THE COMPOSITION OF GROWTH MATTERS FOR POVERTY ALLEVIATION*

Norman V. Loayza
The World Bank

Claudio Raddatz
The World Bank

March 2009

Abstract

This paper contributes to explain the cross-country heterogeneity of the poverty response to changes in economic growth. It does so by focusing on the structure of output growth itself. The paper presents a two-sector theoretical model that clarifies the mechanism through which the sectoral composition of growth and associated labor intensity can affect workers' wages and, thus, poverty alleviation. Then, it presents cross-country empirical evidence that analyzes, first, the differential poverty-reducing impact of sectoral growth at various levels of disaggregation, and, second, the role of unskilled labor intensity in such differential impact. The paper finds evidence that not only the size of economic growth but also its composition matters for poverty alleviation, with the largest contributions from unskilled labor-intensive sectors (agriculture, construction, and manufacturing). The results are robust to the influence of outliers, endogeneity concerns, alternative explanations, and various poverty measures.

Keywords: Poverty, economic growth, production structure, labor intensity.

* We are grateful to Yvonne Chen and Siyan Chen for research assistance and to Koichi Kume and Naotaka Sugawara for editorial assistance. For useful comments, suggestions, and/or data we are indebted to Maros Ivanic, Francisco Ferreira, Oded Galor, Aart Kraay, Humberto López, Ross Levine, Martin Ravallion, Yona Rubinstein, Luis Servén, and seminar participants at Brown University, the IMF, and the World Bank. We are also grateful to Lant Pritchett (as editor of the *JDE*) and three anonymous referees for their valuable comments. Support from the Chief Economist Office of the Latin America and Caribbean Region of the World Bank is gratefully acknowledged. The views expressed in this paper are those of the authors and do not necessarily reflect those of the World Bank, its Board of Directors, or the countries they represent.

THE COMPOSITION OF GROWTH MATTERS FOR POVERTY ALLEVIATION

I. Introduction

There is little doubt that economic growth contributes significantly to poverty alleviation. The evidence is mounting and coming from various sources: cross-country analyses (Besley and Burgess, 2003; Dollar and Kraay, 2005; Kraay, 2006; and López, 2004), cross-regional and time-series comparisons (Ravallion and Chen, 2007; Ravallion and Datt, 2002), and the evaluation of poverty evolution using household data (Bibi, 2005; Contreras, 2001; Menezes-Filho and Vasconcellos, 2004). At the same time, it is clear that the effect of economic growth on poverty reduction is not always the same. In fact, most studies point to considerable heterogeneity in the poverty-growth relationship, and understanding the sources of this divergence is a growing area of investigation (Bourguignon, 2003; Kakwani, Khandker, and Son, 2004; Lucas and Timmer, 2005; and Ravallion, 2004). Most of the received literature focuses on socio-economic conditions of the population as determinants of the relationship between growth and poverty reduction. Thus, wealth and income inequality, literacy rates, urbanization levels, and morbidity and mortality rates, among others, have been found to influence the degree to which output growth helps reduce poverty.

In this paper we take a different, albeit complementary, perspective on the sources of heterogeneity in the poverty-growth relationship. We focus on the characteristics of output growth itself, rather than the demographic, social, or economic conditions of the population. We study how the production structure of the economy and, specifically, the sectoral composition of growth affect its capacity to reduce poverty. Our conjecture is that growth in certain sectors is more poverty reducing than growth in others and that a sector's poverty-reducing capacity is related to its intensity in the employment of unskilled labor.

There are important studies that precede and motivate our work. Thorbecke and Jung (1996) develop a social-accounting method to estimate the impact of various production activities on poverty reduction. The method requires knowledge of complex elasticities connecting the distribution of households with eight employment and production sectors. The authors apply the method to Indonesia in the 1980s and find that agricultural and service sectors contribute more to poverty reduction that industrial sectors do. Khan (1999) applies the same methodology to study sectoral growth and poverty alleviation in South Africa. He finds that higher contributions are derived from growth in agriculture, services, and some manufacturing sectors.

A different approach consists of conducting reduced-form analysis on time-series data for individual countries. This is the approach taken by Ravallion and Datt (1996) to study the evolution of poverty in India during 1951-91. Linking poverty changes to value-added growth rates in the three major sectors of economic activity, they find that growth in agriculture and services correlates with poverty declines in both urban and rural areas whereas industrial growth did not relate to poverty in either. Applying a similar methodology for the case of China over 1980–2001, Ravallion and Chen (2007) find that growth in agriculture emerges as far more important than growth in secondary or tertiary sectors for the purpose of poverty alleviation. Also along these lines, a recent paper by Suryahadi, Suryadarma, and Sumarto (2009) studies the relation between growth and poverty alleviation across productive sectors and locations (urban-rural) in Indonesia, finding that rural services growth is related to poverty declines in all sectors and locations, urban services growth is the most strongly correlated with poverty alleviation, and rural agricultural growth is correlated with poverty declines in rural areas.

Our work contributes to this literature along four dimensions. First, we present a theoretical model that exemplifies how the sectoral composition of growth and associated labor intensity can affect workers' wages and, thus, poverty alleviation. For this purpose we do not rely on the assumption of market segmentation (which would produce our results trivially); rather, allowing wage equalization across sectors, we show the conditions under which labor reallocation --following productivity gains in labor-intensive sectors-- can raise wages in all sectors. Second, we use cross-country evidence --with the pros and cons associated with increasing the underlying variation of the data-- allowing us to relate our results to the empirical macroeconomic literatures on growth and poverty. Third, we employ a level of disaggregation that explores the diversity within the industrial sector, hoping to shed light on why it appears to be less pro poor than agriculture or services. And, fourth, we explicitly consider sectoral employment intensity as the mechanism through which the pattern of growth matters for poverty alleviation.

A caveat on our paper is that it does not address the fundamental determinants of poverty reduction and economic growth, but only the relationship between the two. Both poverty and growth are equilibrium outcomes of complex processes, and it is beyond the scope of the paper to develop and estimate a structural model that considers them as jointly endogenous variables driven by exogenous forces. Our model and its empirical application are semi-structural in that a causal relationship is postulated from economic growth to poverty reduction via a mechanism based on growth's effect on unskilled labor wages. Our objective is limited to understanding whether the *magnitude* of output growth is a sufficient indicator for the economy's ability to reduce poverty or whether this should be augmented by one that considers also its labor employment *composition*.

The plan of the paper is the following. Section II presents a theoretical model that illustrates our initial conjecture. It examines the wage (poverty) effect of output growth in a two-sector economy, where capital and labor are freely mobile and the sectors' technologies vary according to their labor intensity. Section III presents cross-country empirical evidence that analyzes, first, the differential poverty-reducing impact of sectoral growth at various levels of disaggregation, and, second, the role of unskilled labor intensity in such differential impact. Also in this section, we subject our basic result to a comprehensive set of robustness checks that account for the influence of outlier and extreme observations, for potential alternative explanations, and for various poverty measures. Section IV offers some concluding remarks.

II. The Model

We now present a model with a rather specific illustrative purpose. It is designed to show that when the labor intensity in production varies across sectors, the change in workers' income depends not only on aggregate production growth but also on its sectoral composition. The model produces the particular result that wage growth is a linear function of production growth in each sector, with weights corresponding to *both* its relative value added and its labor intensity.[1] Apart from illustrating why heterogeneity in labor intensity matters, the model provides a closed-form solution for workers' income growth in terms of observable variables. This makes the model's solution a useful guide for the empirical analysis. The model does not pretend to offer a general result on how heterogeneity across sectors affects wage growth and consequently poverty alleviation. A general model will involve a non-linear specification, with additional terms that, at least according to our knowledge, could not be readily derived from available data.

The economy is populated by two types of individuals: poor and rich. Only rich individuals have access to assets that allow them to transfer wealth across periods. The poor are endowed with labor only. This setting implies that the income and consumption of poor individuals depend only on the real wage rate. Although this is an extreme assumption, it simplifies considerably the analysis and is roughly consistent with the low saving rates observed both in poor countries and poor households within a country.[2] By construction, then, poverty reduction would be driven by labor income growth .

The final good, *Y,* is produced using a constant elasticity of substitution technology with two intermediate goods, y_1 and y_2, as inputs, according to

$$Y = \left(b_1 y_1^{\beta} + b_2 y_2^{\beta}\right)^{\frac{1}{\beta}} \tag{1}$$

Where $\beta \leq 1$, $b_1, b_2 > 0$, and $b_1 + b_2 = 1$. The final good can be used not only for consumption but also as capital in the production of the intermediate goods.

In turn, each intermediate good is produced using a Cobb-Douglas technology with labor-augmenting technological progress,

[1] The model does not rely on the assumption of labor-market segmentation, which would also generate our basic result but almost tautologically: if a sector that employs more poor people grows faster and workers cannot switch sectors, then average wages of the poor must rise. Rather, the model allows free labor mobility across sectors and, thus, wage equalization. As discussed later, the model exploits a mechanism by which productivity gains in labor-intensive sectors produce a pattern of labor reallocation that raises wages in all sectors.

[2] Schmidt-Hebbel and Serven (1999) show that saving rates increase with income across countries. In poor countries, the saving rates are below 10%. Attanasio and Székely (1998) provide evidence on households' saving rates at different levels of the income distribution in Mexico. Their data show that saving rates increase strongly with income and display even negative values up to the 25th percentile of the household income distribution.

$$y_i = k_i^{(1-\alpha_i)}\left(A_i n_i\right)^{\alpha_i},\ i = 1, 2 \tag{2}$$

Where $0 < \alpha_i < 1$; k_i and n_i are sector i's capital and labor, respectively; and A_i represents the level of technology, which evolves exogenously according to $A_i = exp(g_i t)$. Most importantly for our purposes, the two sectors differ regarding the labor share in production, α_i.

