Poverty Reduction during the Rural-Urban Transformation
- The Role of the Missing Middle

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Abstract [*]

As countries develop, they undergo a structural transformation from agriculture to manufacturing and services as well as a spatial transformation from rural to urban. Historically, this process has been far from uniform across countries, with some fostering rural diversification out of agriculture and others undergoing rapid agglomeration in mega cities. This paper examines whether the nature of these transformations (rural diversification versus agglomeration in mega-cities) affects the rate of poverty reduction. Using cross-country panel data for developing countries spanning 1980-2004, it is found that migration out of agriculture into the missing middle (rural nonfarm economy and secondary towns) is strongly associated with poverty reduction, while expansion of mega-cities is not. Migration to the missing middle leads to more inclusive growth patterns, while agglomeration in mega cities widens income inequality, even though it also generates faster economic growth, as predicted by the new economic geography. These findings bear on the longstanding debate about the appropriate balance of public investment in both portable (education, health) and non-portable (infrastructure) public goods across space.

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1. Introduction

As countries develop, their economies restructure away from agriculture into manufacturing and services and people move from rural to urban areas. While intertwined, these structural and spatial transformation processes typically do not fully overlap. In some countries, the rural-urban transformation is dominated by rapid agglomeration in mega cities (as in South Korea and the Philippines), while in others people predominantly diversify out of agriculture into the rural nonfarm economy and secondary towns (Taiwan, Thailand) (Christiaensen, 2007; Otsuka, 2007). Whether rural diversification and secondary town development or agglomeration in mega cities, is more effective in facilitating poverty reduction remains however poorly documented.

One longstanding and rich strand of literature has highlighted the positive role of rural nonfarm activities in growth and poverty reduction as countries transform (Lanjouw and Lanjouw, 1995; Haggblade, Hazell, and Reardon, 2007). This literature however typically does not take a comparative perspective, exploring the contributions of rural nonfarm activities in a country in isolation of the potential impacts on growth and poverty reduction that rapid mega-city development might generate given the important economies of agglomeration especially in the service sector in more developed countries (World Bank, 2008).

Inspired by Ravallion and Datt (1996) who find that rural income growth is more poverty reducing than urban income growth in India, a number of studies have recently explored whether the sectoral composition of growth matters for poverty reduction using cross-country panel data (Loayza and Raddatz , 2006; Christiaensen and Demery, 2007; Ligon and Sadoulet, 2007). They find that growth originating in agriculture is on average at least twice as poverty reducing as growth originating outside agriculture, with the poverty reducing powers of agriculture typically declining as countries get richer (World Bank, 2007). This paper builds on this literature and examines whether the nature of the spatial and occupational re-allocation of people also affects the rate of poverty reduction.

In particular, and contrary to the literature, which typically deploys either a spatial (rural-urban) or occupational (agriculture-nonagriculture) dichotomy[1], this study classifies the population into three groups according to their occupation and location, i.e. those living in rural areas and employed in agriculture, those living in mega cities and employed in industry and services, and those living in rural areas and secondary cities and employed outside agriculture. The latter group will be referred to as the "missing middle", also reflecting its operational definition as the residual category between the total population and those employed in agriculture and those living in mega-cities. It is empirically examined using a cross-country panel spanning 1980-2004 whether it matters for the rate of poverty reduction whether a country's population expands into the missing middle or into the mega-cities.

The findings suggest that migration out of agriculture into rural nonfarm activities is associated with a reduction of poverty, while agglomeration in mega cities has no significant impact on poverty. Further exploration indicates that rural diversification (including migration into secondary towns) yields more inclusive growth patterns. In contrast, while mega-city agglomeration yields faster income growth, it also rises income inequality, which substantially mitigating its potential impact on poverty, especially for the poorer segments of society. These findings bear on the continuing debate about the appropriate geographical distribution of public investment in portable (education, health) and nonportable (infrastructure) public goods across space. In what follows, section 2 demonstrates the analytical framework underpinning the estimation equation. The data are reviewed in section 3, and the estimation results including a series of robustness tests are presented in section 4. Section 5 concludes.

