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THE EFFECT OF THE SECTORAL COMPOSITION OF ECONOMIC GROWTH ON RURAL AND URBAN POVERTY*

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We examine the relationship between the sectoral composition of economic growth and the rural-urban composition of poverty. To this end, we use a cross-country panel dataset consisting of 146 rural and urban poverty "spells" for 70 low- and middle-income countries. We find that rural (urban) poverty is highly responsive to agricultural (non-agricultural) productivity growth. The effect of agricultural productivity growth on rural poverty is particularly strong for countries with little dependence on natural resources. We also find that growth in the share of employment in the non-agricultural sector (i.e. structural transformation) reduces rural poverty, most notably for countries at a low initial level of development. These findings are robust to changes in key assumptions, including using alternative poverty lines. Finally, we use our estimates to examine the past contribution of different sources of economic growth to rural and urban poverty reduction across regions.

JEL Codes: I32, O11, O47

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1. INTRODUCTION

An understanding of the channels through which economic growth reduces poverty is instrumental for promoting inclusive and sustainable economic development. While it is well documented that growth tends to contribute to poverty reduction, the empirical literature suggests that there is considerable heterogeneity in the relationship across space and over time.[1] For example, using data from the

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[1]See Foster and Székely (2008), Ferreira *et al.* (2010), Ram (2011), or Chambers and Dhongde (2011) for comprehensive reviews of the literature on the growth elasticity of poverty reduction.

1980s to 1990s, Besley and Burgess (2003) showed that the growth elasticity of poverty reduction varies across different regions, with elasticities ranging from −0.49 (for sub-Saharan Africa) to −1.14 (for Eastern Europe and Central Asia). To cite another example, Datt *et al.* (2016) examined changes in the growth elasticity of poverty across time using data from pre- and post-reform India. Across a variety of specifications, they found that the responsiveness of poverty to economic growth was significantly greater for the post-reform period.

Explanations for the observed heterogeneity have emphasized differences in "initial conditions" and "patterns of growth." Initial income inequality has featured prominently in analyses of initial conditions as higher inequality (1) may slow the rate of growth (the "induced-growth argument") and (2) may reduce subsequent gains to the poor from existing growth (the "growth elasticity argument") (Ravallion, 1997). While evidence for the induced-growth argument is highly context dependent (Neves and Silva, 2014), a number of studies have found support for the growth elasticity argument (Kalwij and Verschoor, 2007; Ravallion and Chen, 2007; Fosu, 2009). Bourguignon (2003) further showed that the growth elasticity of poverty relates directly to the ratio of the poverty line to mean income. That the responsiveness of poverty to growth increases with per capita income has been corroborated by multiple subsequent empirical studies (Kalwij and Verschoor, 2007; Fosu, 2009; Chistiaensen *et al.*, 2011).[2]

Regarding patterns of growth, Montalvo and Ravallion (2010) discuss two reasons why the sectoral and/or geographic composition of economic activity affects the growth-poverty relationship: (1) economic growth may occur in sectors or locations that do not benefit poor people and (2) the composition of economic activity can affect income inequality, which has implications for the subsequent effect of growth on poverty (see above). There is a large body of empirical research that finds that growth in the agricultural sector is particularly effective at reducing poverty, not only through its direct effect via agricultural incomes but also indirectly through growth linkages with the rest of the economy (Bezemer and Headey, 2008; Dercon, 2009; de Janvry and Sadoulet, 2010; Chistiaensen *et al.*, 2011). The responsiveness of poverty to agricultural growth, however, has been found to diminish with development (Ravallion and Datt, 2002; Ferreira *et al.*, 2010; Chistiaensen *et al.*, 2011).

The agriculture versus non-agriculture dimension has been a focus in the patterns of growth literature, but other dimensions have been considered as well. Using data from India, Ravallion and Datt (1996) decomposed mean consumption growth into rural and urban components, and found that rural consumption growth was the primary driver of poverty reduction.[3] To the contrary, Datt *et al.*

[2]While the study of initial conditions has focused on initial inequality and the level of development, a number of other factors have been explored. See Datt and Ravallion (1998) on infrastructure and human resources, Ravallion and Datt (2002) on literacy and farm productivity (among other factors), Suryahadi *et al.* (2009) on human capital, Ferreira *et al.* (2010) on human development and worker empowerment, and Chistiaensen *et al.* (2011) on the share of extractive industries in GDP.

[3]See Ravallion and Chen (2007) for a similar result in the context of China. This result is in part a direct implication of the fact that baseline levels of poverty were much higher in rural areas where most people live. Noticeable overall reductions in poverty could only be driven by improvements in consumption in those areas and predominantly driven by agricultural growth.

(2016) found that urban growth came to occupy the leading role in the wake of India's reforms of the early 1990s. Suryahadi *et al.* (2009) took this geographical decomposition a step further by decomposing rural and urban growth by economic sector. Using data from Indonesia, they found that provincial poverty was particularly responsive to growth in the urban and rural services sectors. Finally, in a unique contribution, Loayza and Raddatz (2010) found, using cross-country data, that the composition of growth in terms of the intensive use of unskilled labor is critical for poverty reduction.[4]

While substantial progress has been made towards understanding the growth-poverty relationship, the literature offers an incomplete characterization of the channels through which growth reduces poverty. To what extent does overall and sectoral growth have a differential effect on rural and urban poverty? Are these growth effects driven by labor productivity growth or employment expansion? Are employment expansion effects due to labor force growth or the movement of labor across sectors (i.e. structural transformation)? How do initial conditions, particularly differences in economic inequality and the level of development, influence the above channels? We examine these questions using a novel dataset consisting of 146 rural and urban poverty "spells" for 70 low- and middle-income countries spanning from 1992 to 2013. To the best of our knowledge, our dataset represents the most comprehensive source of internationally-comparable rural and urban poverty measures compiled to date.

Our primary contribution is the analysis of the relationship between the sectoral composition of growth and the rural-urban composition of poverty. Previous research in this area has focused on single-country studies, largely in an Asian context. Research on China has highlighted the association between agricultural growth and rural poverty reduction (Ravallion and Chen, 2007; Montalvo and Ravallion, 2010), whereas work on India and Indonesia has found that both rural and urban poverty are responsive to growth in the agricultural and services sectors (Ravallion and Datt, 1996; Suryahadi *et al.*, 2009).[5] In contrast to these studies, we believe we are the first to address these questions using cross-country panel data. Our dataset is also particularly rich in terms of covering a large number of countries over a relatively long period. While cross-country studies have well-known limitations, we are able to provide new insights into the dynamics of rural and urban poverty by examining other contexts (e.g. sub-Saharan Africa) and exploiting cross-country variation in key variables (e.g. income inequality and level of development).

In addition to providing complementary insights through the use of cross-country panel data, we seek to deepen the analysis of the relationship between sectoral growth and the rural-urban composition of poverty in three ways. First, we examine the growth-poverty channels by decomposing sectoral growth into components associated with labor productivity growth and employment expansion. Second, we further decompose the employment expansion effects into components associated

[4]Again, this result is in part a direct effect derived from the fact that most of the poor are exactly the unskilled that are available to work in a growing economy.

[5]Recent research suggests, however, that the sectoral composition of growth in India has become less important for poverty reduction after the reforms of the early 1990s (Datt *et al.*, 2016).

with labor force growth and structural transformation. Finally, we examine how differences in initial conditions affect the channels through which economic growth reduces rural and urban poverty. Throughout our analysis we do not claim to estimate causal relationships, but rather seek to examine whether robust cross-country empirical regularities can be established.

We report three primary findings. First, the semi-elasticity of rural poverty to agricultural productivity is highly significant and relatively large in magnitude, particularly for countries with little dependence on natural resources. Second, the semi-elasticity of urban poverty to non-agricultural productivity is also large and highly significant. This semi-elasticity is insensitive to initial conditions. Third, structural transformation reduces rural poverty, particularly for countries at a low initial level of development. We find that these results are robust to changes in key assumptions, including using alternative poverty lines, incorporating additional covariates (e.g. changes in the distribution of income), changing the criteria used to drop extreme observations, and focusing on longer spell lengths.

Semi-elasticity estimates alone convey little information about the past contribution of different sources of economic growth to rural and urban poverty reduction. We thus use our estimates to quantify these contributions across six geographical regions. To the best of our knowledge, we are the first to conduct such an exercise on an international level using rural-urban disaggregated poverty rates. We find that agricultural productivity growth has contributed relatively little to rural and urban poverty reduction across all regions of the world. Non-agricultural productivity growth, however, has made substantial contributions in virtually all regions, generally via poverty reductions in urban areas. Lastly, we find that the poverty-reducing effect of structural transformation (employment growth) has primarily been a rural phenomenon and confined to regions with initially lower (higher) levels of development.

The remainder of this paper is organized as follows. Section 2 outlines our methodological framework, and Section 3 discusses our data and provides descriptive analysis. Section 4 presents baseline results, sensitivity analysis, and examines the sources of past poverty reduction. Section 5 provides concluding remarks and policy implications.

2. Methodology

This section outlines a strategy for estimating the effect of the sectoral composition of economic growth on rural and urban poverty. Our framework relies heavily on both Ravallion and Datt (1996) and Christiaensen *et al.* (2011), so the reader is referred to their work for additional discussion.

Let P_{it} denote any decomposable poverty measure and Y_{it} denote GDP per capita for country i at time t. We use the so-called naive model as a starting point (Bourguignon, 2003; Klasen and Misselhorn, 2008):

$$\Delta P_{it} = \alpha_i + \beta_{it} \Delta \ln Y_{it} + \varepsilon_{it} \tag{1}$$

where Δ is the discrete time-difference operator, α_i captures country-specific time trends, β_{it} represents parameters to be estimated, and ε_{it} is the error term. Note that β_{it} is permitted to vary across countries and time (discussed below). Further note that, given the time-differencing of equation (1), we implicitly control for time-invariant unobservable characteristics.

In equation (1), β_{it} represents the growth semi-elasticity of poverty. Klasen and Misselhorn (2008) argue that there are conceptual and empirical advantages to examining absolute rather than proportionate poverty reduction (i.e. semi-elasticities rather than elasticities). Conceptually, policy makers are likely to be more interested in percentage point changes than in percentage changes. For example, a 10 percentage point change in the poverty rate is clearly substantial, but whether a reduction in the poverty rate by 10 percent is large depends on the level of headcount poverty. Regarding empirical advantages, the authors argue that semi-elasticities can be estimated more precisely and do not rely heavily on arbitrary assumptions about dealing with data from countries with low poverty rates. In particular, semi-elasticities permit the use of more data as one does not need to drop "spells where the percentage change … [is] abnormally large in relative value" (Bourguignon, 2003, p. 15).[6]

We are interested in how the sectoral composition of economic growth affects poverty. We thus first decompose GDP per capita growth into components associated with growth in the agricultural sector and growth in the non-agricultural sectors. GDP per capita can be written as $Y = \text{psi}_a Y_a + \text{psi}_n Y_n$ where Y_a and Y_n represent value added per capita in the agricultural and non-agricultural sectors, respectively. The total differential of GDP per capita can then be written as follows:

$$\text{(2)} \qquad \mathrm{d} \ln Y = \psi_a \mathrm{d} \ln Y_a + \psi_n \mathrm{d} \ln Y_n$$

where ψ_a and ψ_n denote the share of the agricultural and non-agricultural sectors in GDP, respectively. Equation (2) thus states that growth in GDP per capita equals the share-weighted sum of value added per capita growth in each sector.

As discussed in Section 1, we go beyond previous studies and consider (1) decomposing sectoral growth into components associated with labor productivity growth and employment expansion, and (2) decomposing employment expansion effects into components associated with labor force growth and structural transformation. To this end, value added per capita for sector $j \in \{a,n\}$ can be expressed as $Y_j = y_j \omega_j$ where y_j and ω_j denote value added per worker and the size of the sector's labor force (in per capita terms), respectively. The total differential of sectoral value added per capita can then be written as $\mathrm{d} \ln Y_j = \mathrm{d} \ln y_j + \mathrm{d} \ln \omega_j$, which we can substitute into equation (2) as follows:

$$\text{(3)} \qquad \mathrm{d} \ln Y = \psi_a \mathrm{d} \ln y_a + \psi_a \mathrm{d} \ln \omega_a + \psi_n \mathrm{d} \ln y_n + \psi_n \mathrm{d} \ln \omega_n$$

According to equation (3), GDP per capita growth can be decomposed into components associated with (1) agricultural productivity growth, (2) agricultural

[6]This occurs when initial poverty rates are low. In the extreme case, when the initial poverty rate is zero, the percentage change in the poverty rate is undefined.

labor force expansion, (3) non-agricultural productivity growth, and (4) non-agricultural labor force expansion.

