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Investing in rural people

Poverty reduction during the rural-urban transformation

Rural development is still more important than urbanization

by
Katsushi S. Imai
Raghav Gaiha
Alessandra Garbero

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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 dynamic is taken into account; (ii) the rural non-agricultural sector also is poverty-reducing in some cases; and (iii) increased population in the megacities has no role in poverty reduction. In fact, the growth of the populations in megacities increases poverty in a few cases. Given that 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 that emphasizes the role of secondary towns and urbanization as the main drivers to reduce extreme poverty.

Introduction

There has been 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 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 the skills necessary for the move into non-agricultural sectors. The structural transformation involves two related, but distinct processes: (i) development of the non-agricultural sector in rural areas; and (ii) urbanization, in which workers in rural areas typically migrate to and seek employment in the non-agricultural sector in urban areas – including both megacities and secondary cities or towns. These processes may have different implications for aggregate poverty reduction.

A recent study by Christiaensen and Todo (2014) – hereafter referred to as CT– argues that the past empirical literature **either** investigated the role of urbanization in development or poverty reduction without disaggregating the urban sector into megacities and secondary cities/towns or suburbs of urban areas, **or** focused on the role of the rural non-agricultural sector in poverty reduction. We argue that it is necessary to examine the role of the "missing middle" (the aggregate of secondary towns and rural non-agricultural sector) and of "megacities" to better understand the relationship between urbanization and poverty reduction. CT's study found that migration out of agriculture into the "missing middle" is **key** to faster poverty reduction than agglomeration in megacities. 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, Cheng and Gaiha (2017) used cross-country panel data and showed that agricultural growth has 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 the different locations of these sectors, the dynamics between non-agricultural and agricultural sectors in rural areas, and the dynamics between the non-agricultural sector in rural areas and secondary towns.[1] 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

1. For illustrative evidence on selected Asian countries, see IFAD (2013).

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) megacities – 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 accelerating poverty reduction. It has also been observed that growth in megacities does not contribute to poverty reduction; indeed in some cases it **increases** poverty. So, the case for urbanization – especially secondary towns – as the key driver to eliminate extreme poverty put forward by CT rests on a somewhat arbitrary merging of the non-agricultural sector in rural areas and secondary towns.[2,3]

In a recent contribution, Cali and Menon (2013) identified and measured the impact of urbanization on rural poverty in India using National Sample Survey (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 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 urbanization has a significant poverty-reducing effect on the surrounding rural areas. An increase in a district's urban population of 200,000 was associated with a reduction in rural poverty in the same district of between 1.3 and 2.6 percentage points. Over the entire period in question, urbanization was associated with a reduction of between 13 and 25 per cent of the reduction in poverty. But this reduction is not as substantial as that 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 urbanization 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. Whether these are valid comparisons, given differences in time periods covered and specifications used, is open to discussion.

Another analysis (Kulkarni, Christiaensen and Gindelsky 2014) based on 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 noteworthy effects. One is the locational effect captured through the ratio of the rural-urban population. This is positive, implying that the greater the number of rural inhabitants relative to the urban, the higher 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 urban areas. 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

2. In another contribution (Christiaensen, Weerdt and Todo 2013), a similar argument is developed by combining the evidence from the panel survey in Kagera (United Republic of Tanzania) and cross-country data analysis. Christiaensen, Weerdt and Todo (2013) 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 megacities in reducing poverty with spillover effects on the rural farm economy.
3. To overcome the limitations of CT, Cali and Menon (2013) identified and measured the impact of urbanization on rural poverty in India using National Sample Survey (NSS) and other relevant district data over the years 1983-84, 1993-94 and 1999-2000.

in urban and rural earnings per capita, has a positive coefficient suggesting that the greater the difference, the higher the incidence of rural poverty, presumably because rural-urban migrants are typically younger, better-endowed persons. The greater 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 to investigate this using cross-country panel data.

The rest of the paper is organized as follows. The next section provides a background for the present study by critically reviewing the methodology and findings of Christiaensen and Todo (2014). The following section outlines the data and the econometric methods. The results of various econometric estimations will be presented in the fourth section. The final section offers concluding observations and policy implications.

Background: review of Christiaensen and Todo (2014)

In some countries, the structural transformation involves rapid agglomeration in megacities (as in Republic of Korea and the Philippines), while in others there is diversification out of agriculture into the rural non-farm economy and secondary towns (e.g. in 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) where the last category, (iii), is referred to as the "missing middle". CT's empirical investigation is based on 206 poverty periods across 51 countries from different regions during 1980-2004.