2. Analytical Framework

Denote by A, the (rural) agriculture sector, by U the (urban) metropolitan sector, and by N, the rural nonfarm sector (including the secondary towns), i.e. the missing middle. Building on the conceptual framework developed in Ravallion and Datt (1996) and Ravallion (2002), the aggregate, decomposable poverty measure, *P*, can then be decomposed as:

$$P = s_U P_U + s_N P_N + s_A P_A \qquad (1)$$

[1] Stifel and Thorbecke (2003) is a noteworthy exception.

where s_i and P_i are the share of the population and the poverty headcount ratio of sector i, respectively. Total differentiating equation (1) leads to

$$\frac{dP}{P} = \frac{s_U P_U}{P}\left(\frac{ds_U}{s_U} + \frac{dP_U}{P_U}\right) + \frac{s_N P_N}{P}\left(\frac{ds_N}{s_N} + \frac{dP_N}{P_N}\right) + \frac{s_A P_A}{P}\left(\frac{ds_A}{s_A} + \frac{dP_A}{P_A}\right) \tag{2}$$

Now, assume that the poverty headcount ratio in each sector is a function of the average income and the population share of the sector:

$$P_i = f_i(y_i,\ s_i) \quad \text{for} \ \ i = U,\ N,\ A, \tag{3}$$

where y_i is the average income of sector i. An increase in average income shifts the distribution of income of each sector to the right and reduces poverty, "*income-level effect*". Following Ravallion (2002), it is assumed that an increase in the population share of the sector, or concentration in the sector, may change its income distribution, holding the average income constant. If the income distribution becomes less equal, the concentration in the sector raises the poverty level, labeled the "*income-distribution effect*".[2] The framework developed here thus combines the insights from Ravallion and Datt (1996) and Christiaensen and Demery (2007, Ch. 3) who focus on the income effects, with those from Ravallion (2002) and Ravallion, Chen, and Sangraula (2007) who focus on the distribution effects. Combining equations (2) and (3) yields:

$$\begin{aligned}\frac{dP}{P} = {} & \frac{s_U P_U}{P}\left(1 + \frac{s_U}{P_U}\frac{\partial P_U}{\partial s_U}\right)\frac{ds_U}{s_U} + \frac{s_N P_N}{P}\left(1 + \frac{s_N}{P_N}\frac{\partial P_N}{\partial s_N}\right)\frac{ds_N}{s_N} + \frac{s_A P_A}{P}\left(1 + \frac{s_A}{P_A}\frac{\partial P_A}{\partial s_A}\right)\frac{ds_A}{s_A} \\ & + \frac{y_U}{P}\frac{\partial P_U}{\partial y_U} s_U \frac{dy_U}{y_U} + \frac{y_N}{P}\frac{\partial P_N}{\partial y_N} s_N \frac{dy_N}{y_N} + \frac{y_A}{P}\frac{\partial P_A}{\partial y_A} s_A \frac{dy_A}{y_A}.\end{aligned} \tag{4}$$

Since $s_U + s_N + s_A = 1$ and hence $ds_U + ds_N + ds_A = 0$, equation (4) can be rewritten as

[2] A better assumption might be that income distribution depends on the population density of the sector, rather than the sectoral share. However, due to data availability, we stick with the simple assumption shown above.

$$
\begin{aligned}
\frac{dP}{P} &= \frac{s_U}{P}\left[\left(P_U + s_U\frac{\partial P_U}{\partial s_U}\right) - \left(P_A + s_A\frac{\partial P_A}{\partial s_A}\right)\right]\frac{ds_U}{s_U} \\
&+ \frac{s_N}{P}\left[\left(P_N + s_N\frac{\partial P_N}{\partial s_N}\right) - \left(P_A + s_A\frac{\partial P_A}{\partial s_A}\right)\right]\frac{ds_N}{s_N} \qquad (5)\\
&+ \frac{y_U}{P}\frac{\partial P_U}{\partial y_U}s_U\frac{dy_U}{y_U} + \frac{y_N}{P}\frac{\partial P_N}{\partial y_N}s_N\frac{dy_N}{y_N} + \frac{y_A}{P}\frac{\partial P_A}{\partial y_A}s_A\frac{dy_A}{y_A}.
\end{aligned}
$$

To estimate equation (5), data is needed on the average income in each of the three sectors. However, the average income of the rural nonfarm sector is only available for a limited set of countries and time periods (Carletto et al., 2007). Consequently, equation (5) is simplified to obtain the following estimable equation:

$$
\frac{dP}{P} = \beta_U\frac{ds_U}{s_U} + \beta_N\frac{ds_N}{s_N} + \gamma\frac{dy}{y} + \varepsilon, \qquad (6)
$$

where y denotes the average income of the whole economy, represented by GDP per capita.

