions.

V. Concluding Observations and Policy Implications

Based on cross-country panel datasets, a recent study by Christiaensen and Todo (2014) has argued that "migration out of agriculture into the missing middle (rural nonfarm economy and secondary towns) yields more inclusive growth patterns and faster poverty reduction than agglomeration in mega cities. This suggests that patterns of urbanization deserve much more attention when striving for faster poverty reduction" (p.1). It is, however, not clear that treating rural nonfarm economy and secondary towns as one aggregate sector is justifiable given that they are different in location as also in their intersectoal dynamics.

Using the revised and updated datasets where "the missing middle" is disaggregated into rural nonfarm economy and secondary towns, the present study has found, contrary to CT, that (i) development of rural agricultural sector is the most poverty reducing in various cases; (ii) rural non-agricultural sector is poverty reducing in some cases, but its magnitude is generally much smaller than that of rural agricultural sector; and (iii) higher population in mega cities has no role in poverty reduction. In fact, it is "poverty-increasing" in a few cases.

Our study has several policy implications. First, giveen that a rapid growth of population or rural-urban migration is likely to increase poverty, more emphasis should be placed on policies that enhance support to the rural agricultural sector and rural non-agricultural sector. An example is to support rural infrastructures, such as rural road, electricity, and irrigation systems, that would reduce the transaction costs significantly (Renkow et al. 2004). However, even if policymakers are aware of the positive role of rural infrastructure in reducing poverty, the question is whether an extra unit of investment in the infrastructure in rural remote areas is more poverty-reducing than an equivalent investment in less-remote rural areas or urban areas given the budget constraint.[16] Our results suggest that, given that rural infrastructure is still underdeveloped in most developing countries, the infrastructure investment in rural areas is likely to be more poverty-reducing than that in small towns or mega cities.

Second, our results may have an implication for migration policies. While policies to restrict rural-urban migrations cannot be generally recommended as they may bring benefits to rural agricultural households (e.g. reducing seasonal income risks), policymakers should be aware of any poverty-increasing effects of too rapid increases of the urban population due to rural-urban migration. Policymakers should rather provide training for migrants from rural areas so that they can develop capabilities as migrants are likely to face poverty or hardships in urban areas.

Focusing on Africa, over 60% of the population is below the age of 25. The youth population will continue to rise in Sub-Saharan Africa throughout the 21st century, even though it is projected to decline in other regions. In rural areas, the number of young people will continue to expand into the 2030s. Even in a most optimistic scenario, non-farm and urban sectors are not likely to absorb more than two-thirds of young labour market entrants over the next decade. But

[16] Fan and Hazell (1999) showed using Indian NSS data that government investments in rural remote areas are more poverty-reducing than those in less remote areas.

there will be vast opportunities for the innovative young people in agricultural systems as they adapt to a range of challenges in the near future. These challenges relate to raising productivity in a sustainable way, and integration into emerging high value chains. While the challenges are daunting, the potential benefits of addressing them are enormous. Higher prices, more integrated value chains, widening connectivity to markets in some areas, and greater private and public engagement in the sector are creating new opportunities. Specific interventions include investing in smallholder farming – the dominant modality of agriculture across Africa – offering access to modern technologies, training, and markets and extending and adapting financial services to serve the needs of young farmers. In addition, targeted measures are necessary to expand the access of and rights to the land of young people, with a particular focus on the needs of young women (Suttie, 2015).

Finally, it would be misleading for donors' long-term strategies to focus on the development of secondary towns or urban cities as the main strategy for poverty reduction at the national level. If our analysis has any validity, doubts are raised about recent research emphasising the role of secondary towns or urbanisation as the key driver of elimination of extreme poverty. In order to achieve Sustainable Development Goal 1 of eradication of extreme poverty, governments and donors should place more importance on investments in rural agricultural sector – e.g. smallholder farming in remote areas - and those in non-agricultural sectors.

References

Arellano, M., and Bond, S. (1991) 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', *Review of Economic Studies* 58: 277-297.

Arellano, M., and Bover, O. (1995) ‘Another look at the instrumental variable estimation of error-components models’, *Journal of Econometrics* 68: 29-51.