The production functions of final and intermediate goods exhibit constant returns to scale. Furthermore, we assume perfect competition in the markets of final and intermediate goods, and full capital and labor mobility.

Intersectoral allocation

Solving the optimization problem of the final-good firm under perfect competition, we obtain the following set of first order conditions,

$$\frac{p_i y_i}{Y} = s_i = b_i\left(\frac{y_i}{Y}\right)^{\frac{\varepsilon-1}{\varepsilon}},\ i = 1,2 \tag{3}$$

Where, the price of the final good is set as numeraire, and $\varepsilon = (1-\beta)^{-1}$ is the elasticity of substitutions between the intermediate goods. Equation (3) characterizes the share of the final good production value that goes to each intermediate sector. Given that the production of the final good exhibits constant returns to scale these shares add up to one.

Analogously for the intermediate-good firms, optimization under perfect competition renders the following first-order conditions,

$$y_i = \frac{\omega n_i}{p_i \alpha_i} = \frac{r k_i}{p_i(1-\alpha_i)}, i = 1, 2, \tag{4}$$

Equations (3) and (4) --which correspond to the standard conditions for static efficiency-- plus the conditions of factor market equilibrium --$k_1 + k_2 = k$, and $n_1 + n_2 = n$ -- determine the allocation of labor and capital across sectors at every moment.

The evolution of real labor income

According to the first-order conditions for intermediate-good firms, and focusing without loss of generality on intermediate good 1, the rate of change of the real wage can be written as

$$\hat{\omega} = \hat{p}_1 + \hat{y}_1 - \hat{n}_1 \tag{5}$$

where the hat denotes the rate of change of a variable ($\hat{x} = dx/x$). The first two terms of this expression correspond to the evolution of the value of sector 1 output in terms of the final good ($p_1 y_1$). From equation (1) this corresponds to

$$\hat{s}_1 + \hat{Y} = \frac{\varepsilon - 1}{\varepsilon}\hat{y}_1 + \frac{1}{\varepsilon}\left(s_1\hat{y}_1 + s_2\hat{y}_2\right) \tag{6}$$

where we have used the fact that $\hat{Y} = s_1\hat{y}_1 + s_2\hat{y}_2$ because of constant returns to scale.

The last term in equation (5) is the evolution of employment in sector 1. This can be derived using the first order conditions for both final and intermediate goods, along with the labor market clearing condition, $n = n_1 + n_2$.

$$\hat{n}_1 = l_2\frac{\varepsilon - 1}{\varepsilon}\left(\hat{y}_1 - \hat{y}_2\right) + \hat{n}, \tag{1}$$

where l_2 is the share of employment in sector 2 (n_2/n).

Finally, putting together equations (6) and (7) and re-arranging terms we obtain the growth rate of the real wage rate,

$$\hat{\omega} = \sum_{i=1}^{2} s_i\hat{y}_i + \left(\frac{\varepsilon - 1}{\varepsilon}\right)\sum_{i=1}^{2}(l_i - s_i)\hat{y}_i \tag{2}$$

where, in a slight abuse of notation, $\hat{y}_i$ now represent the growth rates in per-capita terms.

This equation indicates that the growth of real labor income is related to two components. The first one, corresponding to the first term on the right-hand side of equation (8), is the growth of per-capita GDP. An increase in per-capita GDP corresponds to a higher output per worker that maps into higher wages. The contribution of a sector's growth to this term depends exclusively on its size, as captured by its share on final-good output, s_i. The second component captures the reallocation effects. The impact of a sector's growth on this component depends on the elasticity of substitution across sectors in the production of the final good (ε) and on a sector's labor intensity, as captured by the difference between its labor share of total employment, l_i, and its share in total output s_i. Working with equations (3) and (4), it can be shown that this difference corresponds to

$$l_i - s_i = \frac{1}{1+\left(\frac{\alpha_{-i}}{\alpha_i}\right)\left(\frac{s_i}{s_{-i}}\right)} - \frac{1}{1+\left(\frac{s_i}{s_{-i}}\right)},\ i=1,2 \qquad (3)$$

which indicates that the difference l_i-s_i is higher for sectors with a higher share of labor in total output, α_i. This means that value added growth in a labor intensive sector will be associated with an additional effect on wages beyond its effect through aggregate value added growth, as long as the elasticity of substitution is sufficiently high (specifically above 1, according to Equation (8)). [3]

The elasticity of substitution is relevant because it determines whether (and by how much) labor will move into or out of a growing sector: the higher the elasticity of substitution, the more labor moves into that sector. If the elasticity is too low (below 1) labor actually moves out of an expanding sector; however, as the elasticity increases and surpasses a threshold value (equal to 1), labor starts to flow into the growing sector. With a high (low) elasticity of substitution, the price adjustment required by an increase in the relative output of a sector is small (large) so that labor needs to move into (out of) the expanding sector to achieve wage equalization.

Equation (8) also shows that there are two cases in which the growth rate of real labor income is only related to GDP growth: (i) when the technologies of the intermediate sectors are identical ($\alpha_1 = \alpha_2$), and (ii) when the elasticity of substitution is equal to one

[3] Consider the following example. Suppose that sector 1 is more labor intensive than sector 2 ($\alpha_1/\alpha_2>1$), so that l_1-$s_1>0$, and that it experiences an exogenous increase in productivity. If the elasticity of substitution is sufficiently high, labor will move into sector 1 where it is relatively more productive, pushing the wage rate up. The opposite will happen if the elasticity of substitution is relatively low (below 1).

(the Cobb-Douglas case). The first case is trivial: if there are no asymmetries across sectors, uneven growth is irrelevant. In the second case, under a Cobb-Douglas production function, sectoral shares are constant, and any adjustment in relative quantities results only in a corresponding change in relative prices. Uneven sectoral growth not requiring labor reallocation across sectors would not affect real wages. Thus, omitting the composition of growth as a determinant of real wage increases (and, thus, poverty alleviation) is equivalent to assuming that the sectors do not differ in their labor intensities or their elasticity of substitution is equal to one.

The assumption that the income of the poor consists of labor income implies that, holding constant labor supply, poverty changes are driven by movements in the real wage. In mathematical terms, this means that $\hat{h} = \psi(\hat{\omega})$ with $\psi'(.) > 0$, where $\hat{h}$ is the growth rate of poverty, and $\psi(.)$ represents a broad class of functions. The precise way in which the wage rate affects poverty (that is, the shape of the $\psi(.)$ function) is determined by the specific poverty measure under consideration. More generally, if we allowed for differences across workers, $\psi(.)$ will also depend on the distribution of the poor, in terms of labor supply, skills, and initial endowments. This function could, therefore, be quite complex, containing non-linear terms with country-specific parameters. For the sake of parsimony, in the empirical implementation of the model, we start with a simple, linearized version of this function, given by $\hat{h} = \gamma_0 + \gamma_1 \hat{\omega}$. This implies a linear relationship between poverty reduction and total and labor-intensive growth, with constant parameters across countries. Later in the empirical analysis, we relax this simple assumption by considering the results on several poverty measures and by allowing the estimated relationship to vary with country-specific distributional characteristics (such as initial poverty, Gini coefficient, population density around the poverty line, and educational attainment).

III. Empirical Evidence

Our empirical analysis consists of two related sections. In the first, we address the connection between the pattern of growth and poverty alleviation by disaggregating growth into its sectoral components and examining their corresponding effects on poverty. This is the traditional approach, and, thus, it allows us to place our analysis in the context of the received literature. The second empirical section modifies the sectoral analysis by introducing labor intensity as the source of the differential impact of sectoral growth on poverty reduction. This approach is derived from the theoretical model and, thus, establishes the link between theory and empirics in the paper.

An important clarification is that our analysis relates poverty reduction to the size and structure of *production* growth, and not merely income growth. At sufficient levels of aggregation and data precision, production and income are equivalent measures in an economy where all factors of production are locally owned. However, for our purposes we focus on production, as measured by national accounts, for two related reasons. The first one is conceptual: the mechanism under consideration is based on technological differences across sectors of production. The second one is empirical: sectoral economic activity is better measured by production from national accounts than by employment and income information from household surveys.

Data and sample

Our sample consists of a cross-section of developing countries with comparable measures of poverty changes, disaggregated value-added growth rates at 3- and 6-sector levels, and unskilled employment at the same levels of disaggregation. In practice, our dataset is the result of combining the Kraay (2006) database on poverty spells,[4] World Bank (2005) data on sectoral value added,[5] and Purdue University's Global Trade Analysis Project database (GTAP, 2005) on labor shares. [6, 7]

---

[4] The Kraay database results from processing income distribution data for a large number of developing countries. In turn, its source is the collection of household survey data estimated from primary sources and made comparable across countries by Martin Ravallion and Shaohua Chen at the World Bank. For details, see Kraay (2007).

[5] The World Bank (2005) data on sectoral value added is complemented with statistics from the Inter-American Development Bank and the United Nations.

[6] GTAP separates labor between skilled and unskilled based on occupational categories. Generally, managers, professional, and technicians are considered as skilled and the rest (farm and production workers) as unskilled. Data on the number of each type of workers in each of the 37 sectors used in GTAP is collected from country level sources from 30 countries and then extrapolated to other countries. For a detailed description of the construction of the data see Liu et al. (1998).