Regarding decomposing employment expansion effects, note that $\omega_j = \lambda_j \mu$ where λ_j is the share of employment in sector j and μ is the employment-to-population ratio. We can then write the total differential of ω_j as $\mathrm{d}\ln\omega_j = \mathrm{d}\ln\lambda_j + \mathrm{d}\ln\mu$. Substituting this expression into equation (3) and rearranging yields the following:

$$\mathrm{d}\ln Y = \psi_a \mathrm{d}\ln y_a + \psi_n \mathrm{d}\ln y_n + \left(\psi_n - \frac{\psi_a \lambda_n}{\lambda_a}\right)\mathrm{d}\ln\lambda_n + \mathrm{d}\ln\mu \tag{4}$$

The decomposition in equation (4) again consists of four components. The first two components are associated with growth in agricultural and non-agricultural value added per worker, respectively. The third component can be interpreted as growth in GDP per capita resulting from structural transformation.[7] The final component captures the contribution of growth in the employment-to-population ratio.

We can use equation (4) to rewrite equation (1) as follows (Ravallion and Datt, 1996; Christiaensen *et al.*, 2011):

$$\begin{aligned}\Delta P_{it} = \alpha_i &+ \beta_{ait}\psi_{ait-1}\Delta\ln y_{ait} + \beta_{nit}\psi_{nit-1}\Delta\ln y_{nit} \\ &+ \beta_{sit}\left(\psi_{nit-1} - \frac{\psi_{ait-1}\lambda_{nit-1}}{\lambda_{ait-1}}\right)\Delta\ln\lambda_{nit} + \beta_{eit}\Delta\ln\mu_{it} + \varepsilon_{it}\end{aligned} \tag{5}$$

where we now have four growth-related parameters. The parameters β_{ait} and β_{nit} capture the effect of (share-weighted) growth in value added per worker in the agricultural and non-agricultural sectors, respectively. The parameter β_{sit} captures the effect of growth in the share of employment in the non-agricultural sector (i.e. structural transformation). Note that this coefficient may capture within-sector distributional changes induced by the movement of labor across sectors (Datt *et al.*, 2016). Finally, β_{eit} represents the poverty-reducing effect of growth in the employment-to-population ratio. Note that if $\beta_{ait} = \beta_{nit} = \beta_{sit} = \beta_{eit}$ then equation (5) collapses to equation (1). As such, under the null hypothesis that $\beta_{ait} = \beta_{nit} = \beta_{sit} = \beta_{eit}$ it is the overall growth rate that matters for poverty reduction and not the composition of growth.

[7]Herrendorf *et al.* (2014) define structural transformation as "the reallocation of economic activity across three broad sectors (agriculture, manufacturing, and services) that accompanies the process of modern economic growth" (p. 857). The authors discuss three common measures of structural transformation: (1) employment shares, (2) value added shares, and (3) final consumption expenditure shares. We focus on employment shares for two reasons. First, on a practical level, the employment-oriented approach emerges naturally from our decomposition of GDP per capita. Second, and more substantively, we are interested in how structural transformation affects rural and urban poverty, and the primary mechanism through which this occurs is via the reallocation of labor across sectors. In addition, note that the coefficient on $\mathrm{d}\ln\lambda_n$ can be written as $(y_n - y_a)\,\omega_n / Y$, which indicates that structural transformation will lead to improvements in GDP per capita only if the non-agricultural sector witnesses higher labor productivity than the agricultural sector.

The country fixed effects in equation (5) mitigate concerns about bias arising from country heterogeneity, but the sectoral participation effects (i.e. β_{ait}, β_{nit}, β_{sit}, and β_{eit}) themselves may depend on country-specific characteristics, which we denote by X_{it}. More specifically, the magnitude of the sectoral participation effects depends on the position of the poverty line relative to the mean of the income distribution, in addition to the shape of the income distribution (Bourguignon, 2003; Klasen and Misselhorn, 2008). Sectoral participation may also depend on the share of extractive industries in GDP, in part because of enclave effects whereby growth is less inclusive in resource-dependent countries (Christiaensen *et al.*, 2011). Further, the duration of the poverty spell under consideration may play a critical role as some effects (e.g. cross-sectoral effects) may take time to manifest. Accordingly, following Christiaensen *et al.* (2011), we rewrite equation (5) as follows:

$$\begin{aligned}\Delta P_{it} &= \alpha_i + \pi_a X_{it-1}\psi_{ait-1}\Delta \ln y_{ait} + \pi_n X_{it-1}\psi_{nit-1}\Delta \ln y_{nit} \\ &+\pi_s X_{it-1}\left(\psi_{nit-1} - \frac{\psi_{ait-1}\lambda_{nit-1}}{\lambda_{ait-1}}\right)\Delta \ln \lambda_{nit} + \pi_e X_{it-1}\Delta \ln \mu_{it} + \varepsilon_{it}\end{aligned} \tag{6}$$

where π_a, π_n, π_s and π_e are vectors of parameters and X_{it-1} is a vector of covariates. Included in X_{it-1} is an intercept, the ratio of the poverty line to average daily income, the Gini coefficient of income/consumption, the share of extractive industries in GDP, and poverty spell length. All variables in X_{it-1} are initial levels of those variables.[8]

We are further interested in how the different components of growth affect not only overall poverty, but also rural and urban poverty. The change in the overall poverty rate can be decomposed into three components: poverty changes in rural areas, poverty changes in urban areas, and changes due to rural-urban migration (Ravallion and Datt, 1996). The overall poverty rate P can be written as $\rho_r P_r + \rho_u P_u$ where ρ_r and P_r are the rural population share and rural poverty rate, respectively, and ρ_u and P_u are the analogous quantities for urban areas. The total differential of the overall poverty rate is then as follows:

$$\mathrm{d}P = \rho_r \mathrm{d}P_r + \rho_u \mathrm{d}P_u + \left(P_u - P_r\right)\mathrm{d}\rho_u \tag{7}$$

where the first two terms on the right-hand side of equation (7) represent the intra-regional gains to the poor and the final term represents the independent contribution of rural-urban migration. Note that the coefficient on $\mathrm{d}\rho_u$ indicates that urbanization will lead to reductions in overall poverty rates only if poverty is greater in rural areas than in urban areas.

Following Ravallion and Datt (1996), we can then use equation (7) as a basis for estimating the following system of equations:

$$\begin{aligned}\rho_{rit-1}\Delta P^r_{it} &= \alpha^r_i + \pi^r_a X_{it-1}\psi_{ait-1}\Delta \ln y_{ait} + \pi^r_n X_{it-1}\psi_{nit-1}\Delta \ln y_{nit} \\ &+\pi^r_s X_{it-1}\left(\psi_{nit-1} - \frac{\psi_{ait-1}\lambda_{nit-1}}{\lambda_{ait-1}}\right)\Delta \ln \lambda_{nit} + \pi^r_e X_{it-1}\Delta \ln \mu_{it} + \varepsilon^r_{it}\end{aligned} \tag{8}$$

[8]That is, the variables in X_{it-1} correspond to the start of each poverty spell as $\Delta P_{it} = P_{it} - P_{it-1}$.

$$\begin{aligned}\rho_{uit-1}\Delta P_{it}^{u} &= \alpha_i^u + \pi_a^u X_{it-1}\psi_{ait-1}\Delta \ln y_{ait} + \pi_n^u X_{it-1}\psi_{nit-1}\Delta \ln y_{nit} \\ &+ \pi_s^u X_{it-1}\left(\psi_{nit-1} - \frac{\psi_{ait-1}\lambda_{nit-1}}{\lambda_{ait-1}}\right)\Delta \ln \lambda_{nit} + \pi_e^u X_{it-1}\Delta \ln \mu_{it} + \varepsilon_{it}^{u}\end{aligned} \tag{9}$$

$$\begin{aligned}\left(P_{uit-1} - P_{rit-1}\right)\Delta\rho_{uit} &= \alpha_i^m + \pi_a^m X_{it-1}\psi_{ait-1}\Delta \ln y_{ait} + \pi_n^m X_{it-1}\psi_{nit-1}\Delta \ln y_{nit} \\ &+ \pi_s^m X_{it-1}\left(\psi_{nit-1} - \frac{\psi_{ait-1}\lambda_{nit-1}}{\lambda_{ait-1}}\right)\Delta \ln \lambda_{nit} + \pi_e^m X_{it-1}\Delta \ln \mu_{it} + \varepsilon_{it}^{m}\end{aligned} \tag{10}$$

where the superscripts r, u, and m denote terms associated with rural areas, urban areas, and rural-urban migration, respectively. Equation (8) thus captures the rural-poverty effect of (1) growth of value added per worker within and outside the agricultural sector, (2) changes in the sectoral composition of GDP (i.e. structural transformation), and (3) changes in the employment-to-population ratio. Equation (9) is interpreted analogously but is associated with urban poverty. Finally, equation (10) captures the effect of the composition of economic growth on the rural-urban migration component of the poverty decomposition.

Noting that $\pi_k = \pi_k^r + \pi_k^u + \pi_k^m$ for $k \in \{a,n,s,e\}$, it is evident that summing equations (8–10) yields equation (6). To examine whether the composition of growth matters for poverty reduction in the context of equations (8–10), we can conduct an F-test for the hypothesis that $\pi_a^l = \pi_n^l = \pi_s^l = \pi_e^l$ for $l \in \{r,u,m\}$. While for equation (1) the semi-elasticities are given by the regression coefficients, additional calculations are needed for other specifications. For regressions using national poverty measures (i.e. equations [5] and [6]), the semi-elasticities can be calculated by partially differentiating with respect to $\Delta \ln y_{ait}$, $\Delta \ln y_{nit}$, $\Delta \ln \lambda_{nit}$, or $\Delta \ln \mu_{it}$. For regressions using decomposed poverty rates (i.e. equations [8–10]), the resulting partial derivatives must be divided through by ρ_{rit-1}, ρ_{uit-1}, or $P_{uit-1} - P_{rit-1}$, respectively. With the exception of equation (1), all semi-elasticities are a function of the data and, as such, are evaluated at variable means.

All regressions are estimated using a fixed effects (FE) estimator with standard errors clustered at the country level. The calculation of semi-elasticities entails a linear combination of estimates and the standard errors for these are obtained via conventional methods for calculating the variance of a linear combination.[9] Note that the FE estimator drops any country for which we only observe one poverty spell. In our dataset, this leads to a loss of 28 observations, or 19 percent of the sample. One way to avoid this issue would be to use a random effects (RE) estimator. Using a robust form of the Hausman test, we nevertheless reject the null hypothesis that the RE estimator is consistent.[10] The FE model is thus preferred, but one might argue that the loss of observations biases our estimates. To examine

[9]We use Stata's lincom command for these calculations.

[10]The robust form of the Hausman test is based on the artificial regression approach described in Wooldridge (2002, p. 290–291). This statistic is asymptotically equivalent to the standard Hausman test under conditional homoscedasticity, and can be implemented using Stata's xtoverid command. We run the test using changes in the overall poverty rate as the dependent variable (i.e., using equation [6]), and reject the null hypothesis that the RE estimator is consistent at the 5 percent level (P-value = 0.02).

this issue, we estimate equation (6) via OLS using the full sample of countries and again after dropping countries with one poverty spell.[11] Comparing coefficients across regressions using a Wald test, we fail to reject the null hypothesis of coefficient equality (p-value = 0.91). Similar results are obtained when using rural and urban poverty changes as the dependent variable, and we thus conclude that any bias is unlikely to be substantial.

3. Data and Descriptive Analysis

Table 1 provides sources and definitions for all variables used in the analysis. Internationally-comparable poverty measures come from the International Fund for Agricultural Development (IFAD) (2016). This information was compiled in collaboration with the PovcalNet team of the World Bank for IFAD's 2016 Rural Development Report (RDR).[12] The variable *overall* is defined as the annual change in a country's poverty headcount ratio. We focus on headcount ratios defined on the basis of an "extreme" poverty line ($1.25 per person per day in 2005 PPP), but also consider "moderate" poverty lines ($2.00 per person per day in 2005 PPP). The variables *rural* and *urban* are calculated as the annual change in rural and urban poverty rates, respectively, weighted by the corresponding population shares. Note that rural and urban poverty rates are adjusted for cost-of-living differences using the procedure outlined in Ravallion *et al.* (2007). Rural and urban population share information comes from the World Development Indicators (WDI) database (World Bank, 2017).

The variable *GDP per capita* is defined as the annual growth rate of GDP per person (2011 PPP) where information on GDP per person comes from the WDI database.[13] The variable *agriculture* is calculated as the GDP-share weighted growth of agricultural value added per capita, where GDP share information also comes from the WDI database. As discussed in Section 2, *agriculture* can be decomposed into a productivity growth and an employment expansion component, which yields the variables *agricultural productivity* and *agricultural employment*.[14] The variables associated with the non-agricultural sector are calculated analogously.

[11]Note that these regressions omit the country-specific effects. Nevertheless, if the loss of observations biases our results, we would expect the OLS estimates to differ depending on the sample used. The test of coefficient equality is implemented using Stata's suest command. Standard errors in both regressions are clustered at the country level.

[12]Our poverty data differs from that publicly provided in the World Bank's PovcalNet database. IFAD commissioned the World Bank to compile the data for their 2016 Rural Development Report.