Baltagi, B. H. (2005) *Econometric Analysis of Panel Data*, Third Edition. Chichester: John Wiley & Sons Ltd.

Blundell, R., and Bond, S. (1998) ‘Initial conditions and moment restrictions in dynamic panel data models’, *Journal of Econometrics* 87: 115-143.

Cali, M. and Menon, C. (2013) ‘Does Urbanisation Affect Rural Poverty? Evidence from Indian Districts’, *World Bank Economic Review*, 27(2), 171-201.

Canay, I. A. (2011) A simple approach to quantile regression for panel data. *Econometric Journal*, 14(3), 368-386.

Christiaensen, L. and Y. Todo (2014) ‘Poverty Reduction during the Rural-Urban Transformation –The Role of the Missing Middle’, *World Development*, 63, 43-58.

Christiaensen, L., Weerdt, J. and Todo, Y. (2013) ‘Urbanization and poverty reduction: the role of rural diversification and secondary towns’, *Agricultural Economics*, 44(4-5), pp.435-447.

Collier, P. and Dercon, S. (2014) ‘African Agriculture in 50 years: Smallholders in a Rapidly Changing World?’, *World Development*, 63, 92-101.

Fan, S. and Hazell, P.B. (1999) ‘Are returns to public investment lower in less-favored rural areas?: an empirical analysis of India’. EPTD Discussion Paper No. 43, International Food Policy Research Institute.

IFAD (2013) *Agriculture-Pathways to Prosperity in Asia and the Pacific*, Occasional Paper 17, the Asia and the Pacific Division, IFAD.

Imai, K. S., Cheng, W. and Gaiha, R. (2017) ‘Dynamic and Long-term Linkages among Agricultural and Non-Agricultural Growth, Inequality and Poverty in Developing Countries’, *International Review of Applied Economics*, 31(3), 318-338,

Imai, K., R. Gaiha and G. Thapa (2010) ‘Is the Millennium Development Goal of Poverty Still Achievable? Role of Institutions, Finance and Openness’, *Oxford Development Studies*,38(3), 309-337.

Jayne, T. S., Chamberlin, J. B., Sitko, N., Traub, L. N., Yeboah, F., Muyanga, M., Answeeuw, W., Chapoto, A., Wineman, A. Y., Nkonde, C., & Kachule, R. (2016) 'Africa's changing farm size distribution patterns: the rise of medium-scale farms', *Agricultural Economics*, Volume 47, 197-214.

Jedwab, R., L. Christiaensen and M. Gindelsky (2016) 'Rural Push, Urban Pull and …Urban Push? New Historical Evidence from Developing Countries', *Journal of Urban Economics.*

Kulkarni, Vani. S., M. Pandey and R. Gaiha (2014) "Growth, Inequality and Poverty", *The Hindu Business Line*, 23 May.

Ravallion, M. (2002). "On the urbanization of poverty". *Journal of Development Economics*, 68(2), 435–442.

Ravallion, M. (2012) "Why There is No Poverty Convergence?". *American Economic Review*, 102/1, 504-523.

Renkow, M., Hallstrom, D.G. and Karanja, D.D. (2004) "Rural infrastructure, transactions costs and market participation in Kenya". *Journal of Development Economics*, 73(1), 349-367.

Suttie, D. (2015) 'Youth employment and agriculture in Sub-Saharan Africa, Food and Business Knowledge Platform', 19th November.

Windmeijer, F. (2005) 'A finite sample correction for the variance of linear efficient two-step GMM estimators'. *Journal of Econometrics* 126, 25–51.

You, J., Imai, K. S., and Gaiha, R. (2016) 'Declining nutrient intake in a growing China: Does household heterogeneity matter?' *World Development* 77, 171-191.