The empirical findings of CT suggest that migration out of agriculture into rural non-farm 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 megacities. Further exploration of the channels indicates that rural diversification and secondary-town expansion yield on average more inclusive growth patterns. In contrast, megacity 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 urbanization than migration under some circumstances (Jedwab, Christiaensen and Gindelsky 2016).[4]

CT have shown that urban increase contributes to explain why the cities of the developing world grew so fast post-1960, and why many of these cities may be highly congested today. They report several policy implications. First, any urban population growth slowdown (e.g. through enhanced family planning programmes) could contribute to increasing the urban

4. Using an extensive historical dataset on urbanization and the urban demographic transition, Jedwab, Christiaensen and Gindelsky (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; while not investing in them could make matters worse. Alternatively, more could be invested in rural areas of these countries to slow down excessive migration and relieve the already congested cities. This policy choice is reinforced by our empirical analysis.

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 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 manydeveloping 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?

CT aims 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, CT used a simplified specification as follows.

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

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-town populations, and s_A representing the share of agricultural population). y is the national income. β_u, β_N and γ are coefficients. 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 "missing middle" population shares and per capita income (specifically, gross domestic product [GDP] per worker). In order to allow for country-specific and global year-specific effects, equation (1) is augmented as follows.

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

where ϑ_i denotes a country-specific effect. Equation (2) is estimated using ordinary least squares (OLS) with a correction for heteroscedasticity. By testing whether $\beta_u = \beta_N$, inferences are drawn about whether poverty-reducing effects of movements out of agriculture into the "missing middle" and large cities differ. ε_{it} is an error term.

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, Christiaensen and Gindelsky 2016). Moreover, there is migration out of small cities into metropolitan ones. 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 from that between the non-farm activities and small towns. This is because, for example, many farm households divide their time between farm and 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 subsector 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 the 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 summarize 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 headcount ratios based on both US$1 and US$2 per day poverty lines, while agglomeration in the megacities 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 (CT table 4), there is no effect of megacities on poverty while that of the "missing middle" is robust, with a strong poverty-reducing effect that declines with the rate of migration into this sector. As another robustness check, CT examined the effects of (share weighted) agricultural and non-agricultural growth rates (CT 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 US$2 per day poverty. The conclusion that "Agricultural growth appears not to be driving the results" (CT, p. 6) appears to be false, as in columns (1), (2) and (4), it has a significant **negative** coefficient. CT in fact make the 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" (CT, 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 CT's table 5, both agricultural growth rate and share of the "missing middle" have significant negative coefficients. On the basis 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 CT's 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 slower the poverty change.[5] Two additional results are reported by CT in tables 7 and 8: (i) megacities accelerate growth through agglomeration economies but without any role for agriculture; and (ii) the megacity growth also aggravates inequality. CT conclude that agglomeration in megacities is on average associated with faster growth and greater 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.

5. 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 slower 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.

Data and methodology

Data

Christiaensen and Todo (2014) use the Word Bank's World Development Indicators (WDI) (available from https://data.worldbank.org/data-catalog/world-development-indicators) and POVCAL data to construct the poverty estimates. They also use the data of the United Nations World Urbanization Prospects (UNWUP) (https://esa.un.org/unpd/wup/) to derive the share of the population living in cities with 1 million or more inhabitants. To compute the share of people in agriculture, CT use WDI and FAOSTAT (http://www.fao.org/faostat/en/#data). 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 the agricultural sector available from FAOSTAT and have derived the approximate share of the population in the rural non-agricultural sector as the difference between the share of rural population in the total population (calculated from the WDI data) and the share of the population in the agricultural sector (from FAOSTAT 2013). Here we assume that all the agricultural population lives in rural areas as agricultural activities are predominantly rural, that is, urban agriculture is rarely found in developing countries.[6] This will further reduce the sample size, as we will see later, but (as argued in the previous section) it is crucial to treat the 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 megacities is defined as the population share living in cities with a population of more than 1 million and is based on the 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 (purchasing power parity [PPP]).