[13]Note that the year associated with the PPP conversion for the GDP per capita variable is different from that of our poverty data. Changing the PPP conversion factor used for GDP per capita is, however, inconsequential for our econometric analysis because our regressions are in first differences and thus do not depend on the conversion factors. A proof of this is available upon request. Changing the conversion factor used for the poverty data will affect our estimates and we return to this issue in Subsection 4.2.

[14]Suitable sector-specific value added per worker data is not directly available. We thus calculate agricultural value added per worker by multiplying the share of a given sector in GDP by GDP per person employed, and then divide by the share of employment in that sector. Multiplying a sector's share in GDP by GDP per person employed yields sectoral value added per person employed in the economy. Dividing this quantity by the sector's share of overall employment gives value added per worker in that sector. Employment information comes from the International Labour Organization of the United Nations (2017).

TABLE 1
VARIABLE SOURCES AND DEFINITIONS

Variable	Source	Definition
Overall	International Fund for Agricultural Development (2016) and World Bank (2017)	Annual change in a country's headcount ratio
Rural	International Fund for Agricultural Development (2016) and World Bank (2017)	Change in overall poverty measure due to changes in rural poverty
Urban	International Fund for Agricultural Development (2016) and World Bank (2017)	Change in overall poverty measure due to changes in urban poverty
GDP per capita	World Bank (2017)	Annual growth of GDP per capita
Agriculture	World Bank (2017)	GDP per capita growth due to the agricultural sector
Agricultural productivity	International Labour Organization (2017) and World Bank (2017)	GDP per capita growth due to agricultural productivity growth
Agricultural employment	International Labour Organization (2017) and World Bank (2017)	GDP per capita growth due to agricultural employment expansion
Non-agriculture	World Bank (2017)	GDP per capita growth due to the non-agricultural sector
Non-agricultural productivity	International Labour Organization (2017) and World Bank (2017)	GDP per capita growth due to non-agricultural productivity growth
Non-agricultural employment	International Labour Organization (2017) and World Bank (2017)	GDP per capita growth due to non-agricultural employment expansion
Transformation	International Labour Organization (2017) and World Bank (2017)	GDP per capita growth due to structural transformation
Employment	World Bank (2017)	GDP per capita growth due to overall employment expansion
Gini	Milanovic (2014) and World Bank (2017)	Gini coefficient of income/consumption
PI ratio	World Bank (2017)	Ratio of poverty line to daily GDP per capita
NR rents	World Bank (2017)	Total natural resource rents, including oil, natural gas, coal, mineral, and forest rents (share of GDP)
Spell	International Fund for Agricultural Development (2016)	Duration of poverty spell (in years)

Note: NR rents denotes natural resource rents as a share of GDP and PI ratio denotes the ratio of the poverty line to daily GDP per capita.

Finally, the variable *transformation* is calculated by multiplying the growth rate of the share of non-agricultural employment by the coefficient displayed in equation (4), and *employment* is calculated as the annual growth rate of the employment-to-population ratio.

National estimates of the Gini coefficient of income or consumption (i.e. the variable *Gini*) are drawn from the WDI database. There are, however, a few critical countries for which Gini coefficient estimates are not available in the WDI database (e.g. China, India, and Indonesia). To avoid losing a substantial number of observations, for these countries we use Gini estimates from the All the Ginis Dataset (Milanovic, 2014). While Gini information is relatively scarce, we find that there is considerable overlap with our poverty measures due to the fact that each is often derived from the same underlying data source.[15] The variables *PI ratio* and *NR rents* use information from the WDI database. While *NR rents* requires no further processing, the variable *PI ratio* is calculated by dividing the poverty line by (daily) GDP per capita estimates from WDI. Finally, the variable *spell* is simply the difference between the initial and final year of a given poverty spell.

Table 2 provides an overview of data coverage by region. Each observation in our dataset corresponds to periods of change or "spells," which are derived from comparable household surveys and annualized to accommodate spells of different length. Note that annualization requires the non-trivial assumption that no structural changes took place during the intervening years. Given our focus on spells, we necessarily drop from the analysis any country for which we only have data at one point in time. We further drop (1) all high-income countries, (2) any observation with incomplete information, (3) any spell where the poverty rate is negligible in the initial or final period (i.e. less than one percent),[16] and (4) a few outliers. Regarding outliers, Figure 1 plots the change in the extreme ($1.25 per day) poverty rate on GDP per capita growth. It is evident from the figure that Bhutan (BTN), Indonesia (IND), and Tajikistan (TJK) are clear vertical outliers and, as such, are dropped from the econometric analysis.[17] We are left with a total of 146 spells/observations from 70 countries spanning the years 1992–2013. No region is unrepresented in our data. Further note that 42 of the 70 countries have information from more than one spell, and that the overall average spell length is approximately five years.[18]

Panel (a) in Figure 2 depicts extreme ($1.25 per day) headcount ratio changes by region. Table 2 serves as a key for region abbreviations. For each region, the figure provides overall, rural, and urban headcount ratios for two points in time: late 1990s and *circa* 2010. To calculate regional poverty rates, we take the earliest

[15]The Gini coefficient estimates nevertheless have to be approached with caution, as there are concerns about data comparability. For example, some Gini coefficients are calculated with income data while others are calculated with expenditure data. See the documentation for the All the Gini's Dataset for additional information (Milanovic, 2014).

[16]We are interested in examining how the sectoral composition of growth affects poverty, and countries with negligible poverty have little bearing on this question. Stated differently, we eliminate these countries to avoid biasing our estimates downward. See Kraay (2006) for a similar approach. In Section 4, we consider the sensitivity of our results to changes in this criterion.

[17]We do not drop all observations associated with these countries, only the spells that are outliers.

[18]There is a fair amount of variation in spell lengths.

TABLE 2
DATA COVERAGE

Region	Number of Spells	Number of Countries	Countries With >1 Spell	Avg. Spell Length
East Asia and Pacific (EAP)	32	7	5	2.97
Europe and Central Asia (ECA)	13	7	5	4.92
Latin America and Caribbean (LAC)	32	15	12	5.28
Middle East and North Africa (MNA)	5	5	0	6.60
South Asia (SAS)	11	5	4	6.00
Sub-Saharan Africa (SSA)	53	31	16	6.08
Total	146	70	42	5.13

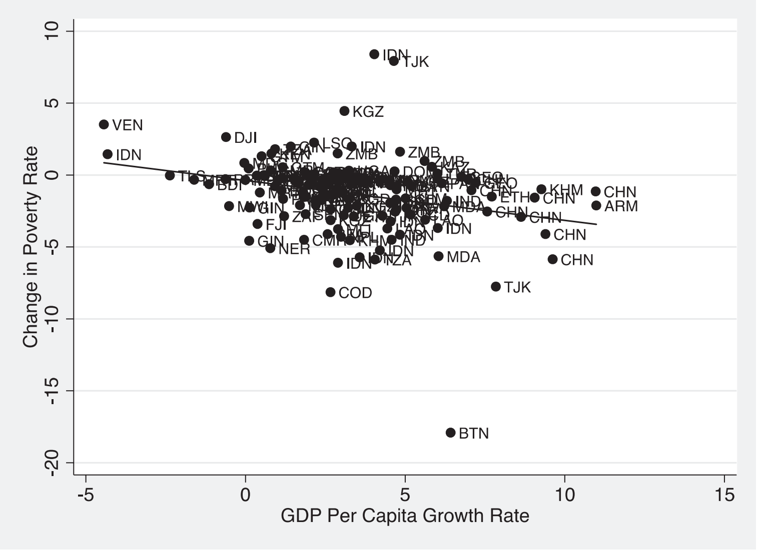

Figure 1. Scatter Plot of Changes in Extreme ($1.25 Per Day) Poverty Rates on GDP Per Capita Growth Rates

and most recently observed rate for each country in a given region. The regional poverty rates for each point in time are then calculated as the population-weighted average of the country poverty rates. For the overall poverty rates, population weights are based on total population, but for rural and urban poverty rates we use rural and urban population estimates. Panel (b) in Figure 2 presents a decomposition of the changes in overall regional poverty rates, calculated as a regional analogue to the country-level procedure discussed above.[19]

Panel (a) in Figure 2 shows that EAP, SAS, and SSA had particularly high poverty rates in the late 1990s. As is well known, EAP (and to a lesser extent SAS) has made considerable progress in reducing poverty and Figure 2 demonstrates this clearly. EAP's reduction in rural poverty has been particularly dramatic, falling from approximately 64 to 11 percent.[20] To the contrary, poverty rates in SSA have remained relatively high, particularly in rural areas. We estimate that SSA's rural poverty rate in the most recent period remains at 49 percent. Panel (b) in Figure 2 shows that, for those regions with the highest initial poverty rates, reductions in overall poverty rates are largely attributable to changes observed in rural areas. For example, we estimate that 72 percent of the reduction in overall poverty in EAP was due to poverty reduction in rural areas. Conversely, urban areas contributed relatively more to reductions in overall poverty rates in regions with relatively low

[19]That is, the component due to changes in rural poverty is the change in a given region's rural poverty rate multiplied by the region's (initial) rural population share. The urban component is calculated analogously. The rural-urban migration component is the change in the region's urban population share multiplied by the initial difference in urban and rural headcount ratios.

[20]China and Indonesia are major contributors to this statistic as both are populous countries that witnessed large reductions in rural poverty. China's rural poverty rate fell from 70 to 11 percent between 1993 and 2012. Indonesia's rate fell from 58 to 11 percent during that same period.

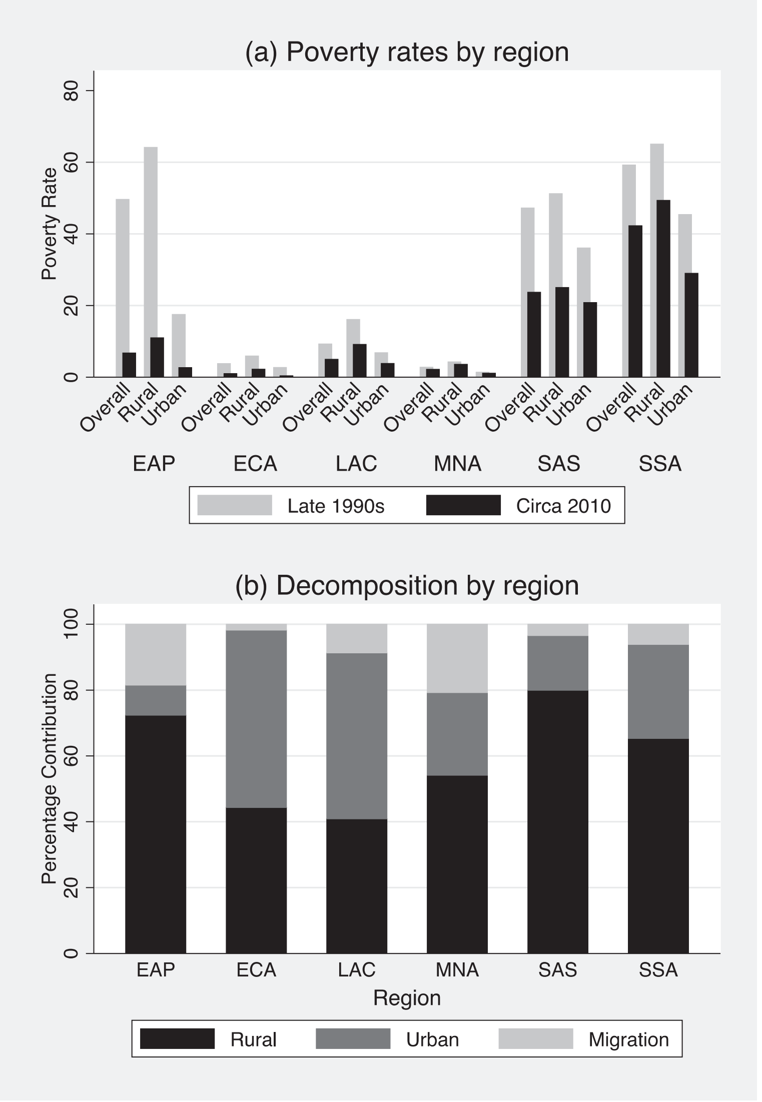

Figure 2. Decomposition of Extreme Poverty Rate Changes by Region

initial poverty rates (i.e. ECA, LAC, and MNA).[21] Finally, note that rural-urban migration has played a relatively small poverty-reducing role in all regions.[22]

[21]Recall that the rural and urban components of the decomposition are constructed by multiplying the corresponding population share by the change in the relevant poverty rate. While the regions with higher initial poverty rates did witness relatively large reductions in rural poverty, they also had a higher share of their populations in rural areas. Conversely, those regions with lower initial poverty rates had a higher share of their populations in urban areas. As urbanization accompanies development, it is natural that regions with higher (lower) initial poverty rates have a larger rural (urban) component in the poverty rate decomposition.

[22]EAP and MNA are potential exceptions to this statement. In EAP, the migration component is larger than the urban component, while in MNA the migration component is almost as large as the urban component.