Equations (5) and (6) indicate that the impact of urban agglomeration on poverty, β_U, consists of two components: the direct impact, represented by $s_U / P \cdot \left(P_U + s_U \cdot \partial P_U / \partial s_U\right)$, and the indirect impact on poverty through decreasing the agriculture population, represented by $-s_U / P \cdot \left(P_A + s_A \cdot \partial P_A / \partial s_A\right)$. An alternative interpretation of β_U is obtained when we rewrite the expression of the first bracket of the right-hand side of equation (5) as $\left(P_U - P_A\right) + \left(s_U \partial P_U / \partial s_U - s_A \partial P_A / \partial s_A\right)$. The first term, $\left(P_U - P_A\right)$, represents a "ceteris-paribus" effect of transformation from agriculture to metropolitan activities due to the difference in the current poverty level between the two sectors. The second term, $\left(s_U \partial P_U / \partial s_U - s_A \partial P_A / \partial s_A\right)$, corresponds to the change in the poverty level due to the effect of sectoral concentration on poverty, or income-distribution effects. Since the ceteris-paribus effect of transformation comes from the difference in income distribution between the two sectors, it can also be interpreted as a type of income-distribution effects. Therefore, the coefficient on the change rate of the share of urban population, β_U, represents effects of transformation from agriculture to metropolitan manufacturing and service activities on poverty through changing income distribution, controlling for the impact of changes in income levels (dy/y). Correspondingly, the coefficient on the change rate of the share of rural nonfarm employment, β_N, indicates income-distribution effects of transformation from (rural) agriculture to rural nonfarm activities on poverty.

Finally, as a descriptive starting point it is useful to consider an even more reduced form, allowing for the possibility that the average income level depends on the sectoral share. Indeed, y may be a function of s_i, for example, because sectoral production is characterized by increasing returns to scale, so that y_i is increasing in s_i. Alternatively, too much congestion in a sector may lower the sectoral productivity so that y_i is decreasing in s_i (Fujita and Thisse, 2002). Allowing for these possibilities, equation (6) reduces to:

$$\frac{dP}{P} = \tilde{\beta}_U \frac{ds_U}{s_U} + \tilde{\beta}_N \frac{ds_N}{s_N} + \varepsilon. \qquad (7)$$

In this equation, $\tilde{\beta}_U$ and $\tilde{\beta}_N$ include both direct impacts of sectoral transformation on poverty through changing income distribution (income-distribution effects) and indirect impacts through changing income levels (income-level effects). In what follows, both equations (6) and (7) are estimated and the coefficients on the change rate of the metropolitan share of the population and the change rate of the share of those living in the intermediate "missing middle" space are compared to examine whether and how the patterns of spatial and occupational transformation matter for poverty reduction.

3. Data

The World Bank's POVCAL data are used to construct the poverty spells and the rate of poverty reduction[3]. The \$1-day and \$2-day poverty headcount ratios are taken as measure of poverty, P. The metropolitan share of the population, s_U, is represented by the share (in %) of the population living in cities with one million or more taken from United Nations' *World Urbanization Prospects (UNWUP)*[4]. In the UNWUP, the population data are available every five years. The data for other years are interpolated, assuming a constant growth rate during each 5-year period. Two sources of data are used to calculate the share (in %) of employment in agriculture, s_A: FAO's database and the World Bank's

[3] http://iresearch.worldbank.org/PovcalNet/ April, 2008 (i.e. before the latest revisions of the poverty numbers using the 2005 poverty purchasing power corrections and \$1.25 as poverty line).
[4] http://esa.un.org/unup/. April, 2008. The use of one million or more as cut-off to define a metropolis also helps circumvent some of the challenges in comparing urban areas across countries, given he widely divergent definitions used.

World Development Indicators (originally from ILO's data according to the notes in WDI). The coverage of FAO's database is larger than that of WDI, and thus we use FAO's data whenever they are available. The share of the population engaged in non-farm activities located in the intermediate space or the "missing middle", s_N, is defined as the residual, i.e. s_N,=100-s_U-s_A. Given the (deliberately) narrow definition of urban areas (i.e. only the mega cities), s_N includes people living and employed in secondary towns as well as those engaged in off-farm employment in rural villages. Real GDP per worker (in thousand PPP US dollars) is taken from WDI. The annual change rate of each variable x, dx/x, is given by $(\ln x_t - \ln x_{t-\tau})/\tau$, where t-τ and t are the initial and the final year of the period, respectively.