[7] Alternative sources of labor intensity are hard to come by, particularly for a large sample of countries and covering several economic sectors. There are, however, some sources specific to a given sector. One such is the Hayami and Ruttan (1985) data on male agricultural workers (see p. 464). It covers only one third of our country sample, which prevents us from using it instead of the corresponding GTAP data. However, as

We focus on changes occurring over long horizons, where the poverty reduction-economic growth relationship is most stable. For this reason we use only one spell per country, where the duration of the spell corresponds to the longest period for which initial and final poverty data exist for the country. The rest of the variables (e.g., value added growth rates and labor ratios) are calculated over the corresponding period per country.

The dependent variable is the proportional change in poverty over a period of time (spell) per country. Specifically, this is the annualized change in poverty, as percentage of the average poverty over the period.[8] Given its importance in the literature, the benchmark poverty measure in the paper is the headcount poverty index, defined as the fraction of the population with income below a given poverty line. In robustness exercises, however, we use alternative measures of poverty, comprising other members of the Foster-Greer-Thorbecke class of measures (the poverty gap and the squared poverty gap) and the Watts index. Following convention for cross-country comparability, the poverty line is set to $1 per person per day, converted into local currency using a purchasing-power-parity adjusted exchange rate.

Regarding the explanatory variables, we work with growth rates of sectoral value-added and employment data at two levels of disaggregation. The first is the traditional sectoral division of agriculture, industry, and services. The second one disaggregates industry further into mining, manufacturing, utilities, and construction. Sectoral growth rates are calculated directly from data on sectoral value added as annualized log changes of per capita value added between the end and start of the corresponding spell. Employment data is calculated indirectly from data on sectoral value added and payments to unskilled workers. Under the assumption of wage equalization, the ratio of unskilled workers in a sector to total unskilled workers in the country is calculated as the ratio of

---

a robustness check, we calculated the correlation coefficient between the Hayami-Ruttan and the GTAP agricultural labor intensities. Fortunately for our purposes, we found it be rather high, 0.72.

[8] That is, proportional poverty change = $\frac{1}{T} * \frac{P_F - P_I}{(P_F + P_I)/2}$, where P represents the poverty measure; T, the length of the spell; and the subscripts I and F, initial and final, respectively. Calculating the proportional change with respect to the average measure allows us to avoid abnormally large proportional changes when very low initial and/or final measures are present, as would be the case if log differences were used. Kraay (2007) uses the latter procedure and then is forced to drop a considerable number of observations. Were we to use Kraay's method, we would be working with 32 country observations, rather than 51, the sample size of our benchmark regression.

payments to unskilled workers in the sector to total payments to unskilled workers in the economy. For this calculation, one observation per country or per similar countries is available from the original source (GTAP), so that labor intensity data are specific and available for each sector and country.[9]

The resulting sample consists of 55 countries for 3-sector data and 51 countries for 6-sector data. Appendix 1 provides the list of countries included in the sample, as well as the initial and final years of their corresponding spell. Appendix 2 provides definitions and sources for all variables used in our empirical exercises, and Appendix 3 presents basic summary statistics on the 51-country sample.

Poverty reduction and sectoral growth

We are interested in estimating the effect of sectoral growth on poverty reduction. The regression equation can then be written as,

$$\hat{h}_j = \delta_0 + \sum_{i=1}^{I} \delta_i \cdot s_{ij} \cdot \hat{y}_{ij} + \varepsilon_j \tag{10}$$

where $\hat{h}$ is the annualized rate of change of the headcount poverty index, $\hat{y}$ is the annualized rate of change of sectoral value added, s is the sectoral value added share in GDP, and the subscript *i* and *j* represent sector and country, respectively. All growth rates are expressed in per capita terms, and the sector shares are calculated from constant-price magnitudes.[10] The set *I* consists of three or six sectors, depending on whether industry is considered as a whole or disaggregated into its four major categories. In principle, it may be possible to estimate the poverty effect of output changes in a levels regression. However, the literature advices a regression in differences to control for fixed

[9] Given that, in most cases, the date of this observation differs significantly from the years of our poverty spell, we first use the GTAP data to compute the ratio of payments to unskilled workers to a sector's value added and assume it to be constant over time, for a given sector and country. We then use this ratio and the sector's share in total value added during our spell (from World Bank, 2005) to compute the corresponding ratio of unskilled workers in the sector to total unskilled workers in the country. Under wage equalization, the ratio of unskilled workers in a sector to total unskilled workers can be written as $l_k / l = \alpha_k s_k \Big/ \sum_i \alpha_i s_i$, where α_k is the ratio of unskilled labor payments to sector's *k* value added, and s_k is the share of sector *k* in total value added.

[10] Calculating the shares from nominal magnitudes would more closely approximate the theoretical model. However, we work with constant-price shares because, first, their resulting country coverage is larger than when using current-price shares, and, second, they are very similar and render basically the same econometric results.

effects that may be driving both poverty and output, such as a host of country-specific development-related variables in our cross-country setting.

Our regression specification weights sectoral growth by its relative size. As Ravallion and Chen (2007) point out, this specification has the advantage that it allows for a simple test of whether the growth composition matters: If the null hypotheses that the coefficients δ_i are equal to each other cannot be rejected, then the sectoral regression collapses to one where GDP growth is the only relevant explanatory variable. In this case, only size and not composition of growth would matter for poverty alleviation. Our regression specification also allows for testing whether these sectors can be grouped in different categories, not according to their output characteristics but according to their relationship with poverty reduction. This will become important when we study the case of six-sector disaggregation.

Table 1 presents the results when GDP is decomposed into agriculture, industry, and services. The regressions are conducted using both the full sample of 55 countries and the subset of 51 countries for which six-sector data are available. The latter exercise is conducted with the purpose of comparison with the six-sector analysis. In both samples (columns 1 and 3, respectively), the size-adjusted value-added growth rates of all sectors fail to carry statistically significant coefficients. Moreover, the hypothesis that the coefficients are the same cannot be rejected.

The lack of individual significance of sectoral growth rates and the inability to separate their effects indicates that the three major sectors are highly linked in their relationship with poverty reduction. This may be interpreted as evidence against the importance of growth composition for poverty alleviation, but it may also be the result of working with insufficiently disaggregated output categories. We examine the latter possibility below when we analyze the six-sector case. Before doing that, however, we can take the failure to reject the equality of coefficients at face value and estimate a constrained regression that assumes equal sectoral effects. Apart from approximation errors, this is equivalent to regressing poverty changes on GDP growth rates. These results are presented in columns 2 and 4 for each of the samples, respectively. In both cases the growth elasticity of poverty is negative, statistically significant, and a little over 1 in magnitude.

Table 2 presents the results when GDP is further disaggregated into agriculture, services, and industry's four major categories. We work with both the full sample of countries and the reduced sample obtained by applying the Kraay (2006) criteria for eliminating extreme observations (see footnote 4). The results are similar in both cases, so we discuss only those using the full sample. In the unconstrained regression, only manufacturing growth carries a significantly negative coefficient, although agriculture growth also approaches a level of significant poverty alleviation effect. The pattern of signs is diverse across sectors, with agriculture, manufacturing, and construction, carrying negative coefficients, while mining, utilities, and services presenting positive ones.

The relatively large dispersion across countries makes it difficult to learn much about differences in growth elasticities of poverty across sectors unless we restrict the model to be estimated. We can do this by pulling together sectors that appear to have similar effects on poverty. A first approximation is to group together sectors that present negative coefficients in the unconstrained regression, and do likewise with those that carry positive coefficients. Before grouping them, we can test the equality of their coefficients. These tests (shown at the bottom of Table 2, column 1) indicate that agriculture, manufacturing, and construction (the sectors carrying negative coefficients) can be pulled together, while mining, utilities, and services (all carrying positive coefficients) can form a single category.

Applying these restrictions, we can estimate the corresponding constrained regression, whose results are presented in column 2. Growth in agriculture, manufacturing, and construction now appear to have a clear, significant poverty reducing effect. In contrast, growth in mining, utilities, and services do not seem to reduce poverty (or worsen it for that matter), once growth in other sectors is controlled for. The test for the equality of coefficients in the constrained regression confirms that the two groups (agriculture/manufacturing/construction on one side and mining/utilities/services on the other) have statistically different impacts on poverty (see bottom of columns 2 and 4).

Poverty reduction and labor-intensive growth

Why would some sectors' growth contribute to poverty alleviation more than growth in others? There are a few potential explanations. One is based on market segmentation, which would prevent wage gains in one sector to be transmitted to the rest. Thus, for instance, the geographic location of a sector's production and the incidence of poverty where it takes place would determine its potential for poverty alleviation. A second one is related to the effect that the pattern of sectoral production has on prices of goods that the poor consume. According to these arguments, agricultural growth would have a larger impact on poverty alleviation because the poor are concentrated in rural areas and because lower food prices improve the poor's consumption basket. Our theoretical model formalizes an alternative explanation according to which a sector's labor intensity determines its impact on poverty reduction, even in the presence of free labor mobility.