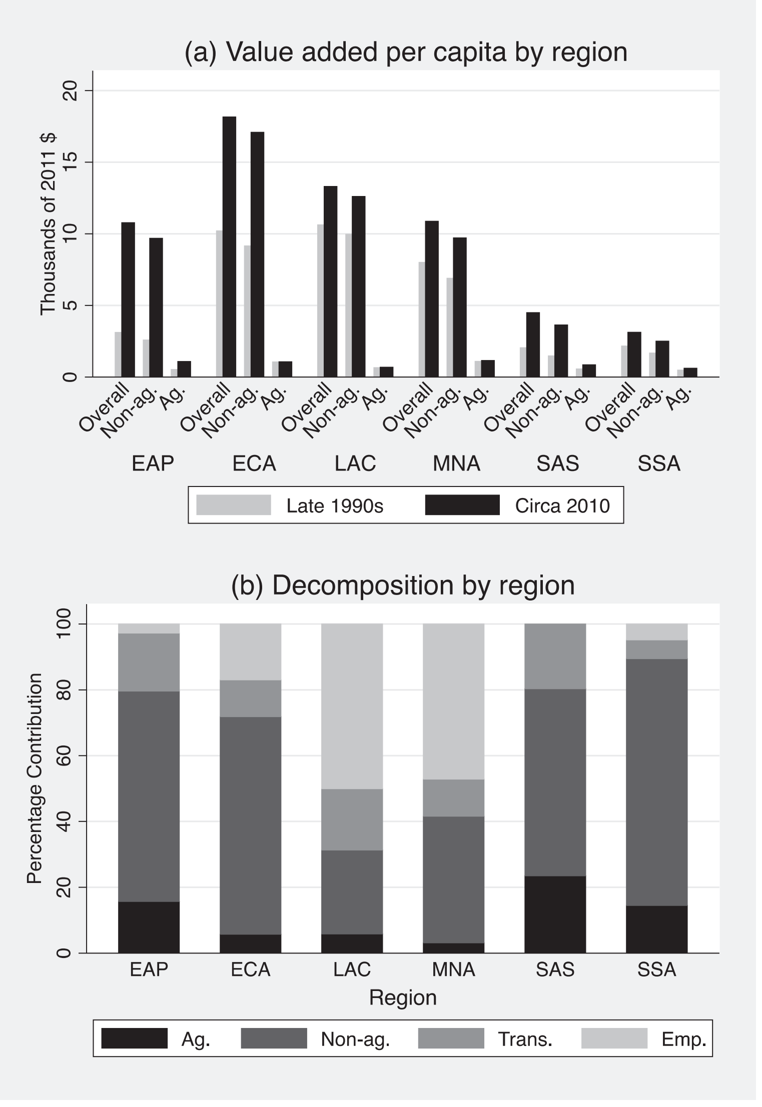

Figure 3. Decomposition of GDP Per Capita Growth by Region

Panel (a) in Figure 3 presents changes in GDP and sectoral value added per capita by region. The estimates were constructed in a manner similar to those in Figure 2 with the exception that the weighted averages are calculated on the basis of total population for each variable. Panel (b) in Figure 3 presents a sectoral decomposition of regional growth in GDP per capita, which we again calculate as a regional analogue to the country-level procedure previously discussed. Note that the GDP per capita decomposition is a decomposition of the growth rate of GDP per capita whereas the poverty rate decomposition is a decomposition of the (percentage point) change in the poverty rate.

TABLE 3
Descriptive Statistics for Interaction Effects

	Descriptive Statistics			
	Gini	PI ratio	NR Rents	Spell
Mean	43.98	0.21	6.58	5.13
SD	8.95	0.19	7.67	2.17
Min.	28.67	0.03	0.10	1.00
Max.	65.76	1.05	55.94	11.00

	Initial/Final Values			
	Gini (1990s)	Gini (c. 2010)	NR rents (1990s)	NR rents (c. 2010)
EAP	37.63	45.80	4.15	5.09
ECA	35.58	36.05	6.93	10.64
LAC	54.92	50.87	2.42	6.20
MNA	38.36	36.23	7.73	15.72
SAS	35.14	34.65	1.74	3.73
SSA	45.16	42.75	15.86	12.63

The considerable growth of EAP countries is evident in panel (a) of Figure 3, as GDP per capita increased by 246 percent throughout this period.[23] EAP also witnessed the fastest growth in agricultural and non-agricultural value added per capita, which we estimate to be 274 and 147 percent, respectively.[24] Among the regions with low initial levels of GDP per capita (i.e. EAP, SAS, and SSA), SSA witnessed the slowest growth. We find that GDP per capita in SSA grew 44 percent during this period, a change that is not only relatively small, but also starting from a much lower base than other regions. Looking to panel (b) in Figure 3, we see that non-agricultural productivity growth is the largest contributor to growth in GDP per capita among regions with initially low levels of GDP per capita whereas employment expansion features prominently in regions with high initial levels of GDP per capita (i.e. ECA, LAC, and MNA). The two fastest growing regions (i.e. EAP and SAS) witnessed relatively large contributions from agricultural productivity growth, though agriculture's absolute contribution is modest in all regions. Structural transformation has also played a secondary role in GDP per capita growth, particularly in the relatively stagnant SSA.

As a final data-related consideration, Table 3 presents descriptive statistics for the variables introduced through interaction effects in equation (6) (i.e. *Gini*, *PI ratio*, *NR rents*, and *spell)*. The top panel of Table 3 presents the overall mean, standard deviation, minimum, and maximum for each variable. Much like Figures 2 and 3, the bottom panel of Table 3 presents initial and final regional averages for the variables *Gini* and *NR rents.* We use population-weighted averages

[23]With an estimated growth rate of GDP per capita at 433 percent across this period, China is a major contributor to this statistic. Cambodia and Lao PDR also witnessed relatively fast growth (148 and 110 percent, respectively), but these countries have considerably smaller populations.

[24]SAS also witnessed relatively rapid growth. We find that GDP per capita grew 120 percent, agricultural value added per capita grew 51 percent, and non-agricultural value added per capita grew 147 percent.

for *Gini* and GDP-weighted averages for *NR rents*. Regarding *Gini*, we see that income is distributed particularly unequally in LAC, as is well known. While LAC witnessed the sharpest reduction in inequality over this time period, EAP saw a substantial increase from 37.63 to 45.80. Finally, regarding *NR rents*, we note that SSA had the highest share of GDP from natural resource rents in the 1990s, but was the only region that saw a reduction in that share by 2010.

4. Results

This section comprises three subsections. In the first subsection, we present our baseline estimates of the effect of the sectoral composition of economic growth on rural and urban poverty. The second subsection analyzes the sensitivity of our results to changes in key assumptions, including using alternative poverty lines. Finally, the third subsection presents the results from our analysis of the past contribution of the various sources of growth to rural and urban poverty reduction.

4.1. *Baseline Results*

The growth *elasticity* of poverty reduction can be obtained by estimating equation (1), but with the percentage change in the headcount ratio as the dependent variable. We find that the growth elasticity of extreme ($1.25 per day) poverty is −0.81, which is statistically insignificant at any conventional level. Results based on the moderate ($2 per day) poverty line suggest an elasticity of −0.73, which is significant at the one percent level. These estimates have been called "empirical" (Ravallion and Chen, 1997) or "total" (Chambers and Dhongde, 2011) elasticities as no attempt is made to control for changes in the distribution of income. While we examine the sensitivity of our results to controlling for distributional changes below, our primary interest is in the poverty-reducing effects of actual—as opposed to hypothetical or distribution-neutral—growth processes (Ravallion and Chen, 1997).

Our elasticity estimates are in line with recent studies. For example, Ram (2011) found a growth elasticity of poverty of −0.84 when using a $2 per day poverty line. Nevertheless, as discussed above, Klasen and Misselhorn (2008) argued that there are conceptual and empirical advantages to examining absolute rather than proportionate poverty reduction. We thus focus on growth *semi-elasticities* of poverty. Estimating equation (1) with the percentage point change in extreme poverty rates as the dependent variable, we find a semi-elasticity of −0.26, which is statistically significant at the five percent level. This says that a one percent increase in GDP per capita reduces extreme poverty rates by 0.26 percentage points on average. Note that this semi-elasticity estimate is statistically significant whereas the corresponding elasticity estimate is not, which is consistent with the argument made by Klasen and Misselhorn (2008) that semi-elasticities can be estimated more precisely. Finally, the analogous semi-elasticity based on the moderate poverty line is −0.31, which is significant at the one percent level.

As discussed in Sections 1 and 2, we are primarily interested in the channels through which economic growth reduces poverty. To this end, Table 4 presents results associated with various decompositions of GDP per capita growth. In

TABLE 4
BASELINE ESTIMATES OF GROWTH SEMI-ELASTICITIES OF EXTREME POVERTY

		Dependent Variable		
Decomposition	Variable	Overall	Rural	Urban
(1)	*Agriculture*	−0.05 (0.07)	−0.06 (0.10)	−0.04 (0.03)
	Non-agriculture	−0.20* (0.11)	−0.21 (0.17)	−0.20*** (0.05)
(2)	*Agricultural productivity*	−0.08 (0.06)	−0.11 (0.09)	−0.04 (0.04)
	Agricultural employment	0.06 (0.10)	0.12 (0.16)	−0.02 (0.04)
	Non-agricultural productivity	−0.16 (0.10)	−0.13 (0.15)	−0.21*** (0.05)
	Non-agricultural employment	−0.31** (0.12)	−0.43** (0.21)	−0.16 (0.10)
(3)	*Agricultural productivity*	−0.08 (0.06)	−0.11 (0.10)	−0.05 (0.03)
	Non-agricultural productivity	−0.11 (0.10)	−0.06 (0.14)	−0.19*** (0.05)
	Transformation	−0.28** (0.12)	−0.42* (0.23)	−0.10* (0.06)
	Employment	−0.17 (0.16)	−0.18 (0.22)	−0.18 (0.16)

Note: All semi-elasticities are a function of the data and thus evaluated at variable means. Country-clustered standard errors are in parentheses. *** denotes P-value < 0.01, ** denotes P-value < 0.05, and * denotes P-value < 0.10. The regression model associated with decomposition (1) results from substituting equation (2) into equation (1). The model for decomposition (2) results from substituting equation (3) into equation (1). Finally, the model for decomposition (3) is presented in equation (5).

accordance with the poverty decomposition in equation (7), each of these growth decompositions is regressed on three alternative dependent variables: (1) the annual percentage point change in extreme poverty rates (i.e. *overall*); (2) the change in overall extreme poverty rates due to changes in rural poverty rates (i.e. *rural*); and (3) the change in overall extreme poverty rates due to changes in urban poverty rates (i.e. *urban*). Each entry in the table presents the relevant semi-elasticity along with its country-clustered standard error.[25] Note that the estimates in Table 4 do not yet incorporate the above-discussed interaction effects accounting for differences in initial conditions.

Decomposition (1) in Table 4 decomposes GDP per capita growth into components corresponding to growth in the agricultural and non-agricultural sectors. This model results from substituting equation (2) into equation (1). These initial estimates suggest a particularly strong relationship between growth in the non-agricultural sector and reductions in overall extreme poverty. While a one percent increase in non-agricultural value added per capita is associated with a 0.20 percentage point decrease in overall poverty rates on average, a similar increase in agricultural value added per capita is associated with a reduction of overall poverty by 0.05 percentage points. Moreover, the agricultural semi-elasticity is statistically insignificant whereas the non-agricultural semi-elasticity is significant, albeit only at the 10 percent level. When looking at the effect of sectoral growth on rural and urban poverty, we find comparable semi-elasticities. Most notably, the semi-elasticity of urban poverty with respect to non-agricultural growth is −0.20 and statistically significant at the one percent level. In no case does the agricultural sector witness a statistically significant effect on poverty reduction.

Decomposition (2) permits us to examine the extent to which the sectoral growth effects are driven by sectoral productivity or employment growth. This model results from substituting equation (3) into equation (1). Each regression now yields four semi-elasticities, consisting of productivity and employment growth semi-elasticities for each sector. Most interestingly, the effect of non-agricultural growth on urban poverty reduction appears to be driven by non-agricultural productivity growth. We find that the semi-elasticity of urban poverty to non-agricultural productivity growth is −0.21, which is statistically significant at any conventional level. Conversely, we find that the effect of non-agricultural growth on rural poverty is largely driven by employment growth. The semi-elasticity of rural poverty to non-agricultural employment growth is statistically significant and relatively large at −0.43. These findings highlight the importance of our rural-urban poverty decomposition as they suggest that the quality of non-agricultural growth may have important implications for the geographic composition of poverty.

Decomposition (3) in Table 4 is based on equation (4) and the further decomposition of sectoral employment growth into components associated with structural transformation and growth in the employment-to-population ratio. The associated regression model is presented in equation (5). This decomposition again yields four semi-elasticities for each regression and permits us to examine the extent

[25]Semi-elasticity calculations are discussed in Section 2.