Secondly, we have updated the data coverage to 2010. Thus, we have covered the period 1980-2010, while CT covered the period 1980-2004. However, we have imposed further restrictions on the dataset by (i) calculating the approximate share of the population in the rural non-agricultural sector, (ii) dropping cases where the agricultural population share exceeds that of rural population and (iii) further dropping a few cases that showed data inconsistencies (e.g. the cases where the sum of the share of rural population and the share of megacity population exceeded one, i.e. the share of small cities is negative). Our approach does suffer from

6. 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 were therefore omitted from our study. 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 used was based on the main occupation and ignores secondary occupations. So we did not consider the agricultural activities conducted by rural non-farming households or by those in small towns.

a few limitations. First, we ignore the cases where the urban agricultural sector is substantial, typically Latin American countries, and thus the number of observations 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] - [megacities]), we have derived "the small or secondary towns" as the residual sector (= 1 - [rural sector (= rural agricultural sector + rural non-agricultural sector)] - [megacities]). 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 annex table 1. In annex table 2 we have summarized 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 megacities population have marginally decreased. The increase of the rural non-agricultural sector is due to the rapid increase of this sector in the Middle East and North Africa as well as in East Asia and 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 in South Asia with only one observation in 2000) and the population share of megacities has increased (except in sub-Saharan Africa).[7]

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 megacities between the initial year and the survey year (CT, p. 4). It is not clear why, in the case where there are more than two data points for a country (e.g. 1992, 1997, 2000), the initial year (1992) is used as the base year for **all** subsequent years (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 three-year average data.[8] As FD in log denotes the approximate value of growth rate (i.e. $\frac{dP_{it}}{P_{it}}$ or $\frac{ds_{uit}}{s_{uit}}$), econometric models for equation (2) should be specified as "FD (in log of one variable)-FD (in log of another variable)" to estimate how changes in, for example, urban metropolitan population share are associated with changes in the poverty ratio where the positive (negative) and significant coefficient estimate implies that if the growth rate of urban population increases then 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., a positive coefficient estimate implies that if the urban population increases, the poverty rate tends to increase) or the FD-Level regression (in which a positive coefficient estimate implies that if the urban population increases, the change in poverty rate tends to increase).

7. These regional patterns should not be generalized due to the small number of observations in each region.

8. 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.

Methodology

As we have noted above, as an extension of CT, we have estimated three sets of models based on "Level-Level," "FD-Level" or "FD-FD" specification for the three-year average panel data and "Level-Level" specification for the annual panel data.[9] We mainly adopt the robust fixed or random effects estimator given that the data are relatively small and unbalanced.[10] 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 megacity population (or its change) as explanatory variables to explain a dependent variable (defined for four 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.

Fixed-effects model

Case A: The "FD-FD" regression (for the three-year average panel)

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

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 the rural non-agricultural sector, and $dlogS_{Uit}$ is the first difference of log of the share of population in megacities; $dlogGDPpc_{it}$ is the growth rate of GDP per capita. $\boldsymbol{X}$ is a vector of the control variables (for example, conflict intensity and the institutional quality of the country). β denotes a coefficient. We have tried the cases with and without the intensity of conflict and the aggregate level of institutional quality. Conflict intensity, taking a 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 Uppsala Conflict Data Programme (UCDP) at the Department of Peace and Conflict Research, Uppsala University (http://ucdp.uu.se/downloads/). The institutional quality is a simple average of four different World Bank governance indicators (political stability, rule of law, control of conflict and voice and accountability [Imai, Gaiha and Thapa 2010]). μ_i is the unobservable fixed effect specific to each country, and e_{it} is the error term, independent and identically distributed. This is a specification in which the growth rate of poverty is estimated by the population growth rate in each sector. For instance, a positive coefficient estimate for β_U implies that if the megacity population grows at a faster rate, poverty headcount ratio also grows at a faster rate. We have used the Huber-White robust estimator in all the cases.

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

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

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 in which the rate of change in poverty is estimated by the level of the share of the population in each sector. For instance, a positive coefficient estimate for β_U implies that if the megacity population increases, poverty headcount ratio rises at a faster rate.

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.

10. The choice between fixed and random effects is guided by the Hausman specification tests.

Case C: The "Level-Level" regression (for the three-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 in which poverty is estimated by the level of the share of the population in each sector. For instance, a positive coefficient estimate for β_U implies that if the megacity population increases, poverty headcount ratio is likely to increase.