Table 1 Effects of Change in log Sectoral Population Compositions on Change in log Poverty Gap or Headcount (FD-FD): Robust Fixed or Random Effects model for poverty based on $1.25 or $2.00 (2005 PPP) (Based on 3-year average panel)

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
	FD-FD				FD-LEVEL				LEVEL-LEVEL			
DEP. VAR	D_log poverty				D_log poverty				log poverty			
	Headcount $1.25 (2005PPP)	Gap $1.25	Headcount $2.00 (2005PPP)	Gap $2.00	Headcount $1.25	Gap $1.25	Headcount $2.00	Gap $2.00	Headcount $1.25	Gap $1.25	Headcount $2.00	Gap $2.00
Model	RE	RE	FE	RE	RE	RE	RE	RE	RE	RE	RE	RE
EXP. VARIABLES												
dloggdppc	1.236	0.0333	-0.459	0.325	2.3	-0.326	1.358	0.521				
	(2.748)	(2.562)	(1.828)	(1.790)	(3.220)	(2.517)	(1.396)	(2.016)				
log gdppc									-1.164***	-1.080***	-0.943***	-0.986***
									(0.194)	(0.119)	(0.202)	(0.153)
D.log share of population in rural agricultural sector	-1.837***	-1.368***	-2.161**	-1.575***								
	(0.540)	(0.330)	(0.909)	(0.280)								
D.log share of population in rural non-agricultural sector	-0.684**	-0.435***	-0.811	-0.473***								
	(0.341)	(0.0744)	(0.589)	(0.121)								
D.log share of population in mega cities	-0.113	-0.146	-0.159	-0.0451								
	(0.216)	(0.171)	(0.290)	(0.145)								
log share of the population in the rural agricultural sector					-0.35	0.0588	-0.479**	-0.0709	0.25	0.148	0.194	0.16
					(0.222)	(0.109)	(0.225)	(0.0903)	(0.294)	(0.272)	(0.255)	(0.249)
log share of population in rural non-agricultural sector					-0.0900*	0.00936	-0.122**	-0.0198	-0.0465	-0.0668	-0.0416	-0.0544
					(0.0519)	(0.0437)	(0.0618)	(0.0276)	(0.0607)	(0.0578)	(0.0518)	(0.0515)
log share of population in mega cities					0.705**	0.447*	0.685**	0.568*	0.0668	0.109	-0.0092	0.0851
					(0.319)	(0.262)	(0.334)	(0.331)	(0.234)	(0.180)	(0.220)	(0.185)
Constant	-0.11	-0.238	-0.011	-0.155	-0.56	-1.585	0.148	-1.286	9.355	8.167	8.922	8.312
	(0.133)	(0.129)	(0.152)	(0.118)	(1.338)	(0.740)	(1.394)	(0.815)	(2.059)	(1.510)	(2.094)	(1.732)
Observations	48	45	48	46	53	50	53	51	126	123	126	124
Number of code1	20	18	20	19	21	19	21	20	45	45	45	45
Hausman test: Chi2(4)	3.48	0.38	29.42**	0.77	2.34	1.15	1.8	2.38	2.58	2.04	6.37	2.83
Prob>Chi2=	0.4802	0.9842	0	0.9428	0.6739	0.887	0.7732	0.6667	0.6303	0.7292	0.1729	0.5861
Chosen Model	RE	RE	RE	RE	RE	RE	RE	RE	RE	RE	RE	RE

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The choice of the model is guided by Hausman test. Statistically significant coefficient estimates are shown in bold. But in Case 3, we have chosen random effects model despite a significant coefficient result of Hausman test as fixed effects model shows an unreasonably coefficient estimate.

Table 2 Effects of log Sectoral Population Compositions on log Poverty Headcount (Level-Level): Arellano-Bover/Blundell-Bond linear dynamic panel estimator based on $1.25 or $2.00 (2005 PPP) (Based on the 3-year average panel)