The sample is limited to low and middle-income countries according to the World Bank's classification in 2007 and spans about a quarter of a century, from 1980-2004. The complete list of available poverty spell observations in *Povcal* consists of 57 countries and 231 country-spell observations. As poverty measures fluctuate substantially in some countries, country-spell observations for which the change rate of the poverty headcount ratio at $1 a day is in the top 1 or bottom 1 percent of the sample are dropped. Missing observations on agricultural employment further reduce the sample, resulting in a sample of 189 poverty spells covering 49 countries from across the world. Table 1 presents the geographical coverage of the sample.

4. Estimation Results

Benchmark estimations

To benchmark our sample, the change rate of the $1 and $2-day poverty headcount ratios are regressed against GDP growth per capita using ordinary least squares with appropriate corrections for heteroskedasticity. To control for (unobserved) country-specific and year-specific effects, a full set of country dummies and year dummies is also included. Unlike most of the poverty to growth elasticity literature so far, the findings presented here are thus controlled both for unobserved country effects in levels *and* changes. The results confirm the critical importance of GDP growth for poverty reduction (Dollar and Kraay, 2002) with poverty to GDP elasticities of 1.82 and 0.98 respectively

(Table 2, columns (1) and (2)).[5]

To explore whether the spatial dynamics of the transformation affect the rate of poverty reduction, columns (1) and (2) are augmented with the rate of rural diversification (the change rate of the population in the missing middle involved in nonfarm activities) and the rate of metropolitan development (the change rate of share of the metropolitan population) (Table 2, columns (3) and (4)). The results indicate that controlling for the overall growth in the economy, rural diversification is associated with poverty reduction, while agglomeration in mega cities is not. This holds both when considering the $1-day and the $2-day poverty head count rates. In addition, the effect of the growth rate of GDP per capita is negative, although it is significant only in column (2). In other words, were two countries to grow at the same rate, poverty would come down faster in the country following rural diversification and secondary town development than in the country following rapid metropolization. This is a pretty striking result, especially given that results are controlled for differences in initial conditions (such as land inequality, institutional and political arrangements) through the inclusion of country specific dummies.

Recall from Section 2 that the coefficient on the sectoral share can be interpreted as the impact of the sectoral transformation on poverty through the income distribution. The findings thus suggest that rural diversification leads to more inclusive growth patterns. This empirical regularity resonates with the findings from in depth comparative studies of country-specific development patterns in East Asia. Taiwan and South Korea experienced for example a similar per capita GDP growth of 7.1 percent between 1965 and 1990. Both countries also started at similar levels of inequality (a Gini of about 0.32), though throughout the subsequent decades inequality has been lower in Taiwan and higher in South Korea. Taiwan's economic development has been based on the development of more labor intensive SMEs located in rural and suburban areas, while South Korea's development has been led by more capital intensive urban based, large enterprises (Otsuka, 2007).

The impact of the diversification into rural nonfarm activities on poverty reduction is quantitatively large. The benchmark results in columns (3) and (4) of Table 2 suggest that a 1-percent (not 1 percentage-point) increase in the share of rural nonfarm employment (and the corresponding

[5] This is commonly referred to as the growth elasticity of poverty, while it should be labeled GDP elasticity of poverty in analogy with price elasticity of demand.

decrease in agricultural employment) reduces the $1-day headcount ratio by 3.5 percent, and the $2-day headcount ratio by 1.2 percent. The average percent change in the $1-day and $2-day headcount ratio across all spells was -4.95 and -2.19 percent respectively, and the average change in the share of the population in the missing middle was 1.23 percent, suggesting that a substantial part of poverty reduction can be explained by diversification out of agriculture into the rural and small town nonfarm economy.