Dynamic panel (for the three-year average panel and the annual panel)

As an alternative to the fixed-effects model,[11] 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 realizations of the explanatory variables as the internal instruments, using the Blundell-Bond (1998) system generalized method of moments (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 that the instruments are uncorrelated with the error terms. The Blundell-Bond system GMM (SGMM) estimator is used, as in CT. A disadvantage of this is that the number of observations is reduced and thus the results have to be interpreted cautiously. We used the robust estimator based on Windmeijer's (2005) 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 ($\widehat{\mu''_i}$). This is used to get rid of fixed effects in $logP_{it}$ by calculating $\widetilde{logP_{it}}= logP_{it} - \widehat{\mu''_i}$. In the second step, we use a standard linear quantile regression and estimate the λth quantile function (i.e. 10 per cent, 25 per cent, 50 per cent, 75 per cent, 90 per cent) conditional on explanatory variables.[12]

11. 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 $\mathbf{X}_{it}$ are weakly exogenous, the generalized method of moments (GMM) first difference estimator (e.g. Arellano and Bond 1991) can be used.

12. See Canay (2011) and You, Imai and Gaiha (2016) for more details.

Results

In this section, we report and discuss the econometric results for the models presented in the previous section.[13] Table 1 shows the results of econometric models for equations (1)-(3) for the three-year average panel data (cases 1-4 for "FD-FD," cases 5-8 for "FD-Level" and cases 9-12 for "Level-Level" specifications). Where the "FD-FD" specification was used, the rate of change in the share of the agricultural population was negatively and significantly associated with the rate of the change in poverty, regardless of the definitions of poverty (cases 1-4). For instance, in a country where the population share in the agricultural sector reduces and the overall poverty also decreases, a faster decline in agricultural population leads to slower poverty reduction. Conversely, a slower decline in agricultural population share leads to faster poverty reduction. For example, if the rate of change in the agricultural population decreases by 10 per cent, the rate of change in poverty headcount based on US$1.25 increases by 18 per cent, 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 megacities has no statistical significance, and the growth of GDP per capita does not significantly influence the rate of change in poverty.

When the "FD-Level" specification was used, the increase of the population share in the megacities led to an accelerated increase in poverty, regardless of the definition of poverty. For instance, a 10 per cent increase in the population share in the megacities is associated with a 0.7 per cent increase in the rate of change of poverty headcount ratio based on US$1.25 or US$2. The population share in the agricultural sector affects poverty negatively and significantly only for poverty headcount based on US$2. The share of the population in the rural non-agricultural sector has negative and significant effect on poverty for the headcount ratios based on US$1.25 and US$2. Overall, we conclude that a shift in population to megacities, or population increase in megacities, increases poverty. In cases 9-12, where the "Level-Level" specification was applied to the three-year average panel, we did not find any statistically significant coefficient for sectoral population shares. This is partly because the log of GDP per capita negatively and highly significantly impacted poverty.

13. 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 the sum of rural non-agricultural sector and 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 annex table 3. It was also noted that even without the recent data (2005-2010) included, the results did not change significantly.

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

In sum, when our estimations were based on the three-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 megacities is positively associated with an increase in national poverty.

Next, the annual panel data were used to estimate the effect of sectoral population shares (in levels) on poverty headcount or poverty gap (in levels).[14] In the case where the dependent variable is the poverty headcount ratio based on US$1.25, the effect of population share in megacities is positive and significant with or without conflict intensity. We also found that higher conflict intensity tends to increase poverty headcount or poverty gap. It is noteworthy that, 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 rural agricultural households to towns or cities) tended to increase poverty until 2000. In other cases, the effects of 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 US$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 at the higher levels of poverty. This implies that the poverty-reducing effect of income growth is limited if the country's poverty level is high.

14. The full set of results is available on request.

Table 1: Effects of change or level in log sectoral population compositions on change or level in log poverty gap or headcount: Robust fixed or random effects model for poverty based on US$1.25 or US$2.00 (2005 PPP) (based on three-year average panel)