TABLE 5
Growth Semi-Elasticities of Extreme Poverty With Interaction Effects

	Dependent Variable		
Variable	Overall	Rural	Urban
Agricultural productivity	−0.14*** (0.04)	−0.23*** (0.07)	−0.03 (0.03)
Gini	−0.08 (0.10)	−0.18 (0.14)	0.04 (0.06)
PI ratio	0.05 (0.11)	0.11 (0.17)	−0.03 (0.05)
NR rents	0.09** (0.04)	0.15** (0.06)	0.01 (0.03)
Spell	−0.13 (0.08)	−0.19 (0.12)	−0.04 (0.05)
Non-agricultural productivity	−0.10 (0.10)	−0.04 (0.14)	−0.19*** (0.06)
Gini	0.14 (0.13)	0.19 (0.19)	0.07 (0.07)
PI ratio	0.07 (0.18)	0.09 (0.26)	0.06 (0.09)
NR rents	0.10 (0.09)	0.18 (0.13)	−0.00 (0.05)
Spell	−0.07 (0.10)	−0.10 (0.14)	−0.04 (0.06)
Transformation	−0.13 (0.10)	−0.16 (0.16)	−0.10** (0.05)
Gini	0.00 (0.15)	0.06 (0.21)	−0.08 (0.08)
PI ratio	−0.59* (0.35)	−0.85* (0.49)	−0.25 (0.19)
NR rents	0.10 (0.12)	0.11 (0.18)	0.08 (0.07)
Spell	0.49** (0.20)	0.80*** (0.28)	0.09 (0.13)
Employment	−0.19 (0.22)	−0.41 (0.33)	0.07 (0.14)
Gini	0.05 (0.31)	0.26 (0.44)	−0.25 (0.19)
PI ratio	0.27 (0.45)	0.51 (0.64)	−0.03 (0.25)
NR rents	−0.06 (0.31)	−0.08 (0.50)	−0.06 (0.16)
Spell	−0.15 (0.38)	−0.49 (0.52)	0.31 (0.23)

Notes: All semi-elasticities are a function of the data and thus evaluated at variable means. Country-clustered standard errors are in parentheses. *** denotes P-value < 0.01, ** denotes P-value < 0.05, and * denotes P-value < 0.10.

NR rents denotes natural resource rents as a share of GDP and PI ratio denotes the ratio of the poverty line to daily GDP per capita.

that the above-discussed employment effects are driven by the reallocation of labor across sectors. With a semi-elasticity of −0.19, we once again see a strong relationship between non-agricultural productivity growth and urban poverty reduction. Perhaps more interestingly, we find that it is structural transformation that appears to be driving the effect of non-agricultural employment growth on rural and (to a lesser extent) urban poverty. Our estimates suggest that a one percent increase in the share of the labor force in the non-agricultural sector is associated with a statistically significant 0.42 (0.10) percentage point reduction in rural (urban) poverty rates. While rural-urban migration provides a potential explanation for this result, the finding is also consistent with the reallocation of rural labor toward more remunerative non-farm activities in rural areas.

In Section 2, we mentioned that the sectoral participation effects—and thus the semi-elasticities—may depend on differences in initial conditions across countries. Further, to the extent that initial conditions affect the process of growth itself, the semi-elasticities presented in Table 4 may be subject to omitted variable bias. Table 5 thus presents results from our full specification, which is based on the full growth decomposition from equation (4) and also includes interaction terms to accommodate the effects of differences in initial conditions. The *overall* column presents semi-elasticities calculated from the specification in equation (6) whereas the *rural* and *urban* columns present semi-elasticities calculated from the specifications in equations (8) and (9). All semi-elasticities are presented in bold. We further want to understand how the semi-elasticities vary with changes in initial conditions. To this end, below each semi-elasticity we present the marginal effect of each of the covariates on the associated semi-elasticity. Each covariate is normalized to have a mean zero and unit standard deviation.

Looking at the *agricultural productivity* results in Table 5, we find that the semi-elasticity associated with *overall* has increased in magnitude relative to the estimate in Table 4. The semi-elasticity is now −0.14 and is significant at the one percent level. This effect appears to be driven by the effect of agricultural growth on rural poverty reduction. We find that a one percent increase in agricultural productivity is now associated with a 0.23 percentage point decrease in rural extreme poverty rates. This effect is also significant at the one percent level. The change in the magnitude of these semi-elasticities from Table 4 is due to omitted variable bias. The variable *NR rents* is an important consideration here as it has a positive and statistically significant effect on both the aforementioned semi-elasticities.[26] More specifically, we find that a one standard deviation increase in *NR rents* increases the *overall* (*rural*) semi-elasticity by 0.09 (0.15) (see Table 3 for descriptive statistics on *NR rents*).

Contrary to the *agricultural productivity* results, the *non-agricultural productivity* semi-elasticities in Table 5 have changed little. Indeed the semi-elasticity associated with *urban* remains −0.19 and significant at the one percent level. While the semi-elasticity of *urban* with respect to *transformation* remains similarly unchanged from Table 4, the semi-elasticity of *rural* to *transformation* is considerably different in Table 5. This semi-elasticity is particularly sensitive to changes in *PI ratio*. We find that a one standard deviation increase in *PI ratio* is associated with a reduction of the semi-elasticity of *rural* to *transformation* by 0.85 (see Table 3 for descriptive statistics on *PI ratio*). Recall that *PI ratio* is inversely related to the level of economic development and, as such, we find that the semi-elasticity of *rural* to *transformation* weakens with development. We also find that *spell* exerts a highly significant and positive effect on the semi-elasticity of *rural* to *transformation*. One potential explanation for this finding is general-equilibrium effects: the movement of labor into rural non-farm activities, for example, may depress wages with time and limit the poverty-reducing effects of structural transformation.

The results presented in Tables 4 and 5 suggest that the sectoral composition of growth matters for poverty reduction, but we can test this conjecture more formally. As discussed in Section 2, this entails an *F*-test of the equality of all vectors of coefficients associated with our growth decomposition. For example, to examine whether the composition of growth matters for rural poverty reduction, we can test $\pi_a^r = \pi_n^r = \pi_s^r = \pi_e^r$ after estimating the specification presented in equation (8). This test yields an *F*-statistic of 15.68 (p-value = 0.00), so we reject the null hypothesis at any conventional level of significance. With an *F*-statistic of 4.98 (p-value = 0.00), we also reject the null hypothesis for our urban poverty regression. We can further test whether the composition of growth matters for overall poverty reduction. We similarly reject the null hypothesis for this test at any conventional level of significance (*F*-statistic = 15.29 and p-value = 0.00).

[26]Of course, the direction of the bias also depends on the relationship between *agricultural productivity* and *NR rents.* We find this relationship to be positive and thus *NR rents* contributes to the upward bias of the *agricultural productivity* semi-elasticities in Table 4.

Finally, we can use the models presented in equations (6), (8), and (9) to examine regional heterogeneity in semi-elasticities. Due to insufficient observations, we are unable to run the regressions for each region, but we can estimate the models using all observations and then evaluate the semi-elasticities with the mean values for different regions. Table 6 presents the results where each column presents 12 semi-elasticities for each region.[27] First, we see that our finding in Table 5 of a significant semi-elasticity of *rural* to *agricultural productivity* is largely driven by LAC, the estimate from which is −0.46 and significant at any conventional level. Second, we find that the effect of *non-agricultural productivity* on *urban* is statistically significant for all regions, consistent with our finding that this effect is insensitive to initial conditions. Finally, the results suggest that EAP and SSA are notable contributors to the effect of *transformation* on *rural* and *urban*, respectively. As we will see, the effect of structural transformation on rural poverty in EAP is a recurring theme in subsequent sections.

4.2. *Sensitivity Analysis*

Our baseline results demonstrate three findings. First, the semi-elasticity of rural poverty to agricultural productivity is highly significant and relatively large in magnitude, particularly for countries with little dependence on natural resources. Second, the semi-elasticity of urban poverty to non-agricultural productivity is also large and highly significant. Like all the urban-poverty semi-elasticities, this semi-elasticity is insensitive to initial conditions. Third, structural transformation tends to reduce both urban and rural poverty, though the rural-poverty effect depends on the initial level of development and the spell length under consideration. Tables 7 and 8 present the results from our analysis of the sensitivity of these findings to key assumptions. Table 7 (Table 8) presents sensitivity analysis results for the rural (urban) poverty regression. For reference, baseline results are provided in column (1) of each table.

We first ask whether our results are sensitive to changes in the poverty line. Column (2) in Tables 7 and 8 presents results from our full specification when using dependent variables calculated on the basis of the moderate ($2 per day) poverty line. The semi-elasticity of rural poverty to agricultural productivity (Table 7) remains negative and statistically significant, and the marginal effect of *NR rents* on this semi-elasticity is virtually unchanged. The semi-elasticity of urban poverty to non-agricultural productivity (Table 8) also remains negative and statistically significant. Though the magnitude of some marginal effects has increased slightly (e.g. *Gini* and *PI ratio*), initial conditions continue to play little role in affecting this semi-elasticity. Finally, our structural transformation results generally hold, with the potential exception of the semi-elasticity of *urban* to *transformation*, which is no longer statistically significant.

As mentioned in Section 4.1, our focus is on estimating "total" semi-elasticities, but one may also be interested in "partial" semi-elasticities, which characterize the poverty-growth relationship while holding distributional changes constant

[27]Once again, Table 2 serves as a key for the region abbreviations. Note that we have only a few observations from MENA, so these results should be interpreted with caution.

TABLE 6

Regional Estimates of Growth Semi-Elasticities of Extreme Poverty

		Region					
Model	Semi-Elasticity	EAP	ECA	LAC	MNA	SAS	SSA
Overall	*Agricultural productivity*	0.00 (0.04)	−0.15 (0.11)	−0.16*** (0.05)	−0.13 (0.10)	−0.19 (0.16)	−0.15 (0.13)
	Non-agricultural productivity	−0.15* (0.08)	−0.26*** (0.09)	−0.07 (0.14)	−0.33 (0.22)	−0.31*** (0.12)	0.02 (0.16)
	Transformation	−0.53*** (0.11)	−0.18 (0.12)	0.07 (0.05)	0.57 (0.53)	−0.05 (0.26)	−0.34* (0.20)
	Employment	−0.18 (0.18)	−0.21 (0.43)	−0.32 (0.22)	−0.45 (0.70)	−0.25 (0.59)	−0.08 (0.43)
Rural	*Agricultural productivity*	−0.00 (0.06)	−0.23 (0.16)	−0.46*** (0.11)	−0.24 (0.17)	−0.19 (0.16)	−0.19 (0.17)
	Non-agricultural productivity	−0.12 (0.10)	−0.32** (0.14)	−0.01 (0.31)	−0.42 (0.37)	−0.28** (0.13)	0.11 (0.21)
	Transformation	−0.83*** (0.17)	−0.28 (0.20)	0.21 (0.14)	1.08 (0.87)	−0.03 (0.29)	−0.36 (0.27)
	Employment	−0.27 (0.26)	−0.62 (0.70)	−0.82 (0.51)	−1.40 (1.16)	−0.62 (0.67)	−0.20 (0.53)
Urban	*Agricultural productivity*	0.00 (0.03)	−0.06 (0.07)	0.00 (0.02)	−0.04 (0.06)	−0.17 (0.19)	−0.08 (0.09)
	Non-agricultural productivity	−0.23*** (0.07)	−0.20*** (0.05)	−0.13* (0.07)	−0.26** (0.10)	−0.41*** (0.11)	−0.17* (0.10)
	Transformation	−0.07 (0.08)	−0.06 (0.06)	−0.01 (0.02)	0.13 (0.25)	−0.09 (0.24)	−0.32*** (0.10)
	Employment	−0.07 (0.12)	0.25 (0.26)	−0.07 (0.11)	0.40 (0.36)	0.79 (0.65)	0.12 (0.31)