The basic result of our theoretical model links wage increases to sectoral growth and is given in equation (9). The multi-sector version of this equation can be written as,

$$\hat{\omega} = \left(\sum_{i=1}^{I} s_i \cdot \hat{y}_i\right) + \left(\frac{\varepsilon - 1}{\varepsilon}\right)\left(\sum_{i=1}^{I} (l_i - s_i) \cdot \hat{y}_i\right) \tag{11}$$

That is, wage grows proportionally to aggregate output (first term) with a premium (second term) if growing sectors are sufficiently labor intensive. Assuming that wage increase and poverty reduction are linearly related, $\hat{h} = \theta_0 + \theta_1 \hat{\omega}.$, then changes in poverty can be expressed as a function of sectoral growth,

$$\hat{h} = \theta_0 + \theta_1\left(\sum_{i=1}^{I} s_i \cdot \hat{y}_i\right) + \theta_2\left(\sum_{i=1}^{I} (l_i - s_i) \cdot \hat{y}_i\right) \tag{12}$$

Collecting terms,

$$\hat{h} = \theta_0 + \sum_{i=1}^{I}\left(\theta_1 - \theta_2 + \theta_2 \frac{l_i}{s_i}\right) s_i \cdot \hat{y}_i \tag{13}$$

This expression indicates that a sector's growth effect on poverty reduction depends on its labor intensity, l_i / s_i. To the extent that sectors differ concerning their labor intensities, this explains why their effects on poverty alleviation are not the same. Moreover, since in principle labor intensities can vary not only across sectors but also across countries for the same sector, then the sectoral growth elasticities of poverty reduction may be country specific. This may explain in part why our sectoral regressions are so lacking in precision.

How different is labor intensity across sectors and across countries? And, is the pattern of sectoral growth elasticities of poverty consistent with their labor intensities? Figure 1 presents box-plots for the cross-country distribution of labor intensities (l_i/s_i) corresponding to the six sectors under examination. We notice that, first, with different degrees, these sectors exhibit a remarkable dispersion across countries; and second, in spite of this dispersion, it is possible to identify a ranking of labor intensities across sectors. Agriculture and construction, followed by manufacturing, seem to be the most labor-intensive sectors, having all of them a median l_i/s_i ratio larger than 1. The construction sector is noticeable for the large dispersion of its cross-country distribution of labor intensity. Conversely, manufacturing shows a concentrated distribution, particularly regarding the inter-quartile range, which may explain why its coefficient is estimated with sufficient precision to achieve statistical significance. Mining and utilities, followed by services, are the least labor-intensive sectors, with median l_i/s_i ratios below 1 in all cases. Mining and utilities also show considerable dispersion across countries in their labor intensity, while services presents the most concentrated distribution of the six major sectors.

The pattern of coefficients on sectoral growth estimated above is consistent with the notion that labor intensity determines a sector's influence on poverty alleviation. The sectors with median labor intensities greater than 1 --agriculture, construction, and manufacturing-- carry negative coefficients; while those with median labor intensities lower than 1 --mining, utilities, and services-- have positive coefficients. Moreover, the ranking of labor intensities (in decreasing order) coincides exactly with the ranking of sectoral coefficients (from more to less negative) estimated for the reduced sample and with those estimated for the full sample with only one exception (mining and services switch places).

The consistency between labor intensities and the pattern of estimated sectoral growth coefficients is suggestive, but a more formal test can be conducted on the basis of our theoretical model. Equation (12) can be written as a regression equation of the change in poverty on aggregate and sectoral growth,

$$\hat{h}_j = \theta_0 + \theta_1 \hat{y}_j + \theta_2 \left(\sum_{i=1}^{I} \left(\frac{l_{ij}}{s_{ij}} - 1 \right) \cdot s_{ij} \cdot \hat{y}_{ij} \right) + \varepsilon_j \tag{14}$$

where, $\hat{y} \cong \left(\sum_{i=1}^{I} s_i \cdot \hat{y}_i \right)$ is (per capita) GDP growth. The coefficient θ_1 indicates the *size* effect of growth on poverty reduction, while θ_2 reveals its *composition* effect. Negative signs are expected for both coefficients if growth helps reduce poverty and if the labor intensity of growing sectors has an additional impact on poverty alleviation.

In order to estimate equation (14), it is crucial to obtain data on labor intensities by sector and country. As explained above, we derive these data from information on sectoral value added from World Bank (2005) and payments to unskilled workers from the Global Trade Analysis Project (GTAP). We focus on unskilled workers as they are likely to best represent the poor in each country.

Equation (14) provides a direct test of the model, and this is our basic and preferred specification. However, there are other possibilities. First, if we believe that labor intensities are technological driven and common across countries, then we can use a single l_i / s_i ratio for each sector for all countries. This may be a good strategy if we are uncertain as to the quality of the data on labor intensities per country. We implement this specification by replacing the country-specific labor intensities in equation (16) by their corresponding sample median per sector. Second, a discrete or categorical version of the test can be derived by assuming that sectoral growth can have either a high or a low impact on poverty reduction depending on whether its labor intensity l_i / s_i is, respectively, above or below a certain threshold, which we set equal to 1. This approach is useful if we are still uncertain as to the precise measure of labor intensities but don't believe that they are common across countries. We implement this specification by allocating sectors into two groups according to their labor intensity, regressing poverty changes on the growth rates of high and low labor-intensity groups, and then testing for the difference between their respective coefficients. Notice that the composition of these groups can vary from country to country.

Table 3 presents the estimation results for the direct regression implied by the model (column 2), the two alternative specifications (columns 3 and 4), and a benchmark regression with (per capita) GDP growth as sole explanatory variable (column 1). The coefficients on aggregate growth (θ_1) are always significantly negative, with larger magnitudes when labor intensity is controlled for. Most relevant for our purposes, the coefficient on labor-intensity-weighted sectoral growth --or labor-intensive growth, for short-- (θ_2) is also negative and highly statistically significant in our preferred specification (column 2). Interestingly, the regression fit increases considerably (from 15 to 28%) once information on labor intensity is added to that on aggregate growth. Figure 2 shows a partial-regression plot linking the change in poverty and labor-intensive growth; it confirms a negative pattern that is well established by most observations in the sample (we consider the issue of outliers below.) Thus, it appears that in addition to the size of growth, the composition of growth regarding its labor intensity is statistically and economically relevant for explaining poverty reduction.

Although using country-specific data on labor intensities increases importantly the variation of our measure of labor-intensive growth and, therefore, the power of our empirical test, one may be concerned that the dispersion of labor intensities observed for a given industry across countries could be driven by noise. In column 3 we address this concern by disregarding the country-specific variation and using instead medians per sector across countries to measure labor intensity. We see that the coefficient on labor-intensive growth is also negative and statistically significant, although the fit of the regression declines somewhat, revealing that country-specific data on labor intensities contribute useful information for growth composition to explain poverty changes. A similar message is obtained from the alternative specification based on grouping sectors by labor intensity (column 4). The coefficient on growth in *high* labor-intensity sectors is negative and statistically significant, while that on growth in *low* labor-intensity sectors is much smaller and not significant. In fact, the null hypothesis that these two coefficients are the same is rejected with a p-value of 0.07. The R-squared in this case falls considerably with respect to the preferred case, confirming that the precise numerical values on country-specific labor intensities provide relevant information that cannot be captured by categorical indicators.

Robustness to outliers and extreme observations

Table 4 presents the results related to the analysis of robustness to outliers, with our basic regression repeated in column 1 for comparison purposes. The data on labor intensity, l_i/s_i, present a few extreme values that are likely to represent either measurement error or rare circumstances; in order to avoid their undue influence, in our basic specification, we truncated the cross-country distribution of labor intensity per sector to values ranging from 5 to 95 percentile of the original distribution. Column 2 presents the regression results when these extreme values are not truncated. The coefficient on labor-intensive growth continues to be statistically negative, although its level of significance and the regression fit diminish a little.

Inspection of Figure 2 may raise questions as to the influence of some countries in our basic results. To dispel these doubts, we run the regression using a procedure that weighs each observation according to how it fits the pattern established by the remaining observations.[11] This is the regression presented in column 3. We also run the regression completely excluding possible outliers, identified as the countries that receive weights below 0.7 of a maximum of 1 in the robust procedure. These countries are Argentina, Estonia, Latvia, and Senegal; and the corresponding results are shown in column 4. In both cases, the coefficient of interest remains negative and highly statistically significant, with a magnitude that is almost the same as that in the benchmark case. It is reassuring that the regression fit increases considerably when the outliers are excluded.

As mentioned above, the way we calculate poverty changes (that is, proportional with respect to the average poverty level in the spell) produces fewer extreme values than the standard way of taking log differences. This allows us to keep a larger number of observations in the sample than would be the case if we applied the criteria in Kraay (2006). We check whether our basic results still hold in this reduced sample (of 32 countries), and the results are presented in column 5. The sign, significance, and even magnitude of the coefficient on labor-intensive growth are remarkably similar as those using the full sample, with a slight gain in regression fit. All in all, the results in Table 4 allow us to conclude that our basic results are robust to the possible presence of outlier or extreme observations.

[11] For this purpose, we use STATA's "rreg" procedure.

Since our data includes poverty spells of various lengths, one may be concerned that this heterogeneity is somehow responsible for our results or that they only apply to either short-run or long-run relations between labor-intensive growth and poverty alleviation. To examine this possibility we split our data among spells above and below the median value of 7 years. With the caveat of reducing importantly the sample, columns 6 and 7 show that the coefficient for labor intensive growth is somewhat larger for the sub-sample of shorter spells but it remains significant and statistically the same in both regressions.[12]

Alternative explanations

It may be argued that the importance of the growth composition term is due to its correlation with other variables that affect poverty changes. The results in Tables 5 and 6 check for this possibility by allowing for alternative explanations in turn. First is the issue of agricultural growth. Given that agriculture is the sector with the highest labor intensity in most countries, it may be argued that our growth composition variable is just capturing the presence of agriculture, which may affect poverty reduction for reasons unrelated to labor intensity.[13] We examine this possibility by adding (size-adjusted) agriculture value added growth as an independent explanatory variable to our basic specification (see Table 5, column 1). The coefficient on agricultural growth is indeed negative, hinting that other poverty-reducing channels may also be relevant, but fails to be statistically significant. On the other hand, the coefficient on labor-intensive growth retains its sign, significance, and magnitude with respect to our basic specification. This suggests that the importance of agricultural growth in poverty reduction that has been recognized in the literature is mostly due to its intensive use of unskilled labor. Furthermore, this result indicates that the importance of labor intensity in growth's ability to reduce poverty is relevant across all sectors.