	Case 1	Case 2	Case 3	Case 4
	FD-FD			
Dependent variable	**D_log poverty**			
	Headcount US$1.25 (2005 PPP)	**Gap US$1.25**	**Headcount US$2.00 (2005 PPP)**	**Gap US$2.00**
Model	RE	RE	RE	RE
Explanatory variables				
Dlog (real GDP/capita)	1.236 (2.748)	0.0333 (2.562)	-0.459 (1.828)	0.325 (1.790)
Log (real GDP/capita)				
Dlog (share of population in rural agricultural sector)	**-1.837***** **(0.540)**	**-1.368***** **(0.330)**	**-2.161**** **(0.909)**	**-1.575***** **(0.280)**
Dlog (share of population in rural non-agricultural sector)	**-0.684**** (0.341)	**-0.435***** (0.0744)	-0.811 (0.589)	**-0.473***** (0.121)
Dlog (share of population in megacities)	-0.113 (0.216)	-0.146 (0.171)	-0.159 (0.290)	-0.0451 (0.145)
Log (share of the population in the rural agricultural sector)				
Log (share of population in rural non-agricultural sector)				
Log (share of population in megacities)				
Constant	-0.11 (0.133)	-0.238 (0.129)	-0.011 (0.152)	-0.155 (0.118)
Number of observations	**48**	**45**	**48**	**46**
Number of countries	**20**	**18**	**20**	**19**
Hausman test: $Chi^2(4)$	3.48	0.38	29.42**	0.77
Prob > chi^2=	0.4802	0.9842	0	0.9428
Chosen model	RE	RE	RE	RE

	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
	FD-Level				Level-Level			
	D_log poverty				Log poverty			
	Headcount US$1.25	**Gap US$1.25**	**Headcount US$2.00**	**Gap US$2.00**	**Headcount US$1.25**	**Gap US$1.25**	**Headcount US$2.00**	**Gap US$2.00**
	RE	RE	RE	RE	RE	RE	RE	RE
	2.3 (3.220)	-0.326 (2.517)	1.358 (1.396)	0.521 (2.016)				
					-1.164* (0.194)**	**-1.080*** (0.119)**	**-0.943*** (0.202)**	**-0.986*** (0.153)**
	-0.35 (0.222)	0.0588 (0.109)	**-0.479** (0.225)**	-0.0709 (0.0903)	0.25 (0.294)	0.148 (0.272)	0.194 (0.255)	0.16 (0.249)
	-0.0900* (0.0519)	0.00936 (0.0437)	**-0.122** (0.0618)**	-0.0198 (0.0276)	-0.0465 (0.0607)	-0.0668 (0.0578)	-0.0416 (0.0518)	-0.0544 (0.0515)
	0.705 (0.319)**	**0.447* (0.262)**	**0.685** (0.334)**	**0.568* (0.331)**	0.0668 (0.234)	0.109 (0.180)	-0.0092 (0.220)	0.0851 (0.185)
	-0.56 (1.338)	-1.585 (0.740)	0.148 (1.394)	-1.286 (0.815)	9.355 (2.059)	8.167 (1.510)	8.922 (2.094)	8.312 (1.732)
	53	**50**	**53**	**51**	**126**	**123**	**126**	**124**
	21	**19**	**21**	**20**	**45**	**45**	**45**	**45**
	2.34	1.15	1.8	2.38	2.58	2.04	6.37	2.83
	0.6739	0.887	0.7732	0.6667	0.6303	0.7292	0.1729	0.5861
	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. However, in case 3, we have chosen random effects model despite a significant coefficient result of Hausman test as fixed effects model shows unreasonably small coefficient estimates for a few variables. Dlog stands for the first difference in the logarithm. RE stands for Random Effects model.

Table 2: Effects of log sectoral population compositions on log poverty headcount (Level-Level): Arellano-Bover/Blundell-Bond linear dynamic panel estimator based on US$1.25 or US$2.00 (2005 PPP) (based on the three-year average panel)

	Case 1	Case 2	Case 3	Case 4
Dependent variable	**Log poverty headcount**		**Log poverty headcount**	
	US$1.25	**US$1.25**	**US$2.00**	**US$2.00**
Model	SGMM	SGMM	SGMM	SGMM
L.log (poverty headcount based on US$1.25 [or US$2] a day PPP)	0.075 (0.190)	**0.367* (0.193)**	**0.453** (0.196)**	**0.381*** (0.136)**
Log (real GDP/capita)	**-1.204*** (0.434)**	**-0.860* (0.445)**	**-0.544* (0.291)**	**-0.630** (0.278)**
Log (share of the population in the rural agricultural sector)	0.784 (0.770)		0.388 (0.470)	
Log (share of the population in the rural non-agricultural sector)	0.0213 (0.359)		-0.0553 (0.147)	
Log (share of the population in megacities)	**1.156** (0.517)**		**1.039*** (0.389)**	
L.log (share of population in rural agricultural sector)		0.923 (0.740)		0.483 (0.445)
L.log (share of population in rural non-agricultural sector)		-0.302 (0.248)		**-0.268* (0.160)**
L.log (share of population in megacities)		0.521 (0.595)		0.325 (0.385)
Constant	4.623 (5.234)	3.444 (6.008)	1.479 (3.583)	4.255 (3.744)
Number of observations	53	54	53	54
Number of countries	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)				
	$Chi^2(32)$=	$Chi^2(33)$=	$Chi^2(31)$=	$Chi^2(33)$=
	26.86	24.15	21.65	25.15
Prob > chi^2	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.
SGMM = Blundell-Bond system generalized method of moments. L.log stands for the first lag of logarithm.