*** denotes P-value < 0.01, ** denotes P-value < 0.05, and * denotes P-value < 0.10.

TABLE 7
Sensitivity Analysis for Extreme Rural Poverty Results

Variable	Baseline Results (1)	Moderate Poverty (2)	Standard Model (3)	Two Percent Threshold (4)	No Threshold (5)	Mean Semi-Elasticities (6)	Country Representation (7)	Dropping Short Spells (8)
Agricultural productivity	−0.23*** (0.07)	−0.16** (0.07)	−0.23*** (0.08)	−0.24*** (0.07)	−0.18*** (0.05)	−0.18*** (0.07)	−0.22*** (0.06)	−0.34*** (0.12)
Gini	−0.18 (0.14)	0.01 (0.17)	−0.17 (0.13)	−0.19 (0.15)	−0.16* (0.08)	−0.18 (0.14)	−0.17 (0.15)	−0.22 (0.17)
PI ratio	0.11 (0.17)	0.33** (0.15)	0.11 (0.17)	0.11 (0.17)	0.02 (0.11)	0.11 (0.17)	0.13 (0.17)	0.03 (0.20)
NR rents	0.15** (0.06)	0.14*** (0.04)	0.15** (0.07)	0.16** (0.06)	0.13** (0.05)	0.15** (0.06)	0.17*** (0.06)	0.34** (0.13)
Spell	−0.19 (0.12)	−0.17* (0.09)	−0.19 (0.12)	−0.20 (0.12)	−0.14* (0.07)	−0.19 (0.12)	−0.27** (0.11)	−0.33* (0.17)
Non-agricultural productivity	−0.04 (0.14)	−0.02 (0.10)	−0.05 (0.15)	−0.06 (0.16)	−0.05 (0.13)	−0.05 (0.15)	0.07 (0.12)	0.15 (0.17)
Gini	0.19 (0.19)	0.32 (0.21)	0.19 (0.17)	0.19 (0.19)	0.13 (0.15)	0.19 (0.19)	0.21 (0.21)	0.33 (0.25)
PI ratio	0.09 (0.26)	0.43* (0.25)	0.09 (0.25)	0.08 (0.26)	0.03 (0.18)	0.09 (0.26)	0.08 (0.27)	0.18 (0.28)
NR rents	0.18 (0.13)	−0.06 (0.14)	0.18 (0.13)	0.20 (0.13)	0.11 (0.09)	0.18 (0.13)	0.23* (0.12)	0.25 (0.16)
Spell	−0.10 (0.14)	−0.08 (0.16)	−0.10 (0.14)	−0.10 (0.14)	−0.07 (0.07)	−0.10 (0.14)	−0.07 (0.14)	−0.01 (0.14)
Transformation	−0.16 (0.16)	0.06 (0.15)	−0.17 (0.20)	−0.21 (0.16)	−0.14 (0.15)	−0.28* (0.16)	−0.13 (0.16)	0.09 (0.18)
Gini	0.06 (0.21)	−0.46** (0.21)	0.07 (0.22)	0.07 (0.21)	0.23 (0.16)	0.06 (0.21)	0.08 (0.21)	−0.00 (0.28)
PI ratio	−0.85* (0.49)	−1.29*** (0.46)	−0.85* (0.50)	−0.83* (0.49)	−0.53* (0.29)	−0.85* (0.49)	−0.50 (0.50)	−0.40 (0.52)
NR rents	0.11 (0.18)	0.41** (0.17)	0.11 (0.17)	0.11 (0.18)	−0.07 (0.15)	0.11 (0.18)	0.05 (0.19)	0.15 (0.27)
Spell	0.80*** (0.28)	0.91*** (0.30)	0.80*** (0.27)	0.77*** (0.27)	0.56*** (0.13)	0.80*** (0.28)	0.66** (0.27)	0.43** (0.19)
Employment	−0.41 (0.33)	−0.35 (0.26)	−0.42 (0.34)	−0.40 (0.33)	−0.24 (0.26)	−0.52 (0.32)	−0.20 (0.31)	−0.15 (0.40)
Gini	0.26 (0.44)	0.82 (0.54)	0.29 (0.31)	0.22 (0.47)	0.00 (0.23)	0.26 (0.44)	0.32 (0.48)	0.05 (0.37)
PI ratio	0.51 (0.64)	1.50 (0.91)	0.52 (0.53)	0.46 (0.66)	0.12 (0.50)	0.51 (0.64)	0.43 (0.64)	−0.65 (0.65)
NR rents	−0.08 (0.50)	−0.23 (0.48)	−0.07 (0.53)	−0.08 (0.52)	0.05 (0.35)	−0.08 (0.50)	0.10 (0.42)	0.67 (0.54)
Spell	−0.49 (0.52)	−0.95 (0.69)	−0.50 (0.43)	−0.45 (0.53)	−0.22 (0.25)	−0.49 (0.52)	−0.43 (0.49)	0.25 (0.33)
% Δ Gini	–	–	0.02 (0.18)	–	–	–	–	–

Notes: All semi-elasticities are a function of the data and thus evaluated at variable means, unless noted otherwise. Country-clustered standard errors are in parentheses. *** denotes P-value < 0.01, ** denotes P-value < 0.05, and * denotes P-value < 0.10.

NR rents denotes natural resource rents as a share of GDP and PI ratio denotes the ratio of the poverty line to daily GDP per capita.

TABLE 8
Sensitivity Analysis for Extreme Urban Poverty Results

Variable	Baseline Results (1)	Moderate Poverty (2)	Standard Model (3)	Two Percent Threshold (4)	No Threshold (5)	Mean Semi-Elasticities (6)	Country Representation (7)	Dropping Short Spells (8)
Agricultural productivity	−0.03 (0.03)	0.01 (0.05)	−0.05 (0.03)	−0.02 (0.03)	−0.03 (0.02)	−0.11* (0.06)	−0.04 (0.03)	−0.08 (0.05)
Gini	0.04 (0.06)	0.19 (0.13)	0.01 (0.05)	0.05 (0.07)	0.03 (0.03)	0.04 (0.06)	0.02 (0.07)	0.05 (0.08)
PI ratio	−0.03 (0.05)	0.08 (0.10)	−0.03 (0.05)	−0.03 (0.05)	−0.03 (0.03)	−0.03 (0.05)	−0.05 (0.06)	−0.09 (0.10)
NR rents	0.01 (0.03)	0.02 (0.04)	0.02 (0.03)	0.00 (0.03)	0.01 (0.02)	0.01 (0.03)	0.01 (0.03)	0.00 (0.14)
Spell	−0.04 (0.05)	−0.08 (0.07)	−0.04 (0.05)	−0.04 (0.05)	−0.03 (0.03)	−0.04 (0.05)	−0.05 (0.05)	−0.02 (0.14)
Non-agricultural productivity	−0.19*** (0.06)	−0.27*** (0.09)	−0.17*** (0.06)	−0.18** (0.07)	−0.16*** (0.05)	−0.21*** (0.08)	−0.17*** (0.05)	−0.18*** (0.06)
Gini	0.07 (0.07)	0.20* (0.12)	0.03 (0.06)	0.07 (0.07)	0.02 (0.06)	0.07 (0.07)	0.01 (0.08)	0.05 (0.11)
PI ratio	0.06 (0.09)	0.25 (0.17)	0.05 (0.09)	0.07 (0.09)	−0.00 (0.06)	0.06 (0.09)	−0.02 (0.10)	−0.01 (0.10)
NR rents	−0.00 (0.05)	−0.04 (0.10)	−0.00 (0.05)	−0.01 (0.05)	−0.00 (0.04)	−0.00 (0.05)	0.04 (0.05)	0.03 (0.05)
Spell	−0.04 (0.06)	−0.13 (0.11)	−0.05 (0.05)	−0.05 (0.06)	−0.01 (0.03)	−0.04 (0.06)	−0.04 (0.06)	−0.04 (0.09)
Transformation	−0.10** (0.05)	−0.13 (0.10)	−0.07 (0.05)	−0.11** (0.04)	−0.04 (0.04)	−0.19*** (0.06)	−0.13** (0.06)	−0.13* (0.07)
Gini	−0.08 (0.08)	−0.28* (0.16)	−0.09 (0.08)	−0.09 (0.08)	−0.06 (0.04)	−0.08 (0.08)	−0.04 (0.08)	−0.04 (0.13)
PI ratio	−0.25 (0.19)	−0.55* (0.32)	−0.25 (0.19)	−0.26 (0.20)	−0.17* (0.09)	−0.25 (0.19)	−0.11 (0.20)	−0.12 (0.20)
NR rents	0.08 (0.07)	0.24* (0.12)	0.07 (0.06)	0.09 (0.07)	0.03 (0.04)	0.08 (0.07)	0.05 (0.08)	0.05 (0.18)
Spell	0.09 (0.13)	0.29 (0.22)	0.08 (0.13)	0.10 (0.13)	0.05 (0.06)	0.09 (0.13)	0.04 (0.13)	0.00 (0.14)
Employment	0.07 (0.14)	−0.05 (0.15)	0.11 (0.15)	0.07 (0.14)	0.03 (0.09)	0.18 (0.23)	0.11 (0.15)	0.19 (0.22)
Gini	−0.25 (0.19)	0.14 (0.40)	−0.38** (0.18)	−0.25 (0.21)	−0.13 (0.09)	−0.25 (0.19)	−0.32 (0.22)	−0.40 (0.25)
PI ratio	−0.03 (0.25)	0.52 (0.59)	−0.11 (0.21)	−0.03 (0.26)	0.15 (0.16)	−0.03 (0.25)	−0.10 (0.25)	−0.46 (0.32)
NR rents	−0.06 (0.16)	0.05 (0.30)	−0.10 (0.16)	−0.07 (0.18)	−0.01 (0.10)	−0.06 (0.16)	−0.08 (0.17)	−0.10 (0.33)
Spell	0.31 (0.23)	0.01 (0.49)	0.38* (0.20)	0.31 (0.24)	0.17* (0.09)	0.31 (0.23)	0.40 (0.25)	0.51** (0.25)
% Δ Gini	–	–	−0.08** (0.04)	–	–	–	–	–

Notes: All semi-elasticities are a function of the data and thus evaluated at variable means, unless noted otherwise. Country-clustered standard errors are in parentheses. *** denotes P-value < 0.01, ** denotes P-value < 0.05, and * denotes P-value < 0.10.

NR rents denotes natural resource rents as a share of GDP and PI ratio denotes the ratio of the poverty line to daily GDP per capita.

(Chambers and Dhongde, 2011). Our next robustness check thus includes the percentage change in the Gini coefficient as an additional explanatory variable, resulting in a specification Bourguignon (2003) called the "standard model." The results are presented in column (3) of Tables 7 and 8 where we see that the poverty-inequality semi-elasticity is statistically significant in one case (bottom of Table 8). The other results are, however, essentially identical to the baseline. The one exception to this statement is the semi-elasticity of *urban* to *transformation* (Table 8), which again loses statistical significance. There is thus no meaningful distinction between total and partial semi-elasticities in our data, which is not unexpected given previous findings on the weak relationship between economic growth and changes in inequality (Ravallion and Chen, 1997; Ravallion, 2001; Dollar and Kraay, 2002).

One may also be concerned about the sensitivity of our results to the criterion used to drop extreme observations. While our baseline estimates drop any spell where the poverty rate is less than one percent in the initial or final period, in columns (4) and (5) of Tables 7 and 8 we consider a two percent threshold and no threshold (i.e. no spells are dropped), respectively. The two percent threshold reduces the sample size from 146 to 140 whereas the sample size increases from 146 to 186 with no threshold. Our results with these alternative thresholds are very similar to the baseline results. Note, however, that the magnitude of some of the estimates is slightly subdued in column (5) of both tables (i.e. the no threshold results), but this is to be expected as the sample includes countries with little extreme poverty and thus little or no responsiveness of poverty to economic growth. Note also that the semi-elasticity of *urban* to *transformation* (Table 8), which was statistically insignificant in columns (2) and (3), once again witnesses significance in column (4).

Recall that our semi-elasticity estimates are evaluated at the sample means. While this approach is common, one might argue that the values used are not necessarily representative of any country in the sample. In column (6) of Tables 7 and 8, we thus present alternative estimates where the semi-elasticities are calculated for each observation and then subsequently averaged (i.e. we use mean semi-elasticities as opposed to semi-elasticities evaluated at the mean). The marginal effects of the initial conditions are numerically equivalent to the baseline in this case, so we focus our attention on the semi-elasticities associated with the various growth components. While the semi-elasticity of *rural* to *agricultural productivity* diminishes slightly in magnitude, the effect remains significant at any conventional level. In other cases, we find that magnitude of our estimates increases. For example, the semi-elasticity of *urban* to *agricultural productivity* increases from −0.03 in the baseline to −0.11 and becomes significant at the 10 percent level.

One could further argue that our results are unrepresentative in a different sense: as there is a fair amount of variation in the number of spells per country, it is possible that our estimates are heavily influenced by countries with a relatively large number of spells. To examine this issue, we weight each observation in our regressions by the inverse of the number of spells associated with each country. It is important to mention that weighting in this manner has implications for the regional representation of our data. In particular, the distribution of observations across regions in our data coincides reasonably well with the regional distribution of countries, but with this weighting approach those regions with a larger number of spells per country become underrepresented (e.g. EAP). Column (7) in Tables 7 and 8 presents the estimates and we see that our results are not substantively affected by the weighting. One potentially notable change is that the marginal effect of *PI ratio* on *transformation* in Table 7 loses statistical significance, though the point estimate remains negative.

An additional concern with our baseline results is that the sample includes a number of short spells and, as such, our estimates may capture the effects of short-term fluctuations more than longer-term structural transformation. While our baseline regressions include *spell* as an interaction term to permit the semi-elasticities to vary with spell length, it is possible that the linear specification is inadequate. Column (8) of Tables 7 and 8 thus presents results from an additional robustness check where we only use data from spells with a minimum length of four years. We chose this threshold because it is the highest we could use while maintaining an acceptable number of observations. Restricting the sample in this way reduces the number of observations to 111. Like the previous robustness check, dropping short spells also has implications for the regional representation of our data: regions with a larger number of spells per country (i.e. EAP) tend to have shorter spells and become underrepresented after short spells are dropped. The results, especially the urban-poverty results, are thus very similar to those presented in column (7). Accordingly, we once again see that the marginal effect of *PI ratio* on *transformation* in Table 7 is insignificant.