Taking a country specific example, Indonesia experienced a 129-percent reduction in the poverty headcount ratio at $1 a day from 28.2 percent in 1987 to 7.8 percent in 2002[6] and a 21-percent increase in the population share of the missing middle from 36.4 percent in 1987 to 44.8 percent in 2002. These figures imply that more than 50 percent[7] of the poverty reduction attributes to the increase in rural nonfarm employment in Indonesia. In the case of the poverty line at $2 a day, the contribution of rural nonfarm activities is about 70 percent. This echoes the findings based on household survey panel data by McCulloch, Weisbrod and Timmer (2007), who also highlight the critical role of the rural nonfarm economy in mediating the poor's transition out of poverty in Indonesia during the 1990s. Together these numerical exercises would suggest that, controlling for the overall growth rate, rural diversification out of agriculture plays a very important role in poverty reduction. Note furthermore, the larger coefficient on change rate of the population share in the intermediate space when considering the very poor ($1-day poor) does not necessarily imply that its contribution to poverty reduction is larger for the very poor than the poor ($2-day).

The results discussed above are conditional on the growth rates being the same across the different transformational patterns. Yet, the new economic geography emphasizes the critical importance of agglomeration economies and density in fostering growth (World Bank, 2008). As a result, metropolization may well put countries on a much faster growth path, which could offset the less inclusive nature of its growth pattern in terms of poverty reduction over time. One test of this proposition would be to exclude GDP per capita growth from the set of regressors in columns (3) and (4), in effect estimating equation (7). By so doing, the total effect of the transformation from agriculture to rural nonfarm and metropolitan activities on poverty is estimated, including the indirect

[6] This reduction rate is calculated taking the difference between the log of the two headcount ratios: -1.29 = log7.8-log28.2.
[7] 21*3.2/129 = 0.521.

effects through changing the aggregate income level. The results presented in columns (5) and (6) of Table 2 show that the overall impact of rural nonfarm activities is negative and significant as before, whereas the overall impact of the urban share remains insignificant. The coefficient on the share of rural nonfarm activities in columns (5) and (6) are only slightly larger in absolute terms than that in columns (1) and (2), suggesting that the effects of rural diversification on poverty reduction mainly work through the income distribution channel. This is further explored below.

Robustness checks

To check the robustness of the results, five alternative specifications are explored (results not reported here due to space constraints). First, instead of using percent change in the poverty headcount as dependent variable, the percentage point change is used. This is not only intuitively more appealing and easier to understand for poverty practitioners—a 1 percentage point growth in GDP per capita yields x percentage points change in poverty—it also avoids some of the numerical anomalies introduced when changing poverty at low levels, with small percentage point changes translating into high percentage changes (Klasen and Misselhorn, 2006). Second, another definition of metropolis was used, i.e. the population in cities with population of 750,000 or more in 2007. This avoids discontinuous jumps as cities grow beyond one million during the period of the sample. A disadvantage of this definition is that even if a city has a population of more than 750,000 in 2007, it may not have been large ten years ago. Therefore, the metropolitan definitions complement each other.

Third, the regressions are augmented with a quadratic term of the change rate of the sectoral shares to allow for nonlinearity in the impact of the sectoral transformations. In another specification, we employ the amount of change in the sectoral shares, rather than their change rate, as independent variables. Fourth, the poverty *gap* is used rather than the poverty headcount ratio to account for the depth of shortfall from the poverty line. Finally, the regressions were also repeated using the revised povcal data which contain revised poverty numbers based on the 2005 purchasing power parity corrections and a $1.25-day poverty line.

Overall, he results from these alternative specifications were qualitatively and quantitatively very similar to the benchmark results in Table 2. There were no signs of non-linearity in the effects of change rates of the sectoral shares and defining the changes in terms of percentage point changes (as opposed to percent changes) did not change the results. While the nature of the transformation was not found to affect $1.25-day poverty reduction using the new povcal data, rural diversification was found to be poverty reducing (while metropolization was not) when looking at $2.30-day poverty and when expressing poverty in terms of percentage point changes as opposed to percentage changes. Using the alternative metropolitan definition, metropolitization was also associated with $1-day poverty reduction, though not with $2-day poverty, and the effects on poverty reduction on rural diversification were quantitatively at least 50 percent larger, also when GDP growth per capita was excluded.

Together these different specifications are taken to support the notion that, controlling for growth, rural diversification and secondary town development are associated with more inclusive growth patterns and more rapid poverty reduction than rapid metropolization. The reduced form specifications, excluding growth, further suggest that the negative effects on poverty reduction from rising income inequality associated with metropolization are not offset by the potentially larger growth agglomeration in mega cities may generate through better exploitation of agglomeration economies. The channels through which rural diversification and metropolization affect poverty reduction are further explored below.