Table 3: Heterogeneous effects of log sectoral population compositions on log poverty headcount (Level-Level): Robust quantile regression for poverty headcount ration based on $1.25 (2005 PPP) (based on annual panel)

	Log poverty headcount				
Percentile points	**10%**	**25%**	**50%**	**75%**	**90%**
	US$1.25 (2005 purchasing power parity)				
Model	QR	QR	QR	QR	QR
Log (real GDP/capita)	**-1.657*** (0.134)**	**-1.812*** (0.205)**	**-1.053*** (0.217)**	**-0.851*** (0.0681)**	**-0.597*** (0.102)**
Log (share of population in rural agricultural sector)	**0.908*** (0.270)**	0.672 (0.484)	0.0931 (0.293)	-0.163 (0.134)	**-0.227* (0.116)**
Log (share of population in rural non-agricultural sector)	-0.0689 (0.106)	-0.0543 (0.0895)	**-0.0822** (0.0348)**	**-0.0341** (0.0170)**	**-0.0422** (0.0199)**
Log (share of population in megacities)	**-0.396* (0.217)**	0.182 (0.442)	-0.0253 (0.244)	-0.127 (0.130)	**-0.362*** (0.122)**
Constant	9.499 (1.693)	10.79 (2.968)	9.654 (1.987)	9.933 (0.922)	9.487 (0.923)
Number of 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. loggdppc stands for logarithm of GDP per capita. QR stands for quantile regression.

An interesting result is obtained on the coefficient estimates of the log of the population share in the agricultural sector. At the 10 per cent percentile point in the distribution of poverty headcount based on US$1.25 (e.g. in the upper- or lower-middle-income countries which had already reduced extreme poverty), an increase in the share of the agricultural population tends to increase poverty, while an increase in the share of the population in megacities is associated with poverty reduction. However, at the 90 per cent percentile point in the same distribution (for instance, in low-income countries with a higher level of poverty), an increase in the share of the agricultural population decreases poverty. Here, given that the coefficient estimates for the shares of agricultural population, rural non-agricultural population and megacities are negative and significant, the increase in the share of urban small towns is likely to increase poverty. At 50 per cent and 75 per cent, an increase in the share of the population in the 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 US$1.25 or US$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) an increase in the share of the agricultural population tends to reduce poverty regardless of the definition of poverty; (ii) an increase in the share of the population in the rural non-agricultural sector also tends to reduce poverty, but the size of the effect is smaller than that of the agricultural population share; and (iii) an increase in the share of the population in megacities tends to increase poverty.

Table 4: Effects of log sectoral population compositions on log poverty headcount (Level-Level): Arellano-Bover/Blundell-Bond linear dynamic panel estimator based on US$1.25 or US$2.00 (2005 PPP) (based on annual panel)

	Case 1	Case 2	Case 3	Case 4
Dependent variable	**Log poverty headcount**		**Log poverty headcount**	
	US$1.25	**US$1.25**	**US$2.00**	**US$2.00**
Model	SGMM	SGMM	SGMM	SGMM
L.log (poverty headcount based on US$1.25 [or US$2] a day PPP)	**0.214*** **(0.129)**	**0.626***** **(0.148)**	**0.895***** **(0.111)**	**0.845***** **(0.115)**
Log (real GDP/capita)	**-2.218***** **(0.355)**	**-1.173***** **(0.407)**	-0.328 (0.239)	**-0.479*** **(0.262)**
Log (share of the population in the rural agricultural sector)	**-1.580***** **(0.302)**		**-0.665***** **(0.246)**	
Log (share of the population in the rural non-agricultural sector)	**-1.156***** **(0.177)**		**-0.153*** **(0.0812)**	
Log (share of the population in megacities)	**3.664***** **(0.687)**		0.0713 (0.231)	
L.log (share of population in rural agricultural sector)		**-1.022***** **(0.388)**		**-0.845***** **(0.275)**
L.log (share of population in rural non-agricultural sector)		**-0.610***** **(0.219)**		**-0.173*** **(0.0910)**
L.log (share of population in megacities)		**1.697*** **(0.883)**		**0.0641** **(0.238)**
Constant	14.83 (2.390)	9.085 (2.862)	5.134 (2.398)	7.098 (2.747)
Number of observations	35	32	35	32
Number of countries	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)				
	$Chi^2(30)$=	$Chi^2(27)$=	$Chi^2(31)$=	$Chi^2(28)$=
	36.492	21.202	19.741	16.399
Prob > chi^2	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.
SGMM = Blundell-Bond system generalized method of moments. L.log stands for the first lag of logarithm.