Related to agricultural activity there is the issue of geographic isolation. In many countries the poor are located in geographically distant places. As they form larger

[12] We also estimated a regression only controlling for the length of the spell in an additive fashion, and the results were almost identical to the benchmark.

[13] Those reasons were outlined before, namely, that agricultural growth occurs in rural areas where the poor are concentrated and that agricultural growth decreases food prices which figure prominently in the poor's consumption basket.

communities, they have an improved opportunity to interact and gain from each other, leading to a decrease in poverty. It can be argued that this demographic transformation is behind the relationship between the level and composition of growth and poverty alleviation that is the focus of our paper. To account for this possibility, we control for the initial level (Table 5, column 2) and growth rate (Table 5, column 3) of rural population density in the country, measured by the ratio of rural population to the area of arable land (from World Bank, 2005). Neither of these variables appear to be significantly related to poverty changes, and, most importantly, the coefficients on GDP and labor intensive growth remain negative, statistically significant, and about the same size as in the benchmark case. A similar argument can be made regarding education and human capital in general. As the population become more educated, their productivity increases and poverty declines. To consider this argument, we add to the basic regression equation the initial level (Table 5, column 4) and growth rate (Table 5, column 5) of the average years of secondary schooling in the adult population (from Barro and Lee, 2001). The growth of secondary school years carries an insignificant coefficient. On the other hand, its initial level has a positive and significant coefficient, which can be interpreted as a sort of convergence effect: countries with initially more educated populations are richer and, other things equal, tend to experience lower reductions in poverty (below, when we control for initial poverty, we see more direct evidence of this convergence effect). For the immediate purposes of our paper, however, the main results remain unchanged: both the size and labor intensity of GDP growth continue to be negative and statistically significant. Before moving to the next alternative explanation, we should note that the fact that the growth rates of rural density and schooling do not carry significant coefficients does not mean that they are unimportant regarding poverty alleviation. Rather, this may imply that their effect works through the volume and composition of economic growth, the mechanisms studied in this paper.

Next is the connection with inequality. A prominent explanation in the literature as to the differing effect of income growth on poverty reduction is that higher inequality dampens the beneficial impact of growth (see Ravallion 2004 for references). If more unequal countries have growth biased against labor-intensive sectors --because, for instance, inequality induces policies that make labor markets more rigid--, then excluding inequality from our analysis could be biasing the results in our favor. To account for this possibility, we control for inequality by adding the Gini coefficient as an independent explanatory variable (Table 6, column 1) and by interacting it with both the GDP growth size and composition terms (Table 6, column 2). This also captures possible non-linearities in the relation between wage growth and poverty reduction. The Gini coefficient is not significant either by itself or interacted with the economic growth terms. The significance of the size of GDP growth suffers when the interactions with the Gini coefficient are added given its high collinearity with the interaction term. However, in both cases, labor intensive growth remains negative and statistically significant, as in our benchmark specification.

Another aspect of the distribution of income that may be relevant to the focus of the paper is the concentration of people around the poverty line. As a matter of fact, Kraay (2006) shows that the elasticity of poverty reduction with respect to marginal changes in average growth is a function of population density at the poverty line. However, our theoretical model assumes that the relationship between poverty and wage changes is linear, which implies the linear regression equation of poverty changes on economic growth that we estimate. This may generate a possible misspecification of the empirical model, particularly if countries differ significantly regarding the distribution of income around the poverty line. To consider this possibility, we interact both the size and labor intensity of growth with the population density at the poverty line (Table 6, column 3). As expected, both interaction terms carry negative coefficients (meaning that economic growth has a larger effect on poverty reduction if more people need only a small push to overcome poverty) but fail to be significant. Most importantly for our purposes, GDP growth and labor intensive growth retain their negative and significant coefficients. This result, together with the lack of significance of the interaction terms, allows us to keep our simpler, linear specification.

As mentioned above, poverty reduction may experience a “convergence” process by which, *ceteris paribus*, poorer countries tend to undergo larger poverty reductions. It can be argued that labor-intensive growth may be capturing this convergence effect related to the initial level of poverty: poorer countries may experience both higher growth of unskilled labor-intensive sectors and faster poverty reduction. To control for this possibility, we add to the benchmark regression the (log of the) initial headcount poverty index (Table 6, column 4). We find that initial poverty does enter significantly in the regression, carrying a negative coefficient as evidence of poverty convergence. However, this does not affect the coefficients on either GDP growth or labor intensive growth regarding their respective size, sign, and statistical significance relative to the benchmark regression.

Finally, there is the issue of measurement error due to the discrepancy between national accounts and household surveys on data for economic growth. As mentioned above, poverty measures are constructed from household survey information; and in most studies connecting poverty and mean income growth, the same source is used for both variables. We, however, do it otherwise: since our focus is on production and its composition, we have to use data from national accounts for the explanatory variables. It is well-known that the measure of economic growth derived from household survey data shows large and sometimes systematic differences with that obtained from national accounts (see Deaton, 2005). If these differences are correlated with labor intensity in the country, the coefficient on growth composition may be biased. Moreover, the bias could be in our favor if national accounts underreported production from unskilled workers. To account for this possibility, we include mean income growth from household surveys as an additional explanatory variable (Table 6, column 5). As expected, this variable carries a negative and significant coefficient, and its inclusion produces both an improvement in the regression fit and a decline in the magnitude of the coefficients on the size and composition of growth. However, both coefficients remain negative and statically significant, confirming our hypothesis.

Endogeneity

Our analysis has been conducted in *differences* in order to control for country-specific structural factors that affect poverty and production jointly. Still, it can be argued that improvements in poverty drive production growth --possibly through higher rates of accumulation of human capital and savings-- thus making the analysis in differences also subject to the endogeneity critique. Although this argument does not apply to the variable on the composition of growth, its coefficient may still be biased if composition and size of growth are correlated. However, in our sample the correlation between these variables is small (-0.24) and only significant at the 12 percent level, so this is unlikely to be a first order concern.

Poverty reduction can also directly affect the composition of growth by changing the supply of unskilled labor and by shifting the demand for unskilled labor intensive goods. However, both these channels would tend to bias the coefficient on labor-intensive growth towards zero: A reduction in poverty would most likely lead to a reduction in the supply of unskilled labor, which in turn would hamper the growth of sectors that are more intensive in its use; similarly, a reduction in poverty would tend to reduce the demand for goods intensive in the use of unskilled labor such as agriculture and increase the demand for capital-intensive goods such as utility services.

This discussion suggests that potential endogeneity problems are likely to bias our tests against finding any significant poverty-reducing effect for labor-intensive growth. However, properly addressing these concerns requires the use of instrumental variable techniques. This is difficult since a recurrent problem in this literature is the lack of instruments that unambiguously hold the necessary exclusion restrictions and are strong enough for proper inference. This problem is exacerbated by our relatively small sample. With these caveats in mind, in Table 7 we present a series of regressions where we address these endogeneity concerns.

We start by focusing only on the potential endogeneity of average growth. We instrument for it using both the average growth rate of the country during the decade just prior to the corresponding poverty spell and the average GDP growth of the country's trading partners as the sources of exogenous variation. The results obtained by two-stages least squares (2SLS) render coefficients on the size and labor-intensity of growth that remain negative and significant (column 1).[14] Standard specification tests reported at the bottom of the column support the validity of the instruments but also indicate they are

[14] We report the results without correcting for heteroskedasticity to interpret correctly the results of the Stock-Yogo test, which are based on the Cragg-Donald statistic. Results with robust standard errors yield slightly wider confidence intervals in the structural equation; nevertheless, the Anderson-Rubin tests strongly reject the null of joint zero coefficients. We also estimated the regressions weighting the observations to improve the fit of the first stage regressions and increase the strength of the instruments (which yield slightly better results in terms of significance of all tests) but reported only the non-weighted regressions to ease comparison with the previous results.

weak.[15] Nevertheless, a robust-to-weak-instruments test for the significance of the endogenous regressor (GDP growth) in the structural equation (Anderson and Rubin, 1949) confirms the results. In the regression reported in column (2) we address the possibility that labor-intensive growth itself may contemporaneously respond to changes in poverty by instrumenting for it using as sources of exogenous variation the country's labor-intensive growth in the decade before the beginning of the spell and contemporaneous labor-intensive growth using world median (instead of country specific) sectoral growth rates and value added sizes. The coefficients obtained for each variable are very similar to those reported before and both remain statistically significant. Although the 2SLS results are again affected by weak instruments, the Anderson-Rubin test supports the significance of our explanatory variables.[16] Notwithstanding its limitations, the evidence does not indicate that our results are mainly driven by reverse causality.

Alternative poverty measures

Our analysis has used the headcount poverty index as the benchmark measure of poverty given its prominence in both the empirical literature and policy circles. However, our simple theoretical model builds the case for the importance of the composition of growth by focusing on its relationship not with poverty directly but with labor wages. As noted above, the connection with poverty is made by assuming that wages affect poverty according to a linear function, which combined with the basic result of the model brings about the paper's main regression equation. However, the linearity of the relationship between wages and the headcount poverty index may be called into question once we consider that the effect of *small* income changes on the headcount

[15] The Sargan test and Kleibergen-Paap LM statistic cannot reject the validity and rank of the instrument set, which is reassuring considering that at least in the case of the growth of the trading partners we can be relatively confident of the instrument exogeneity. The Cragg-Donald F-statistic indicates that the instruments are weak, as the Stock-Yogo (2005) critical value for a 25% maximal IV-size is 7.3, twice as large as the value obtained for the statistic.