Impacts on inequality

Table 3 presents regression results exploring the relation between income inequality (as captured by the Gini coefficient) and the distribution of people across space, controlling for GDP per capita (and its square). GDP per capita regressors are included as an inverted relation between income and inequality, known as the Kuznets curve, is often observed.[8] Ideally, and consistent with the analysis before, changes in income inequality should be regressed on changes in the share of people in the missing middle and changes in the metropolitan share of the population, controlling for growth in GDP per capita, to control for unobserved country effects. Unsurprisingly, doing so, does not yield

[8] Nonetheless, a consensus is emerging that there is on average no statistical relationship between changes in per capita income and changes in inequality taking countries as unit of analysis. Yet, many observations fall on both sides of the line rendering the average rather uninformative from a policy perspective (Kanbur, 2005).

any statistically significant results (Table 3, column 1). As Kraay (2006) explains in his exploration of the sources of pro-poor growth (growth in average income and changes in relative incomes), there is likely substantial measurement error in the measures of distributional change. While classical measurement error in the dependent variable does not lead to biased estimates, it inflates standard errors and reduces the significance of the estimated coefficients. With relatively few spells per country, identification from within-country variation thus becomes difficult. This also highlights the power of the results obtained in the poverty regressions above, which do control for unobserved country effects.

Pursuing the more modest objective of exploring correlations between income inequality and occupational and spatial settlement patterns, columns (2) presents the OLS regression results of the level equations. Consistent with the insights derived from the poverty regressions discussed above, rural diversification is associated with a decline in income inequality, while agglomeration in mega cities is strongly associated with higher income inequality. Both results are statistically significant at the 1 percent level.

Including regional dummies in an attempt to control for some of the unobserved country specific characteristics (such as the characteristically higher inequality in Latin America) yields similar results (column 3). Metropolization remains strongly associated with higher income inequality, while rural diversification remains negatively associated, even though the quantitative association weakens substantially. Similar results are obtained using the mean log deviation (the mean across the population of the log of the mean divided by individual income) or the ratio of the average income of the richest 20 percent to that of the poorest 20 percent as measures of inequality.

Impacts on aggregate income growth

Two specifications are used to explore the effect of the patterns of the spatial and occupational transformation on GDP per capita growth (Table 4). In column (1) the average annual growth rate of GDP per capita during 5 year periods is regressed on the average annual change rate of the sectoral shares during the same 5 year periods (t to t-5). In column (2), initial GDP per capita is added as an additional regressor to allow for convergence following the tradition in growth empirics. Period effects are further incorporated to control for global shocks and country fixed effects are included to control for unobserved (time invariant) country characteristics. Since the focus is on the impact of the patterns of spatial transformation and given that the impact of many other potential determinants of GDP growth remains somewhat disputed (Durlauf et al., 2005), no other regressors have been considered.

OLS estimation of these specifications may be biased due to reverse causality. If, for example, income growth affects the spatial transformation (e.g. by fostering migration to the metropole), this reverse causality would introduce endogeneity. Following Caselli, Esquivel and Lefort (1996), a two-stage least squares (2SLS) estimation is thus performed using the *levels* of the share of the population employed in the missing middle and the metropolitan population share in the previous period (t-10) as well as the initial GDP per capita in the previous period (i.e. t-10) as instruments. These lagged variables are likely to be correlated with the regressors, while unrelated to the contemporaneous error term. This strategy is akin to the difference Generalized Method of Moments proposed by Arellano and Bond (1991), though their dynamic panel data estimator was not used here given the limited number of time periods considered (1980-2000). As the data for the period 1980-1985 are used only for instruments, only 3 observations per country are left.

As predicted by the new economic geography, metropolization has a large positive effect on GDP per capita growth (Table 4, column (1)). A one percent increase in the metropolitan share of the population is associated with a 1.16 percentage point increase in GDP per capita. This holds when controlling for the initial income level (column 2). Rural diversification also positively affects income growth, after controlling for the initial income level, though it less precisely estimated and at 0.6 percentage point per capita GDP growth per percent change in the population share of the missing middle, the growth effect is substantially smaller.