The pattern of the results on the effects of population compositions in different sectors differs according to which econometric model or specification is adopted, and whether the three-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 three-year average panel; when the "Level-Level" specification is applied to the headcount based on US$1.25 before 2000 or at the high percentile [90 per cent]; when the dynamic panel is used for the annual data). In some cases, the rural non-agricultural sector is also poverty-reducing (e.g. when the "FD-FD" specification and the static panel model are used for the three-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, an increase in the share of the population in megacities tends to **increase** poverty (e.g. the "FD-Level" specification for the three-year average panel; the dynamic panel for the annual panel), though at the low and high percentiles its coefficient estimates are negative and significant in the fixed-effects quantile regressions.

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" (CT, p. 1). It is, however, not clear that treating the rural non-farm economy and secondary towns as one aggregate sector is justifiable given that they are different in locations and also differ in their intersectoral dynamics.

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

Our study has several policy implications. First, given 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 and rural non-agricultural sectors. An example is to support rural infrastructure, such as rural roads, electrification and irrigation systems, that would significantly reduce the transaction costs (Renkow, Hallstrom and Karanja 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 infrastructure in remote rural areas is more poverty-reducing than an equivalent investment in less-remote rural areas or urban areas given the budget constraint.[15] 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 megacities.

Second, our results may have an implication for migration policies. While policies to restrict rural-urban migrations cannot be generally recommended as such migrations may bring benefits to rural agricultural households (e.g. reducing seasonal income risks), policymakers should be aware of 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 they are likely to face poverty or hardships in urban areas.

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

Focusing on Africa, over 60 per cent of the population is below the age of 25. The youth population will continue to rise in sub-Saharan Africa throughout the twenty-first 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. However, 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 – by 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 young people's access and rights to the land, 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 emphasizing the role of secondary towns or urbanization as a key driver to eliminate extreme poverty. To achieve Sustainable Development Goal 1 (i.e. eradication of extreme poverty), governments and donors should place more importance on investments in the rural agricultural sector – for example smallholder farming in remote areas – and those in non-agricultural sectors.

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Annex Table 1

Descriptive statistics

Variable	Definition	Number of observations	Mean	Standard deviation	Minimum	Maximum
povertyhc125	Poverty headcount based on US$1.25 a day PPP	367	20.4	22.7	0.0	92.6
povertyhc200	Poverty headcount based on US$2.00 a day PPP	367	41.1	29.1	0.0	98.5
povertyg125	Poverty gap based on US$1.25 a day PPP	320	9.7	11.5	0.0	63.3
povertyg200	Poverty gap based on US$2.00 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 megacities	Share of population in megacities	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 four World Bank Governance indicators: political stability, rule of law, control of conflict and voice and accountability (Imai, Gaiha and Thapa 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 the "missing middle" (based on CT)	250	40.9	18.2	5.6	79.0
The share of the population in megacities~CT	Share of population in megacities (based on CT)	250	18.9	10.1	3.8	37.1
pov1_CT	Poverty headcount based on US$1.25 a day PPP (based on CT)	250	17.6	20.2	0.1	90.3
pov2_CT	Poverty headcount based on US$2.00 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

Annex Table 2

Regional changes of sectoral population shares in 2000-2010

		Sector (population share) (%)				
		Agriculture	**Rural non-agriculture**	**Secondary towns**	**Megacities**	**Total**
Eastern Europe and Central Asia (ECA)	2000	34.7	16.7	33.7	14.8	100.0
	2010	36.5	16.2	31.0	16.3	100.0
Middle East and North Africa (MENA)	2000	52.5	7.4	25.5	14.5	100.0
	2010	49.6	18.1	15.3	17.0	100.0
Sub-Saharan Africa (SSA)	2000	35.2	12.0	30.8	22.0	100.0
	2010	37.3	12.4	31.5	18.8	100.0
Latin America and the Caribbean (LAC)	2000	43.9	15.8	26.6	13.7	100.0
	2010	39.7	14.5	29.8	16.1	100.0
East Asia and the Pacific (EAP)	2000	74.0	7.2	8.9	9.9	100.0
	2010	57.5	17.3	11.0	14.2	100.0
South Asia (SA)	2000	26.2	12.4	57.1	4.3	100.0
	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: This table is based on three-year average data. The average for 2000 is based on 1998-2000 and that for 2010 is based on 2009-2011.
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.