[16] Unfortunately, there are no robust tests for the values of subsets of endogenous regressors that could be used to separately tests for the hypothesis that the coefficient of labor intensive growth is different from zero. The Moreira (2003) test applies only to the case of one endogenous regressor, and the Kleibergen (2004) test to the case in which one of the regressors does not suffer from weak instruments problems.

index depend only on movements around the poverty line.[17] To dispel these doubts, we use other poverty measures that are more closely related to wages and that respond to changes in economic growth over a wider range of the income distribution.

Table 8 shows the results when alternative poverty measures are used to construct the dependent variable. The other standard measures used in the literature are the average poverty gap, the average squared poverty gap, and the Watt's poverty index (columns 1-3, respectively). In all cases, the size of GDP growth and --most importantly for our purposes-- its labor intensity carry negative and quite significant coefficients. The regression fit does not improve when we use these alternative poverty measures instead of the standard headcount index; actually, the R^2 is one-third lower when using the simple poverty gap. Another measure of poverty reduction that is even more directly related to wage growth (and therefore to the mechanism of our model) is the growth of income of the poor. Column 4 shows the results using this measure of poverty reduction. The size of GDP growth has a significantly positive effect on incomes of the poor. Moreover, in countries where production growth is more labor intensive, the income of the poor grow at rates faster than predicted by the size of GDP growth alone. (Note that the positive sign on both coefficients of interest is the opposite as before because in this case an increase in the dependent variable denotes poverty *reduction*). In the absence of comparable wage data across countries, this set of results is the most straightforward test of our hypothesis.

The mechanism: distribution or mean component of poverty changes?

The last issue we examine is the mechanism through which the labor intensity of GDP growth matters for poverty alleviation. In particular, does it affect the distribution or the mean component of poverty changes? To answer this question we implement the decomposition introduced by Datt and Ravallion (1992), according to which changes in poverty can be broken down into the portion due to changes in mean income holding income distribution constant (i.e., unchanged Lorenz curve), the portion due to changes in the distribution of income holding its mean constant, and an approximation residual.

[17] As mentioned above, apart from simplicity and clarity, our justification for the linear assumption is that we are dealing with sufficiently *large* changes in income/production with *homogeneous* effects across countries.

Then, we estimate the respective effects of the size and the labor-intensity of GDP growth on each of these components, applying the restriction that the combined effect of each explanatory variable must be the same as its corresponding effect on the overall poverty change (which is given by the benchmark regression). We implement this estimation through a constrained Seemingly-Unrelated-Regression-Equation procedure (SURE).

The results are presented in Table 9. When SURE estimation ignores the influence of outliers (columns 1 and 2), we find that labor-intensive growth affects poverty changes exclusively through their mean component. When we control for the influence of outliers (Cols. 3 and 4), labor-intensive growth still affects significantly the mean component, but now it appears to also affect the distribution component though less strongly and significantly. The strength of the mean-income channel relative to the distribution channel indicates that labor-intensive growth should not be associated with zero-sum income changes across households. It's not that labor-intensive growth is poverty reducing mainly because it implies redistribution from rich to poor. Although labor-intensive growth improves the *relative* standing of the poor, its main effect on poverty is through its beneficial impact on their *absolute* income.

IV. Concluding Remarks

The first concern that developing countries face in their objective to reduce poverty is the lack of sufficient economic growth. This is justifiably so given that no lasting poverty alleviation has occurred in the absence of sustained production growth. However, growth's sheer size does not appear to be a sufficient condition for profound poverty reduction. In fact, a complaint often heard in countries around the world is that the poverty response to growth is sometimes disappointing.

A general argument on the difficulty of poverty reduction is based on either the lack of opportunities presented to the poor or their inability to take advantage of them. If the poor are malnourished, are uneducated, live in remote areas, or are discriminated against, the gains of economic growth are likely to escape them. This paper offers a complementary perspective supporting the general argument on the lack of opportunities. In a nutshell, the paper argues that not only the size of economic growth matters for poverty alleviation but also its composition in terms of intensive use of unskilled labor, the kind of input that the poor can offer to the production process.

The paper first illustrates the connection between wage expansion (poverty reduction), labor intensity, and sectoral growth through a two-sector theoretical model. Then, considering the model's insights, it conducts a cross-country empirical analysis with the change in poverty as the dependent variable of interest. The paper finds that the impact of production growth on poverty reduction varies from sector to sector and that there is a systematic pattern to this variation. Sectors that are more labor intensive (in relation to their size) tend to have stronger effects on poverty alleviation. Thus, agriculture is the most poverty-reducing sector, followed by construction, and manufacturing; while mining, utilities, and services by themselves do not seem to help poverty reduction.

After this sectoral-driven empirical analysis, the paper applies the model directly by considering poverty change a function of not only aggregate growth (which would represent growth's *size* effect) but also a measure of labor-intensive growth (which would represent its *composition* effect). The results confirm that poverty alleviation indeed depends on the size of growth. Moreover, they also indicate that poverty reduction is stronger when growth has a labor-intensive inclination. This central result of the paper is robust to the influence of outlier and extreme observations, holds true for various poverty measures (such as the headcount index, the average poverty gap, and the Watt's index), remains when potential endogeneity concerns are addressed, and is not driven away by alternative explanations --such as the importance of agricultural growth in reducing rural poverty, the role of inequality in dampening the beneficial impact of growth, and the statistical discrepancy between household surveys and national accounts.

Finally, analysis on the mechanisms through which labor-intensive growth reduces poverty allows us to conclude that this positive effect does not require or imply redistribution from rich to poor. Although labor-intensive growth improves the relative standing of the poor, its main effect on poverty is given by its beneficial impact on their absolute income.

From a positive perspective, these results may help understand the considerable disparity in the poverty reaction to economic growth and, in particular, why in some circumstances poverty is irresponsive to production improvements. This would be the case of, for instance, a country experiencing a mining or oil boom that is unaccompanied by growth in other sectors.

Our results should be mostly interpreted from this positive, factual perspective. The normative usefulness of the study is, on the other hand, rather limited because the paper is not based on a structural model where truly exogenous variables are the driving forces of growth and poverty alleviation. Specifically, the paper does not provide grounds for "industrial" or selective policies and interventions as necessary elements in a poverty reduction strategy. Why? Because our study does not deal with the sources of sectoral growth, the complex links across sectors, or the political economy of government intervention. Moreover, it does not take into account the long-run incentives that particular policy interventions may generate. For instance, agricultural subsidies may be ill-advised even if they promote a sector that employs the poor because these subsidies could distort the incentives for industrialization and human capital formation that in the *long run* are essential for both economic growth and poverty alleviation. If anything, the results of the paper suggest that policy distortions that discourage labor employment or induce capital-biased firm dynamics may hinder the ability of economic growth to reduce poverty. More generally, removing biases against labor, whether policy-induced or not, may effectively create opportunities for the poor in growing economic activities and, thus, help them break away from their condition.

References

Anderson, T. W. and H. Rubin, 1949. "Estimation of the parameters of a single equation in a complete system of stochastic equations." *Annals of Mathematical Statistics*, 20: 46-63.

Attanasio, Orazio P., and Miguel Szekely. 1998. "Household Savings and Income Distribution in Mexico." Working Paper 390. Inter-American Development Bank.

Barro, R., and J.-W. Lee. 2001. "International data on educational attainment: updates and implications." *Oxford Economic Papers*, 3: 541-63.

Besley, Timothy, and Robin Burgess. 2003. "Having Global Poverty." *Journal of Economic Perspectives* 17(3): 3-22.

Bibi, Sami. 2005. "When is Economic Growth Pro-Poor? Evidence from Tunisia." Working Paper 05-22. Inter-university Center on Risk, Economic Policies and Employment.

Bourguignon, Francois. 2003. "The Growth Elasticity of Poverty Reduction: Explaining Heterogeneity Across Countries and Time Periods." In *Inequality and Growth: Theory and Policy Implications*, ed. Theo S. Eicher and Stephen J. Turnovsky, 3-26. Cambridge: MIT Press.

Contreras, Dante. 2001. "Economic Growth and Poverty Reduction by Region: Chile 1990-96." *Development Policy Review* 19(3): 291-302.

Deaton, Angus. 2005. "Measuring Poverty in a Growing World (or Measuring Growth in a Poor World)." *The Review of Economics and Statistics* 87(1): 1-19.

Dollar, David, and Aart Kraay. 2002. "Growth is Good for the Poor." *Journal of Economic Growth* 7(3): 195-225.

Hayami, Yujiro and Vernon Ruttan. 1985. *Agricultural Development – An International Perspective: Revised and Expanded*, TJHU Press.

Kakwani, Nanak, Shahid Khandker, and Hyun H. Son. 2004. "Pro-Poor Growth: Concepts and Measurement with Country Case Studies." International Poverty Centre Working Paper 1. United Nations Development Programme.

Khan, Haider. 1999. "Sectoral Growth and Poverty Alleviation: A Multiplier Decomposition Technique Applied to South Africa." *World Development* 27(3): 521-30.

Kleibergen, Frank, 2004. "Testing Subsets of Structural Parameters in the IV Regression Model", *Review of Economics and Statistics,* 86: 418-423.