5. Concluding Remarks

This paper examines whether the nature of the spatial transformation affects the rate of poverty reduction, using cross-country panel data for developing countries. It is found that agglomeration in mega cities is on average associated with faster growth and higher income inequality, while diversification into rural nonfarm and secondary town activities appears to facilitate a more inclusive, albeit on average also slower, growth process. Joint evaluation of the trade-offs between these two counteracting forces (higher/lower average income growth and more unequal/equal income distribution) suggests that migration out of agriculture into the rural economy (rural diversification) is substantially more poverty reducing than rapid metropolization. As a matter of fact, no statistical association could be established between metropolization and poverty reduction.

These results suggest that the nature of the spatial transformation matters for the rate of economic growth and poverty reduction observed during the spatial and structural transformation, and that, when rapid poverty reduction is the primary objective, more attention should be given to fostering rural diversification, including through public investment in rural infrastructure and secondary town development. However, when fostering overall economic growth is taken as key target, the balance of public investment and policy choice should be shifted in favor of more rapid urbanization and mega city development.

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Table 1: Geographical Coverage of Poverty Data

	Number of countries	Number of survey periods	Percent of survey periods
Sub-Saharan Africa	14	34	18.0
South Asia	2	10	5.3
East Asia and Pacific	6	29	15.3
East Europe and Central Asia	9	29	15.3
Latin America and the Caribbean	13	78	41.3
Middle East and North Africa	5	9	4.8
Total	49	189	100.0

Table 2. Baseline Estimation Results

Dependent variable		Change rate of the poverty headcount ratio					
		(1)	(2)	(3)	(4)	(5)	(6)
	(Poverty line)	\$1	\$2	\$1	\$2	\$1	\$2
$\frac{ds_N}{s_N}$	Change rate of the share of people in the missing middle			-3.504	-1.198	-3.623	-1.266
				(0.982)**	(0.464)*	(0.900)**	(0.457)**
$\frac{ds_U}{s_U}$	Change rate of the metropolitan share of the population			-1.028	-1.220	1.919	0.451
				(4.708)	(1.983)	(4.908)	(1.820)
$\frac{dy}{y}$	Growth rate of GDP per capita	-1.823	-0.986	-1.743	-0.988		
		(1.012)+	(0.421)*	(1.055)	(0.459)*		
Observations		189	189	189	189	189	189
R-squared		0.430	0.388	0.459	0.406	0.431	0.359
Year dummies		Yes	Yes	Yes	Yes	Yes	Yes
Country dummies		Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results from OLS estimations. Robust standard errors are in parentheses. **, *, and + denote statistical significance at the 1-, 5-, and 10-percent level, respectively.

Table 3. Impacts on Inequality

	Dependent variable: Gini coefficient	(1)	(2)	(3)
	Dependent variable	First Difference	OLS	OLS
s_N	Share of people in the missing middle	0.210	-0.246	-0.080
		(0.239)	(0.045)**	(0.035)*
s_U	Metropolitan share of the population	0.536	0.513	0.245
		(0.720)	(0.058)**	(0.065)**
y	GDP per capita	1.289	3.151	2.175
		(1.615)	(0.758)**	(0.680)**
y^2	GDP per capita squared	-0.068	-0.218	-0.151
		(0.068)	(0.046)**	(0.040)**
Observations		230	232	232
R-squared		0.152	0.596	0.790
Year dummies		Yes	Yes	Yes
Regional dummies		No	No	Yes
Country dummies		No	No	No

Notes: This table shows results from OLS estimations. Robust standard errors are in parentheses. **, *, and + denote statistical significance at the 1-, 5-, and 10-percent level, respectively.

Table 4. Impacts on GDP Growth

		(1)	(2)
	Dependent variable	Growth rate of GDP per capita	
$\frac{ds_N}{s_N}$	Change rate of the share of people in the missing middle	0.418	0.630
		(0.388)	(0.336)+
$\frac{ds_U}{s_U}$	Change rate of the metropolitan share of the population	1.159	1.072
		(0.485)*	(0.402)**
y_0	Initial GDP per capita		-0.373
			(0.124)**
Year dummies		Yes	Yes
Country dummies		Yes	Yes
Estimation method		2SLS	2SLS
Observations		209	209

Notes: Robust standard errors are in parentheses. **, *, and + denote statistical significance at the 1-, 5-, and 10-percent level, respectively.