Annex Table 3

Effects of the “missing middle” on log poverty headcount (US$1.25 or US$2), using data from Christiaensen and Todo (2014): Robust fixed estimator or robust Arellano-Bover/Blundell-Bond linear dynamic panel estimator

	First difference (dep) - First difference (exp)			
	Fixed-effects, robust		Dynamic panel, robust	
	Case 1 **Dlog (poverty HC US$1.25)**	Case 2 **Dlog (poverty HC US$2.00)**	Case 3 **Dlog (poverty HC US$1.25)**	Case 4 **Dlog (poverty HC US$2.00)**
Variable				
Dlog (2° towns) (CT)	**-9.809** (3.511)**	**-4.130*** (1.224)**	**-15.29*** (4.860)**	**-9.953*** (1.447)**
Dlog (share of population in megacities) (CT)	**-5.53 (10.42)**	**-1.13 (3.931)**	**1.99 (7.075)**	**2.83 (2.591)**
Log (2° towns) (CT)				
Log (share of population in megacities) (CT)				
Dlog (real GDP/capita)	-3.656*** (1.153)	-2.718*** (0.630)	5.45 (4.611)	-0.65 (1.435)
L.dlog (poverty HC at US$1.25) (CT)			-1.298*** (0.247)	
L.dlog (poverty HC at US$2) (CT)				-0.779** (0.320)
L.log (poverty HC at US$1.25) (CT)				
L.log (poverty HC at US$2) (CT)				
Constant	0.16 (0.128)	0.106** (0.0492)	-0.44 (0.272)	-0.01 (0.0740)
Number of observations	67	68	35	36
R^2	0.08	0.21		
Number of countries	21	21	15	16

	First difference (dep) - Level (exp)				Level (dep) - Level (exp)			
	Fixed-effects, robust		**Dynamic panel, robust**		**Fixed-effects, robust**		**Dynamic panel, robust**	
	Case 5 **Dlog (poverty HC US$1.25)**	Case 6 **Dlog (poverty HC US$2.00)**	Case 7 **Dlog (poverty HC US$1.25)**	Case 8 **Dlog (poverty HC US$2.00)**	Case 9 **Log (poverty HC US$1.25)**	Case 10 **Log (poverty HC US$2.00)**	Case 11 **Log (poverty HC US$1.25)**	Case 12 **Log (poverty HC US$2.00)**
	-2.959 **(1.317)**	**-1.321** **(0.628)**	**-0.39** **(0.295)**	**-0.161***** **(0.0583)**	**-2.111*** **(1.165)**	**-0.52** **(0.404)**	**-1.037***** **(0.362)**	**-0.308***** **(0.0747)**
	2.720* **(1.427)**	**0.93** **(0.782)**	**0.03** **(0.191)**	**-0.02** **(0.0520)**	**1.02** **(1.509)**	**-0.14** **(0.604)**	**0.21** **(0.286)**	**0.02** **(0.0513)**
	-3.147** (1.343)	-2.596*** (0.645)	-2.42 (5.289)	-2.200* (1.247)	-0.86 (1.306)	-0.22 (0.566)	-2.24 (1.876)	-1.589** (0.740)
			-0.636* (0.380)					
				-0.35 (0.219)				
							0.598*** (0.198)	
								0.858*** (0.0491)
	3.04 (3.361)	2.26 (1.630)	1.31 (1.372)	0.705 (0.280)	6.814 (3.166)	5.683 (1.389)	3.924 (1.590)	1.551 (0.393)
	67	68	35	36	250	254	67	68
	0.04	0.15			0.08	0.04		
	21	21	15	16	48	48	21	21

Robust standard errors in parentheses. *** P<0.01, ** P<0.05, * P<0.1.
dep. = dependent; exp. = explanatory; HC = headcount.
Dlog stands for the first difference of logarithm. LDlog stands for the first lag of the first difference of logarithm.

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