Kraay, Aart. 2006. "When is growth pro-poor? Evidence from a panel of countries." *Journal of Development Economics* 80(1): 198-227.

Liu, Jing, Nico van Leeuwen, Tri Thanh Vo, Rod Tyers, and Thomas W. Hertel. 1998. "Disaggregating Labor Payments by Skill Level in GTAP". Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University. http://ideas.repec.org/p/gta/techpp/314.html

Lopez, J. Humberto. 2004. "Pro-growth, pro-poor: Is there a tradeoff?" Policy Research Working Paper 3378. The World Bank.

Lucas, Sarah, and Peter Timmer. 2005. "Connecting the Poor to Economic Growth: Eight Key Questions." CGD Brief. Center for Global Development.

Menezes-Filho, Naércio, and Ligia Vasconcellos. 2004. "Has Economic Growth Been Pro-Poor in Brazil? Why?" Paper prepared as part of the Operationalizing Pro-Poor Growth Work Program co-funded by AFD, BMZ, DFID and The World Bank.

Miyagiwa, Kaz, and Chris Papageorgiou. 2007. "Endogenous aggregate elasticity of substitution." *Journal of Economic Dynamics and Control*. Forthcoming.

Moreira, M.J. 2003. "A conditional likelihood ratio test for structural models." *Econometrica*, 71 (4), 1027-1048.

Ravallion, Martin. 2004. "Pro-Poor Growth: A Primer." Policy Research Working Paper 3242. The World Bank.

Ravallion, Martin, and Gaurav Datt. 1996. "How Important to India's Poor Is the Sectoral Composition of Economic Growth?" *The World Bank Economic Review* 10(1): 1-25.

Ravallion, Martin, and Gaurav Datt. 2002. "Why has economic growth been more pro-poor in some states of India than others?" *Journal of Development Economics* 68(2): 381-400.

Ravallion, Martin, and Shaohua Chen. 2007. "China's (uneven) progress against poverty." *Journal of Development Economics* 82(1): 1-42.

Schmidt-Hebbel, Klaus, and Luis Servén. 1999. "Saving in the world: the stylized facts?" In *The Economics of Savings and Growth: Theory, Evidence, and Implications for Policy*, ed. Klaus Schmidt-Hebbel and Luis Servén, 6-32. Cambridge: Cambridge University Press.

Stock, J.H. and Yogo, M. 2005. "Testing for Weak Instruments in Linear IV Regression". In D.W.K. Andrews and J.H.Stock, eds. Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge: Cambridge University Press.

Suryahadi, Asep, Daniel Suryadarma, and Sudarno Sumarto. 2009. *Journal of Development Economics,* 89 (1): 109-117.

Thorbecke, Eric, and Hong-Sang Jung. 1996. "A multiplier decomposition method to analyze poverty alleviation." *Journal of Development Economics* 48(2): 279-300.

World Bank. 2005. *World Development Indicators.* World Bank, Washington D.C.

Table 1. Poverty Reduction and Sectoral Growth: 3-Sector Disaggregation

In all regressions, the dependent variable is the annualized growth rate of the headcount poverty index during the longest spell available for each country. The independent variables are individual sector's per capita value added growth weighted by the share of this sector's value added in total GDP. In the fully constrained regression, all sectors are forced to have a common coefficient. The test presented at the bottom of the unconstrained regression support this restriction.

	Full Sample with 3-sector data		Full sample with 6-sector Data	
	Unconstrained	Fully constrained	Unconstrained	Fully constrained
	(1)	(2)	(3)	(4)
Agriculture growth	-3.718	-1.470**	-5.351	-1.359**
(per capita, share-weighted)	(3.647)	(0.582)	(6.119)	(0.638)
Industry growth	-2.343	-1.470**	-2.420	-1.359**
(per capita, share-weighted)	(1.636)	(0.582)	(1.738)	(0.638)
Services growth	0.167	-1.470**	0.591	-1.359**
(per capita, share-weighted)	(2.041)	(0.582)	(2.135)	(0.638)
Constant	0.006	0.015	-0.000	0.010
	(0.020)	(0.017)	(0.022)	(0.018)
Test	$\beta_{AG}=\beta_{IND}=\beta_{SER}$		$\beta_{AG}=\beta_{IND}=\beta_{SER}$	
Test p-value	0.62		0.51	
Observations	55	55	51	51
R-squared	0.13	--	0.12	--

Numbers in parentheses are robust standard errors.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2. Poverty Reduction and Sectoral Growth: 6-Sector Disaggregation

In all regressions, the dependent variable is the annualized growth rate of the headcount poverty index during the longest spell available for each country. The independent variables are individual sector's per capita value added growth weighted by the share of this sector's value added in total GDP. In the partially constrained regressions, the sectors carrying coefficients of the same sign (in the unconstrained regression) are forced to have a common coefficient. The tests presented at the bottom of the unconstrained regressions support these restrictions. The reduced sample results from applying the criteria in Kraay (2005).

	Full sample		Reduced sample	
	Unconstrained (1)	Partially constrained (2)	Unconstrained (3)	Partially constrained (4)
Agriculture growth	-11.204	-4.119**	-11.695	-3.416**
(per capita, share-weighted)	(7.269)	(1.629)	(7.010)	(1.353)
Mining growth	1.120	1.373	4.661	2.386
(per capita, share-weighted)	(4.628)	(1.459)	(4.171)	(1.507)
Manufacturing growth	-3.829*	-4.119**	-3.624**	-3.416**
(per capita, share-weighted)	(2.175)	(1.629)	(1.422)	(1.353)
Utilities growth	10.726	1.373	12.329**	2.386
(per capita, share-weighted)	(9.605)	(1.459)	(5.651)	(1.507)
Construction growth	-6.314	-4.119**	-4.518	-3.416**
(per capita, share-weighted)	(5.699)	(1.629)	(4.614)	(1.353)
Services growth	1.491	1.373	2.123	2.386
(per capita, share-weighted)	(2.308)	(1.459)	(2.645)	(1.507)
Constant	-0.005	0.001	-0.036	-0.031*
	(0.026)	(0.019)	(0.022)	(0.018)
Test 1	$\beta_{MIN}=\beta_{U}=\beta_{SER}$		$\beta_{MIN}=\beta_{U}=\beta_{SER}$	
Test p-value	0.65		0.43	
Test 2	$\beta_{AG}=\beta_{MA}=\beta_{C}$		$\beta_{AG}=\beta_{MA}=\beta_{C}$	
Test p-value	0.58		0.16	
Test 3		$\beta_{AG}=\beta_{MIN}$		$\beta_{AG}=\beta_{MIN}$
Test p-value		0.06		0.04
Observations	51	51	31	31
R-squared	0.17	--	0.29	--

Numbers in parentheses are robust standard errors.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. Poverty Reduction and Labor-Intensive Growth

In all regressions, the dependent variable is the annualized growth rate of the poverty headcount during the longest spell available for each country. GDP growth is the average growth rate of real GDP per capita during the corresponding spell. Labor intensive growth is, for each country, the sum across sectors of the product of a sector's per capita value-added growth, its share on total GDP, and its surplus use of unskilled labor. For each sector and country, the surplus use of unskilled labor is the difference between its labor intensity (the ratio of a sector's share of total unskilled labor employment to its share of total value added) and one. In the calculation of the median-weighted labor intensive growth, country-specific sectoral labor intensity is replaced by the cross-country median sectoral labor intensity. The growth of high (low) labor intensity sectors is the share-weighted growth of the sectors with labor intensity greater (lower) than 1.

	Only volume of growth	Adding composition of growth		
		Country-specific *lj/sj*	Median *lj/sj*	High and low *lj/sj*
	(1)	(2)	(3)	(4)
GDP growth	-1.597**	-1.936***	-2.640***	
	(0.657)	(0.569)	(0.653)	
Labor intensive growth		-13.622***		
		(4.607)		
Median-weighed labor intensive growth			-21.419**	
			(9.429)	
Growth of high labor intensity sectors (β_H)				-3.429**
				(1.521)
Growth of low labor intensity sectors (β_L)				-0.194
				(0.650)
Constant	0.014	0.007	0.006	0.010
	(0.018)	(0.016)	(0.017)	(0.019)
Test				$\beta_H=\beta_L$
Test p-value				0.07
Observations	51	51	51	51
R-squared	0.15	0.28	0.25	0.13

Numbers in parentheses are robust standard errors.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Robustness to Outliers and Different Samples

In all regressions, the dependent variable is the annualized growth rate of the poverty headcount during the longest spell available for each country. GDP growth is the average growth rate of real GDP per capita during the corresponding spell. Labor intensive growth is, for each country, the sum across sectors of the product of a sector's per capita value-added growth, its share on total GDP, and its surplus use of unskilled labor. For each sector and country, the surplus use of unskilled labor is the difference between its labor intensity (the ratio of a sector's share of total unskilled labor employment to its share of total value added) and one. Column (1) reproduces the benchmark regression for reference. In Column (2), the measure of unskilled labor intensity did not trim the outliers. Column (3) shows the results obtained a procedure that is robust to outliers. Column (4) reports the results obtained after dropping Argentina, Estonia, Latvia, and Senegal, the largest outliers, from the sample. Column (5) shows the results obtained using the restricted sample that results from applying the criteria in Kraay (2005). Columns (6) and (7) report the results obtained with the sub-samples consisting of spells above and below the median value of 7 years, respectively.