	Case 1	Case 2	Case 3	Case 4
DEP. VAR.	**log poverty Headcount**		**log poverty Headcount**	
	$1.25	**$1.25**	**$2.00**	**$2.00**
Model	SGMM	SGMM	SGMM	SGMM
L.logpovertyhc125 (or 200)	0.075	**0.367***	**0.453****	**0.381*****
	(0.190)	**(0.193)**	**(0.196)**	**(0.136)**
Loggdppc	**-1.204*****	**-0.860***	**-0.544***	**-0.630****
	(0.434)	**(0.445)**	**(0.291)**	**(0.278)**
log share of the population in the rural agricultural sector	0.784		0.388	
	(0.770)		(0.470)	
log share of the population in the rural non-agricultural sector	0.0213		-0.0553	
	(0.359)		(0.147)	
log share of the population in mega cities	**1.156****		**1.039*****	
	(0.517)		**(0.389)**	
L.log share of population in rural agricultural sector		0.923		0.483
		(0.740)		(0.445)
L.log share of population in rural non-agricultural sector		-0.302		**-0.268***
		(0.248)		**(0.160)**
L.log share of population in mega cities		0.521		0.325
		(0.595)		(0.385)
Constant	4.623	3.444	1.479	4.255
	(5.234)	(6.008)	(3.583)	(3.744)
	53	54	53	54
Number of code1	21	22	21	22
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)				
Prob > z				
Order 1	0.0739	0.1034	0.2103	0.1875
2	0.3560.	0.5802	0.3321	0.3962
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)				
	Chi2(32)= 26.86	Chi2(33)= 24.15	Chi2(31)= 21.65	Chi2(33)= 25.15
Prob > chi2	0.1924	0.8689	0.9164	0.8343

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: Heterogeneous Effects of log Sectoral Population Compositions on log Poverty Headcount (Level-Level): Robust Qantile Regression for poverty headcount ration based on $1.25 (2005PPP) (Based on annual panel)

	log Poverty Headcount				
Percentile Points	**10%**	**25%**	**50%**	**75%**	**90%**
			$1.25 (2005PPP)		
Model			QR		
loggdppc	**-1.657*** **	**-1.812*** **	**-1.053*** **	**-0.851*** **	**-0.597*** **
	(0.134)	**(0.205)**	**(0.217)**	**(0.0681)**	**(0.102)**
log share of population in rural agricultural sector	**0.908*** **	0.672	0.0931	-0.163	**-0.227***
	(0.270)	(0.484)	(0.293)	(0.134)	**(0.116)**
log share of population in rural non-agricultural sector	-0.0689	-0.0543	**-0.0822** **	**-0.0341** **	**-0.0422** **
	(0.106)	(0.0895)	**(0.0348)**	**(0.0170)**	**(0.0199)**
log share of population in mega cities	**-0.396***	0.182	-0.0253	-0.127	**-0.362*** **
	(0.217)	(0.442)	(0.244)	(0.130)	**(0.122)**
Constant	9.499	10.79	9.654	9.933	9.487
	(1.693)	(2.968)	(1.987)	(0.922)	(0.923)
Observations	129	129	129	129	129

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 Effects of log Sectoral Population Compositions on log Poverty Headcount (Level-Level): Arellano-Bover/Blundell-Bond linear dynamic panel estimator based on $1.25 or $2.00 (2005 PPP) (Based on annual panel)

	Case 1	Case 2	Case 3	Case 4
DEP. VAR.	**log poverty Headcount**		**log poverty Headcount**	
	$1.25	**$1.25**	**$2.00**	**$2.00**
Model	SGMM	SGMM	SGMM	SGMM
L.logpovertyhc125 (or 200)	**0.214***	**0.626*****	**0.895*****	**0.845*****
	(0.129)	**(0.148)**	**(0.111)**	**(0.115)**
loggdppc	**-2.218*****	**-1.173*****	-0.328	**-0.479***
	(0.355)	**(0.407)**	(0.239)	**(0.262)**
log share of the population in the rural agricultural sector	**-1.580*****		**-0.665*****	
	(0.302)		**(0.246)**	
log share of the population in the rural non-agricultural sector	**-1.156*****		**-0.153***	
	(0.177)		**(0.0812)**	
log share of the population in mega cities	**3.664*****		0.0713	
	(0.687)		(0.231)	
L.log share of population in rural agricultural sector		**-1.022*****		**-0.845*****
		(0.388)		**(0.275)**
L.log share of population in rural non-agricultural sector		**-0.610*****		**-0.173***
		(0.219)		**(0.0910)**
L.log share of population in mega cities		**1.697***		**0.0641**
		(0.883)		**(0.238)**
Constant	14.83	9.085	5.134	7.098
	(2.390)	(2.862)	(2.398)	(2.747)
	35	32	35	32
Number of code1	12	9	12	9
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)				
Prob > z				
Order 1	0.1712	0.1258	0.2321	0.2479
2	0.1461	0.2647	0.2817	0.2837
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)				
	Chi2(30)=	Chi2(27)=	Chi2(31)=	Chi2(28)=
	36.492	21.202	19.741	16.399
Prob > chi2	0.1924	0.7767	0.9412	0.9595