Finally, we mention two robustness checks not reported in Tables 7 and 8.[28] First, recall that our poverty data is based on 2005 PPP conversion factors. It is well known that using conversion factors from alternative years, namely 2011, can change poverty estimates considerably (Deaton and Aten, 2017). Rural and urban poverty rates using 2011 conversion factors are unavailable, so we conducted a robustness check by re-estimating equation (6) using national poverty rates from PovcalNet that are based on 2011 PPP conversion factors (World Bank, 2019). Our estimates, particularly the semi-elasticity estimates, are notably similar across comparable specifications. In particular, we only reject the null hypothesis of equivalent estimates twice in a total of 20 hypothesis tests.[29] Second, we examined the issue of measurement error because our growth decomposition relies heavily on national accounts data whereas our poverty measures are derived from household surveys.[30] Following Loayza and Raddatz (2010), we examined this issue by including in our regressions an estimate of mean income/consumption growth based on household survey data.[31] We find that (1) the semi-elasticity of poverty to survey-mean growth

[28]The results from these additional robustness checks are available upon request.

[29]We used five percent as the threshold of statistical significance. Our models are associated with 20 estimates because we have four semi-elasticity estimates, each of which is associated with four estimates of the marginal effects of the initial conditions. The two rejections correspond to the effect of *Gini* on *non-agricultural productivity* and *NR rents* on *transformation*. Neither of these estimates relate directly to our core conclusions.

[30]Given the well-known discrepancies between economic growth estimates based on national accounts data and those based on household surveys (Ravallion, 2001; Ravallion, 2003; Deaton, 2005), we would expect our estimates to be biased if such measurement errors are correlated with our explanatory variables.

[31]The data we use for this exercise was compiled for the World Bank's PovcalNet tool and made publicly available by Dykstra *et al.* (2014). The regressions have fewer observations (139) than our baseline (146) as some countries do not have any mean income/consumption information.

is insignificant in all cases, and (2) there are no notable differences in the semi-elasticity estimates from the baseline.

4.3. *Sources of Past Poverty Reduction Across Regions*

The analysis of semi-elasticities provides information regarding the responsiveness of rural and urban poverty to different sources of economic growth, but conveys little information about the past contribution of the various sources of growth to poverty reduction. The estimates can nevertheless serve as the basis for an exercise in quantifying the contribution of the various growth components. In particular, each of the components on the right-hand side of our regression models (e.g. see equation [6]) embodies a prediction of the poverty rate change due to growth from a given source. We thus use our estimates and data to calculate component-wise contributions for each poverty spell and then average each contribution across time for each country.[32] Given estimates of the past contribution of each growth component for each country, we then summarize the results by region using population-weighted averaging.[33] For readers interested in more disaggregated results, country-level estimates are provided in Tables A1-A3 in the Online Appendix.

Before presenting the results of the exercise, it is important to make two clarifying points. First, we do not attribute a causal interpretation to our estimates of the contribution of each growth component to poverty reduction. If the poverty-reducing effect of growth in component X occurs via component Y, the nature of the exercise is such that component Y is attributed the poverty reduction. We thus estimate what may be termed as the proximate contribution of each growth component to poverty reduction. Second, given that we are interested in summarizing results at the regional level, one could argue that the parameters of the underlying regressions should be allowed to vary by region. While we are unable to run the regressions separately for each region due to insufficient observations, we did examine the option of including regional dummies in our regressions via the interactions effects. We nevertheless opted for our baseline specification due to the fact that the regional dummies were largely insignificant.

Figure 4 presents results when using the overall poverty rate as the dependent variable (i.e. equation [6] serves as the basis for the calculations). Each bar in the figure represents the average annual change in the overall poverty rate due to growth in a given component for a given region.[34] Despite the relatively large and statistically significant semi-elasticity in Table 5, agricultural productivity growth has played a comparatively small role in poverty reduction in all regions, except in SAS.[35] Non-agricultural productivity growth, however, has made relatively large

[32]The averaging in this step must take into account the differing duration of poverty spells.

[33]That is, the contribution of a given source of growth for a given region is calculated as the population-weighted average of that source's contribution for each country in the region. Population data can be incorporated in a variety of ways here (e.g. using initial or final population levels as the basis of the weights). We find that the particular approach used is inconsequential and thus (arbitrarily) choose initial population estimates to calculate the weights.

[34]Table 2 serves as a key for region abbreviations in the figure.

[35]Agricultural productivity growth has made a non-negligible contribution in that region, but its contribution is still small relative to non-agricultural productivity growth.

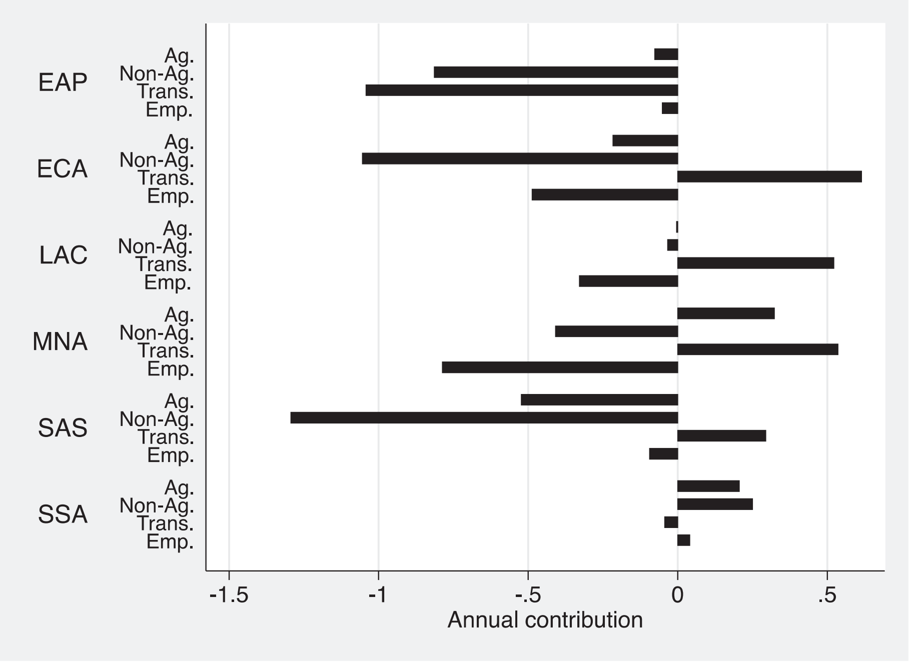

Figure 4. Annual Contribution of Different Sources of Economic Growth to Changes in Overall Extreme Poverty Rates

contributions to poverty reduction in all regions except SSA. Most notably, we estimate that non-agricultural productivity growth in SAS reduced poverty rates by an average of 1.29 percentage points annually, an effect heavily influenced by India (see Table A1). This result is due in part to the large contribution of non-agricultural productivity growth to each region's GDP per capita growth (see Figure 3).

Structural transformation has played a leading role in EAP and SSA. In EAP, we estimate that structural transformation has reduced poverty rates by an average of 1.04 percentage points annually. As is evident from Table A1, both China and Indonesia have played a critical role in this poverty reduction. While the contribution of structural transformation is much smaller in SSA, it is the only factor that contributed to reductions in overall poverty rates in that region. In Madagascar, for example, we estimate that structural transformation was the only growth component to reduce poverty, contributing a reduction of 1.76 percentage points annually. Regarding growth in the employment-to-population ratio, we find that such growth has been central to poverty reduction in ECA, LAC, and MNA. For example, employment growth in MNA is associated with an average annual poverty rate reduction of 0.79 percentage points. While employment growth has also contributed to poverty reduction in EAP and SAS, the magnitude of this effect is relatively small.

Figure 5 presents results from the exercise when using rural and urban poverty rates as the dependent variable (i.e. equations [8] and [9] serve as the basis for the calculations). One key difference here is that population-weighted averaging

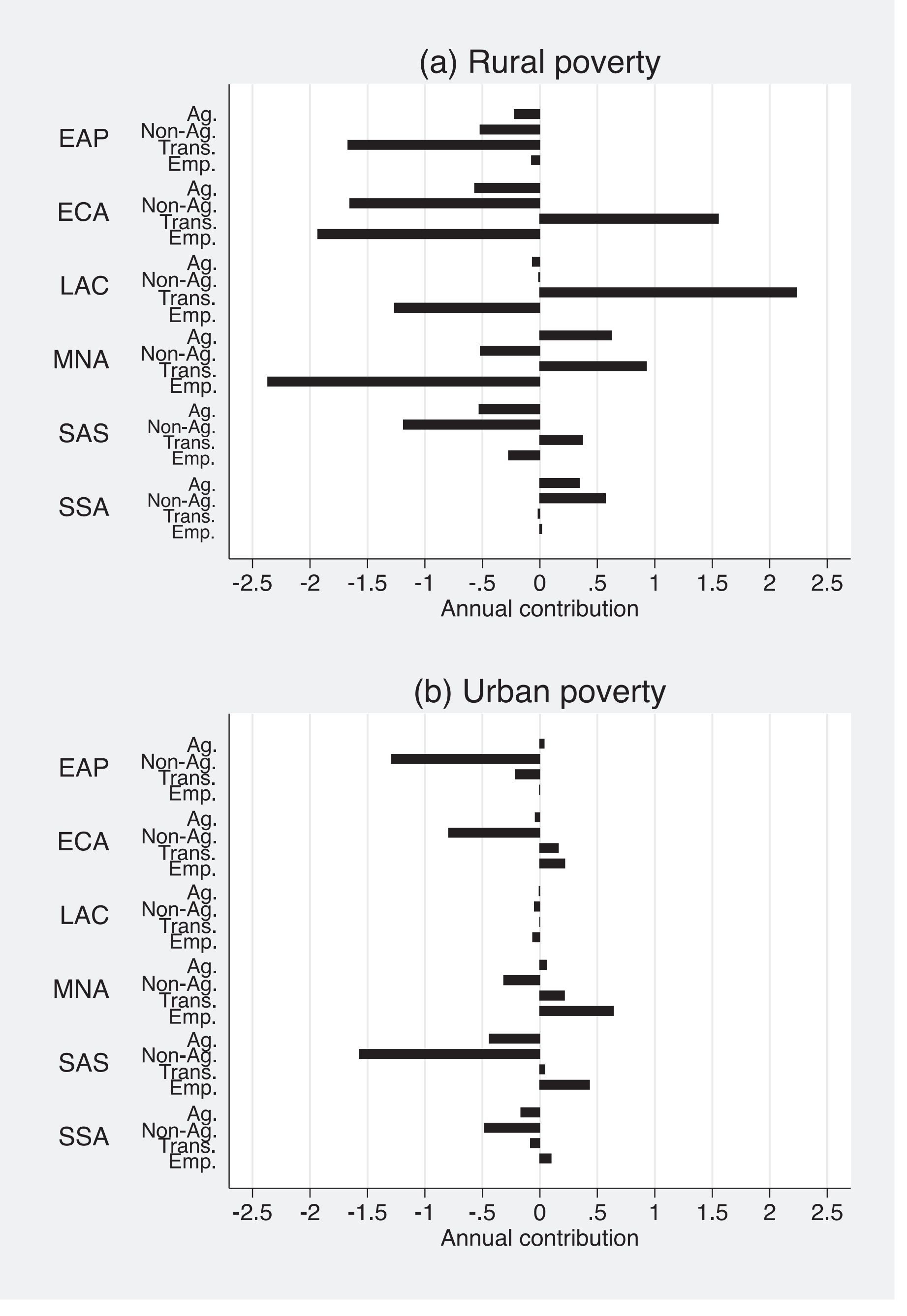

Figure 5. Annual Contribution of Different Sources of Economic Growth to Changes in Rural and Urban Extreme Poverty Rates

is based on the population (i.e. rural or urban) that corresponds to the dependent variable. Panel (a) presents rural poverty results and panel (b) presents urban poverty results. Recall that the semi-elasticity of *rural* to *agricultural productivity* was found to be particularly large and statistically significant (see Table 5). One might thus expect the poverty-reducing effect of agricultural productivity growth to be more clearly evident in panel (a). We nevertheless find that the contribution of agricultural productivity growth to rural poverty reduction has been relatively modest.

Additionally, recall that we found the semi-elasticity of *urban* to *non-agricultural productivity* to be relatively large and statistically significant. Contrary to the previous case, the expectation that non-agricultural productivity growth has made relatively large contributions to urban poverty reduction is consistent with our results. In EAP, for example, non-agricultural productivity growth is associated with an average annual reduction of the urban poverty rate by 1.29 percentage points. This effect is nearly three times the analogous contribution to rural poverty reduction, and is largely driven by China and Lao PDR. With the exception of ECA and SAS, we find that the poverty-reducing effect of non-agricultural productivity growth is concentrated in urban areas. This result is due to the fact that (1) the associated semi-elasticity is relatively large and (2) the contribution of non-agricultural productivity growth to each region's GDP per capita growth is sizable.