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 Descriptive Statistics

Variable	Definitions	Obs	Mean	Std. Dev.	Min	Max
povertyhc125	Poverty Headcount based on US1.25 a day PPP	367	20.4	22.7	0.0	92.6
povertyhc200	Poverty Headcount based on US2.00 a day PPP	367	41.1	29.1	0.0	98.5
povertyg125	Poverty Gap based on US1.25 a day PPP	320	9.7	11.5	0.0	63.3
povertyg200	Poverty Gap based on US2.00 a day PPP	320	18.0	17.0	0.0	75.6
share of agricultural population	Share of Agricultural Population	135	40.2	24.6	5.8	92.4
the share of the population in mega cities	Share of Population in Mega Cities	135	16.4	9.0	3.4	48.7
rural_non_~e	Share of Population in Rural Non Agricultural Population	135	15.0	12.8	0.0	64.2
mmid_share	Share of Population in Small/Secondary Towns	135	28.4	16.3	1.3	63.8
Institutional Quality	A Simple Average of 4 World Bank's Governance Indicators: political stability, rule of law, control of conflict and voice and accountability (Imai et al., 2010).	211	-0.4	0.5	-1.7	1.1
Conflict Intensity	conflict intensity (data obtained from CSCW and Uppsala Conflict Data Program (UCDP) at the Department of Peace and Conflict Research, Uppsala University covering armed conflicts, both internal and external, in the period 1946 to the present.	367	0.3	0.5	0.0	2.0
share of agricultural population~CT	Share of Agricultural Population (based on CT)	250	40.2	22.0	6.6	86.1
mmid_share~CT	Share of Population in Missing Middle (based on CT)	250	40.9	18.2	5.6	79.0
the share of the population in mega cities~CT	Share of Population in megacities (based on CT)	250	18.9	10.1	3.8	37.1
pov1_CT	Poverty Headcount based on US1.25 a day PPP (based on CT)	250	17.6	20.2	0.1	90.3
pov2_CT	Poverty Headcount based on US2.00 a day PPP (based on CT)	250	41.2	27.3	1.2	98.1
Loggdppc	log of real GDP per capita	361	7.007059	1.068369	4.710151	8.824546

Appendix 2 Regional Changes of Sectoral Population Shares in 2000-2010

		Sector (Population Share) (%)				
		Agriculture	Rural Non-Agriculture	Secondary Towns	Mega Cities	Total
East Europe and Central Asia	2000	34.7	16.7	33.7	14.8	100.0
(ECA)	2010	36.5	16.2	31.0	16.3	100.0
Middle East & North Africa	2000	52.5	7.4	25.5	14.5	100.0
(MENA)	2010	49.6	18.1	15.3	17.0	100.0
Sub-Saharan Africa	2000	35.2	12.0	30.8	22.0	100.0
(SSA)	2010	37.3	12.4	31.5	18.8	100.0
Latin America & Caribbean	2000	43.9	15.8	26.6	13.7	100.0
(LAC)	2010	39.7	14.5	29.8	16.1	100.0
East Asia & Pacific	2000	74.0	7.2	8.9	9.9	100.0
(EAP)	2010	57.5	17.3	11.0	14.2	100.0
South Asia	2000	26.2	12.4	57.1	4.3	100.0
(SA)	2010	38.0	12.8	40.2	9.0	100.0
Total	2000	41.2	12.6	28.9	17.4	100.0
	2010	39.4	14.0	29.8	16.7	100.0

Notes: 1. This is based on 3-year average data. The average for 2000 is based on 1998-2000 and that for 2010 is based on 201-2011.
2. Numbers of observation are: 5 for 2000 and 6 for 2010 for ECA), 3 and 2 for MENA, 17 and 17 for SSA, 6 and 7 for LAC, 3 and 2 for EAP, 1 and 3 for SA, and 35 and 37 for total. Details are shown in Appendix 2.

Appendix 3 Effects of "Missing Middle" on log Poverty Headcount ($1.25 or $2), using Christiaensen-Todo (2014)'s data: Robust Fixed Estimator, or Robust Arellano-Bover/Blundell-Bond linear dynamic panel estimator

	First Difference (dep)- First Difference (exp)				**First Difference (dep)- Level (exp)**				**Level (dep)- Level (exp)**			
	Fixed-effects, robust		**Dynamic panel, robust**		**Fixed-effects, robust**		**Dynamic panel, robust**		**Fixed-effects, robust**		**Dynamic panel, robust**	
	Case 1 **Dlogpovertyhc125 HC $1.25**	Case 2 **Dlogpovertyhc200 HC $2.00**	Case 3 **Dlogpovertyhc125 HC $1.25**	Case 4 **Dlogpovertyhc200 HC $2.00**	Case 5 **Dlogpovertyhc125 HC $1.25**	Case 6 **Dlogpovertyhc200 HC $2.00**	Case 7 **Dlogpovertyhc125 HC $1.25**	Case 8 **Dlogpovertyhc200 HC $2.00**	Case 9 **logpovertyhc125 HC $1.25**	Case 10 **logpovertyhc200 HC $2.00**	Case 11 **logpovertyhc125 HC $1.25**	Case 12 **logpovertyhc200 HC $2.00**
VARIABLES												
D.logmmid_share_CT	**-9.809****	**-4.130*****	**-15.29*****	**-9.953*****								
	(3.511)	**(1.224)**	**(4.860)**	**(1.447)**								
D.log share of population in mega cities_CT	**-5.53**	**-1.13**	**1.99**	**2.83**								
	(10.42)	**(3.931)**	**(7.075)**	**(2.591)**								
logmmid_share_CT					**-2.959****	**-1.321****	**-0.39**	**-0.161*****	**-2.111***	**-0.52**	**-1.037*****	**-0.308*****
					(1.317)	**(0.628)**	**(0.295)**	**(0.0583)**	**(1.165)**	**(0.404)**	**(0.362)**	**(0.0747)**
log share of population in mega cities_CT					**2.720***	**0.93**	**0.03**	**-0.02**	**1.02**	**-0.14**	**0.21**	**0.02**
					(1.427)	**(0.782)**	**(0.191)**	**(0.0520)**	**(1.509)**	**(0.604)**	**(0.286)**	**(0.0513)**
dloggdppc	-3.656***	-2.718***	5.45	-0.65	-3.147**	-2.596***	-2.42	-2.200*	-0.86	-0.22	-2.24	-1.589**
	(1.153)	(0.630)	(4.611)	(1.435)	(1.343)	(0.645)	(5.289)	(1.247)	(1.306)	(0.566)	(1.876)	(0.740)
L.dlogpov1_CT			-1.298***				-0.636*					
			(0.247)				(0.380)					
L.dlogpov2_CT				-0.779**				-0.35				
				(0.320)				(0.219)				
L.logpov1_CT											0.598***	
											(0.198)	
L.logpov2_CT												0.858***
												(0.0491)
Constant	0.16	0.106**	-0.44	-0.01	3.04	2.26	1.31	0.705	6.814	5.683	3.924	1.551

	(0.128)	(0.0492)	(0.272)	(0.0740)	(3.361)	(1.630)	(1.372)	(0.280)	(3.166)	(1.389)	(1.590)	(0.393)
Observations	67	68	35	36	67	68	35	36	250	254	67	68
R-squared	0.08	0.21			0.04	0.15			0.08	0.04		
Number of countries	21	21	15	16	21	21	15	16	48	48	21	21
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1												
Arellano-Bond test for zero autocorrelation in first-differenced errors (H0: No autocorrelation)												
Prob > z												
Order 1			0.066*	0.17			0.15	0.21			0.23	0.11
2			0.33	0.49			0.4	0.46			0.27	0.27
Sargan test of overidentifying restrictions (H0: overidentifying restrictions are valid)												
			Chi2(28)	Chi2(28)			Chi2(36)	Chi2(28)			Chi2(56)	Chi2(52)
			26.4	22.2			26.6	22.2			47.5	41.2
Prob > chi2			0.55	0.77			0.87	0.77			0.78	0.86