Regarding structural transformation, Figure 5 shows that its large contribution to overall poverty reduction in EAP is driven by a rural poverty effect. More specifically, we find that structural transformation has reduced rural poverty rates in EAP at an average annual rate of 1.69 percentage points. China, with an annual rural poverty rate reduction due to structural transformation at 1.91 percentage points, is a major contributor to this statistic. In SSA, the only other region where structural transformation contributed to poverty reduction, the effect is conversely more urban in nature. Finally, Figure 5 shows that the large employment effect witnessed in ECA, LAC, and MNA is primarily a rural phenomenon. For example, we find that employment growth in MNA is associated with an average annual reduction of rural poverty rates of 2.37 percentage points. This finding can be attributed to the large semi-elasticity of *rural* to *employment* (see Table 5) and the large contribution of employment growth to GDP per capita growth in these regions.

The results of our attribution exercise can be summarized as follows: First, agricultural productivity growth has contributed relatively little to rural and urban poverty reduction across all regions. Second, non-agricultural productivity growth has made substantial contributions to reducing overall poverty rates in virtually all regions, generally via poverty reductions in urban areas. Third, the poverty-reducing effect of structural transformation has been confined to regions with initially lower levels of GDP per capita and, at least for EAP, this effect is primarily a rural phenomenon. Lastly, growth in the employment-to-population ratio has contributed to poverty reductions in regions with higher initial levels of GDP per capita (e.g. LAC). This effect is also driven by rural poverty reduction.

Our finding that agricultural productivity growth has contributed little to poverty reduction appears at odds with previous research regarding the effectiveness of the agricultural sector at reducing poverty (see Section 1). It is important, however,

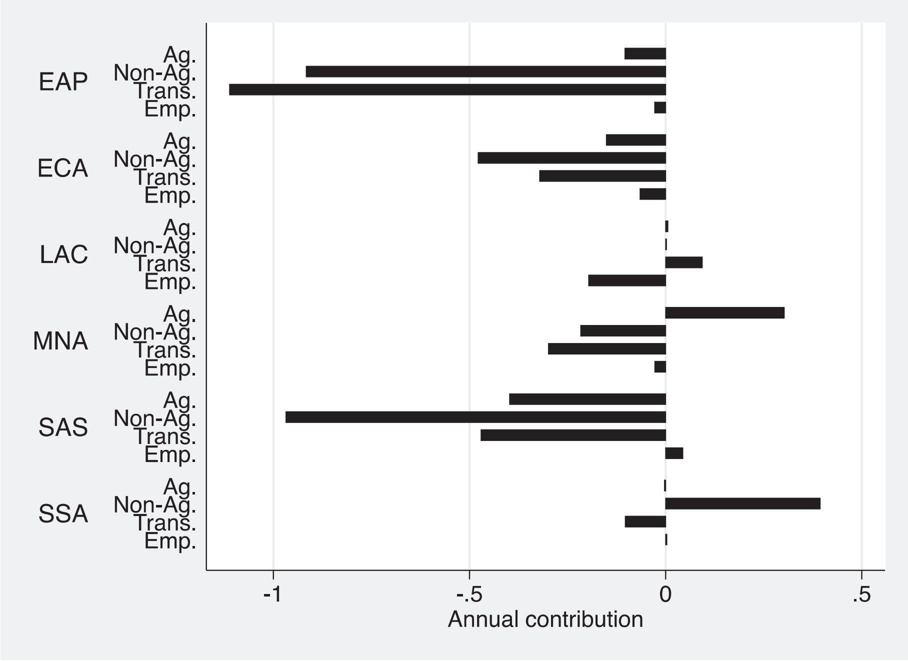

Figure 6. Sensitivity Analysis for Attribution Exercise on Overall Extreme Poverty Rates

to distinguish between the responsiveness of poverty to agricultural productivity and the amount of agricultural productivity growth that has occurred. Our results show that it is possible for poverty to be highly responsive to agricultural productivity growth, but without notable productivity growth (see Figure 3) such responsiveness will not lead to poverty reduction. In addition, recall that our attribution exercise estimates the proximate contribution of each growth component. The effect of agricultural productivity growth that occurs via the movement of workers to urban areas would then be attributed to the structural transformation component. We indeed find that structural transformation has had some sizable effects, particularly in EAP.

We conclude this section by noting that we conducted some robustness checks related to the above attribution exercise. In particular, due to the large number of insignificant interaction effects in our full model (see Table 5), one might be concerned that our model is overspecified. For each of our dependent variables, we thus conducted four *F*-tests examining the joint significance of the interaction effects associated with *Gini*, *PI ratio*, *NR rents*, and *spell*. We found that the effects associated with *PI ratio* were insignificant for all three models and thus rerun the attribution exercise using a more parsimonious model that omits those terms.[36] The results are presented in Figures 6 and 7. We highlight two notable differences

[36]We wish to maintain the same specification across all dependent variables. As such, we only omit the interaction effects that were insignificant for all models. All effects other than those associated with *PI ratio* witnessed statistical significance.

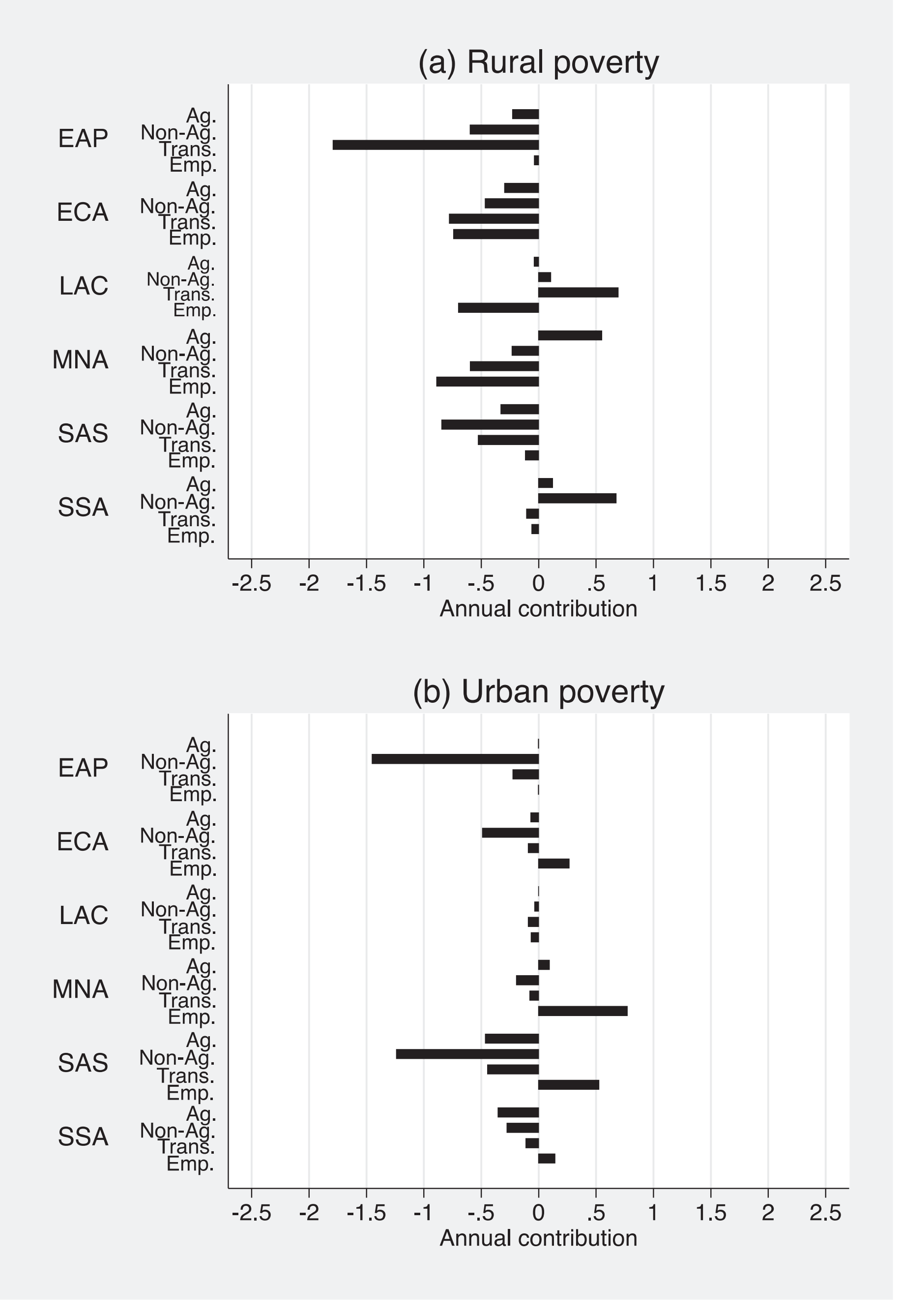

Figure 7. Sensitivity Analysis for Attribution Exercise on Rural and Urban Extreme Poverty Rates

from our previous results: (1) structural transformation now displays prominent poverty-reducing effects in ECA, MNA, and SAS; and (2) the employment effects become more modest for ECA and MNA, particularly when looking at the effects related to overall poverty rates. Our general conclusions, however, remain qualitatively unchanged.

5. Conclusions and Policy Implications

We examined the effect of the sectoral composition of economic growth on the geographic composition of poverty using a new cross-country panel dataset of internationally-comparable rural and urban poverty rates. We reported three primary findings. First, we found that rural poverty is highly responsive to agricultural productivity growth: our best estimate suggests that a one percent increase in agricultural productivity is associated with a statistically significant 0.23 percentage point decrease in rural poverty rates. This semi-elasticity diminishes in absolute magnitude with increased dependence on natural resources. Specifically, a one standard deviation increase in the share of GDP from natural resource rents is estimated to increase the semi-elasticity by 0.15. Second, we found that urban poverty is highly responsive to non-agricultural productivity growth: a one percent increase in non-agricultural productivity is associated with a 0.19 percentage point reduction in urban poverty rates. This effect is insensitive to initial conditions.

Finally, we found that structural transformation reduces rural poverty, particularly for countries at a low level of development. While a one percent increase in the share of employment in the non-agricultural sector reduces the rural poverty headcount ratio by 0.16 percentage points, a one standard deviation increase in the ratio of the extreme poverty line to daily GDP per capita reduces this semi-elasticity by 0.85. Structural transformation also leads to reductions in urban poverty. We found that our results were robust to a number of different specification checks. In particular, we examined the sensitivity of our results to alternative poverty lines, controlling for changes in the distribution of income, and modifying the criterion used to drop extreme observations. While we believe our findings constitute a robust set of empirical regularities, we do not claim to have estimated causal relationships.

We additionally reported a number of results regarding the past contribution of the various growth sources to reductions in rural and urban poverty rates. First, our results suggested that agricultural productivity growth has played a relatively minor role in reducing rural and urban poverty. Second, the poverty-reducing effect of non-agricultural productivity growth has been substantial in nearly all regions, generally via poverty reduction in urban areas. Third, we found that structural transformation has served to reduce poverty in regions with initially lower levels of GDP per capita. Lastly, for those regions with initially higher levels of GDP per capita, growth in the employment-to-population ratio has been critical for poverty reduction, particularly in rural areas.

As mentioned, our result regarding the relatively minor contribution of agricultural productivity growth to poverty reduction may appear inconsistent with previous research on the responsiveness of poverty to agricultural growth. We nevertheless argued that the result emerges due to relatively weak agricultural productivity growth in the recent past and not a general lack of responsiveness of rural poverty to such growth. Our results thus underscore the importance of continued investments in agricultural productivity and diversification to foster inclusive structural and rural transformation, particularly for lesser-developed countries. Our results, however, also reinforce the need to sustain non-agricultural productivity growth in urban areas to consolidate poverty reduction achievements. Interestingly, the responsiveness of urban poverty to non-agricultural productivity growth is robust to initial conditions, which suggests that investments in non-agricultural productivity growth can be a viable poverty-reduction strategy in a wide array of contexts.

We believe we are the first to examine the effect of the sectoral composition of economic growth on rural and urban poverty using cross-country panel data. While cross-country data has well-known limitations, we believe that our study provides new insights into the dynamics of rural and urban poverty, particularly by exploiting cross-country variation in key variables to examine the effects of initial conditions. We have further sought to deepen the analysis of the relationship between the sectoral composition of growth and the rural-urban composition of poverty. In particular, we decomposed sectoral growth into components associated with labor productivity growth and employment expansion, and then further decomposed the employment expansion effects into components associated with labor force growth and structural transformation. Our analysis of the relationship between structural transformation and poverty rates in rural and urban areas is particularly novel.

We conclude with directions for further research. Our analysis only considered the agricultural and non-agricultural sectors. Future research may consider further decomposing the non-agricultural sector (e.g. into manufacturing and services) to gain additional insights into the effect of non-agricultural productivity growth on poverty reduction. Further, we only examined the effect of the sectoral composition of growth on poverty headcount ratios. Complementary insights could be provided by alternative poverty measures, including poverty gaps and squared poverty gaps. Finally, we did not attribute a causal interpretation to our estimates of the contribution of each growth component to poverty reduction. If the effect of agricultural productivity growth, for example, largely occurs through inducing structural transformation, the nature of our exercise was such that the structural transformation component was attributed the poverty reduction. We hope to remedy this issue in subsequent work.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Table A1. Country-level results from attribution exercise of overall poverty
Table A2. Country-level results from attribution exercise of rural poverty
Table A3. Country-level results from attribution exercise of urban poverty