	Benchmark	Including Outliers for lj/sj	Robust to Outliers	Excluding Outliers	Reduced Sample	Only short spells	Only long spells
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP growth	-1.936***	-1.872***	-2.134***	-2.483***	-1.754***	-2.027**	-1.578***
	(0.569)	(0.582)	(0.531)	(0.485)	(0.625)	(0.845)	(0.538)
Labor intensive growth	-13.622***	-11.069**	-13.174***	-13.147***	-11.350**	-16.949**	-11.017*
	(4.607)	(4.954)	(4.772)	(4.274)	(4.861)	(6.496)	(5.510)
Constant	0.007	0.008	0.008	0.009	-0.006	0.030	-0.016
	(0.016)	(0.016)	(0.016)	(0.013)	(0.014)	(0.025)	(0.018)
Observations	51	51	51	47	32	24	27
R-squared	0.28	0.25	0.29	0.48	0.31	0.31	0.30

Numbers in parentheses are robust standard errors.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Allowing for Alternative Explanations (1)

In all regressions, the dependent variable is the annualized growth rate of the poverty headcount during the longest spell available for each country. GDP growth is the average growth rate of real GDP per capita during the corresponding spell. Labor intensive growth is, for each country, the sum across sectors of the product of a sector's per capita value-added growth, its share on total GDP, and its surplus use of unskilled labor. For each sector and country, the surplus use of unskilled labor is the difference between its labor intensity (the ratio of a sector's share of total unskilled labor employment to its share of total value added) and one. Column (1) controls for the (share-weighed) growth in agricultural value added. Column (2) controls for the initial level of rural population density, measured by rural population per square km of arable land, and column (3) controls for the growth in rural population density. Columns (4) and (5) control for, respectively, the initial level and the growth rate of the average years of secondary schooling of the adult population.

	Controlling for:				
	Agricultural Growth	Rural Density - Initial	Rural Density - Growth	Secondary School Yrs - Initial	Secondary School Yrs - Growth
	(1)	(2)	(3)	(4)	(5)
GDP growth	-1.706***	-1.541**	-1.535**	-2.043***	-1.689**
	(0.635)	(0.664)	(0.659)	(0.591)	(0.690)
Labor intensive growth	-13.500***	-12.486**	-12.471**	-10.664**	-9.467*
	(4.692)	(4.956)	(4.909)	(5.213)	(5.407)
Agricultural growth (share-weighted)	-6.523				
	(6.123)				
Initial rural density		-0.000			
		(0.000)			
Growth of rural density			0.561		
			(0.665)		
Initial secondary school years				0.041**	
				(0.020)	
Growth of secondary school years					0.139
					(0.561)
Constant	0.006	0.002	-0.007	-0.054	-0.010
	(0.017)	(0.022)	(0.018)	(0.033)	(0.026)
Observations	51	50	50	41	41
R-squared	0.30	0.20	0.22	0.29	0.20

Numbers in parentheses are robust standard errors.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Allowing for Alternative Explanations (2)

In all regressions, the dependent variable is the annualized growth rate of the poverty headcount during the longest spell available for each country. GDP growth is the average growth rate of real GDP per capita during the corresponding spell. Labor intensive growth is, for each country, the sum across sectors of the product of a sector's per capita value-added growth, its share on total GDP, and its surplus use of unskilled labor. For each sector and country, the surplus use of unskilled labor is the difference between its labor intensity (the ratio of a sector's share of total unskilled labor employment to its share of total value added) and one. Column (1) controls for a direct effect of the Gini coefficient. Column (2) controls for potential interactions between the Gini inequality coefficient and, respectively, the volume and composition of growth. Column (3) takes into account that the effect of growth and its composition may be affected by the density or frequency of people with income around the poverty line. Column (4) controls for the log of the initial headcount poverty index. Column (5) controls for the growth in mean income (or expenditure) from household surveys.

	Controlling for:				
	Inequality	Interactions with Inequality	Interactions with Density at Poverty Line	Initial Headcount	Survey Mean Growth
	(1)	(2)	(3)	(4)	(5)
GDP growth	-1.999***	-1.309	-3.050**	-1.885***	-1.239*
	(0.546)	(2.040)	(1.319)	(0.486)	(0.627)
Labor intensive growth	-13.483***	-25.776*	-23.681**	-14.074***	-9.194**
	(4.718)	(13.734)	(10.951)	(4.891)	(4.218)
Gini	-0.001				
	(0.001)				
Gini*GDP growth		-1.568			
		(4.797)			
Gini*Labor intensive growth		27.726			
		(28.883)			
Density at poverty line*GDP growth			-0.096		
			(0.139)		
Density at poverty line*Labor intensive growth			-1.453		
			(1.296)		
(log) Initial headcount				-0.023***	
				(0.008)	
Survey mean growth					-0.515***
					(0.162)
Constant	0.059	0.007	0.008	-0.048*	0.005
	(0.047)	(0.017)	(0.017)	(0.028)	(0.015)
Observations	51	51	49	51	51
R-squared	0.30	0.30	0.35	0.40	0.44

Numbers in parentheses are robust standard errors.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. Controlling for Endogeneity

In all regressions, the dependent variable is the annualized growth rate of the poverty headcount during the longest spell available for each country. GDP growth is the average growth rate of real GDP per capita during the corresponding spell. Labor intensive growth is, for each country, the sum across sectors of the product of a sector's per capita value-added growth, its share on total GDP, and its surplus use of unskilled labor. For each sector and country, the surplus use of unskilled labor is the difference between its labor intensity (the ratio of a sector's share of total unskilled labor employment to its share of total value added) and one. Column (1) instruments for GDP growth with both the country's GDP growth during the decade before the beginning of the spell and the average GDP growth of the country's trading partners. Column (2) instruments for GDP growth as in column 1 and instruments for labor-intensive growth with the country's labor-intensive growth in the decade before the beginning of the spell and contemporaneous labor-intensive growth using world median (instead of country specific) sectoral growth rates and value added sizes.

	Instrumenting GDP Growth	Instrumenting GDP Growth and Labor-intensive Growth
	(1)	(2)
GDP growth	-3.944**	-2.415**
	(1.919)	(1.042)
Labor intensive growth	-18.566***	-17.208*
	(6.994)	(10.564)
Constant	0.042	0.012
	(0.038)	(0.023)
Specfication and instrument strength tests		
Sargan Test (p-value)	0.47	0.53
Underidentification test (Kleibergen-Paap, p-value)	0.05	0.01
Joint significance of endogenous regressors (Anderson-Rubin)	0.04	0.10
Cragg-Donald Wald statistic	3.03	3.64
Observations	48	42

Numbers in parentheses are robust standard errors.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. Using Alternative Poverty Measures

In all regressions, the dependent variable is the annualized growth rate of the corresponding poverty measure indicated below during the longest spell available for each country. GDP growth is the average growth rate of real GDP per capita during the corresponding spell. Labor intensive growth is, for each country, the sum across sectors of the product of a sector's per capita value-added growth, its share on total GDP, and its surplus use of unskilled labor. For each sector and country, the surplus use of unskilled labor is the difference between its labor intensity (the ratio of a sector's share of total unskilled labor employment to its share of total value added) and one. In columns (1)-(4), the poverty measure is the (average) poverty gap, the (average) squared poverty gap, the Watt's index, and (average) income of the poor, respectively.

	Alternative poverty measure:			
	Poverty Gap	Squared Poverty Gap	Watt's Poverty Index	Income of the Poor
	(1)	(2)	(3)	(4)
GDP growth	-2.068***	-5.283**	-4.228**	0.141**
	(0.725)	(2.430)	(1.658)	(0.067)
Labor intensitve growth	-14.220**	-29.159**	-24.260**	1.970***
	(6.940)	(12.588)	(10.478)	(0.639)
Constant	0.017	0.079	0.058	-0.000
	(0.025)	(0.062)	(0.046)	(0.002)
Observations	51	51	51	45
R-squared	0.19	0.28	0.27	0.22

Numbers in parentheses are robust standard errors.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. The Effect on Distribution and Mean Components of Poverty Changes

In these regressions, changes in poverty are decomposed into the portion due to changes in mean income holding income distribution constant (i.e., unchanged Lorenz curve), the portion due to changes in the distribution of income holding constant its mean, and an approximation residual. This is the decomposition introduced by Datt and Ravallion (1992) and implemented by Kraay (2003) for the cross-section of countries we use in this paper. Estimation is obtained through a seemingly-unrelated-regression-equation (SURE) system, where the sum of the corresponding coefficients on the growth, distribution, and residual components is restricted to be the same as the respective coefficient in the benchmark regression. (The coefficients on the residual component are not presented.) SURE estimation is conducted ignoring (Cols. 1 and 2) and controlling for (Cols. 3 and 4) the influence of outliers. Regarding the explanatory variables, GDP growth is the average growth rate of real GDP per capita during the corresponding spell, and labor intensive growth is, for each country, the sum across sectors of the product of a sector's per capita value-added growth, its share on total GDP, and its surplus use of unskilled labor.

	SURE		SURE - Robust to Outliers	
	Mean Component	Distribution Component	Mean Component	Distribution Component
	(1)	(2)	(3)	(4)
GDP growth	-2.142***	0.005	-2.231***	0.041
	(0.425)	(0.360)	(0.253)	(0.265)
Labor intensive growth	-12.510***	-0.862	-8.586***	-4.318*
	(3.792)	(3.216)	(2.371)	(2.482)
Constant	-0.001	0.003	0.008	-0.004
	(0.015)	(0.012)	(0.010)	(0.010)
Observations	49	49	48	48

Numbers in parentheses are robust standard errors.
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1. Cross-Country Distribution of Labor Intensity (li/si) per Sector

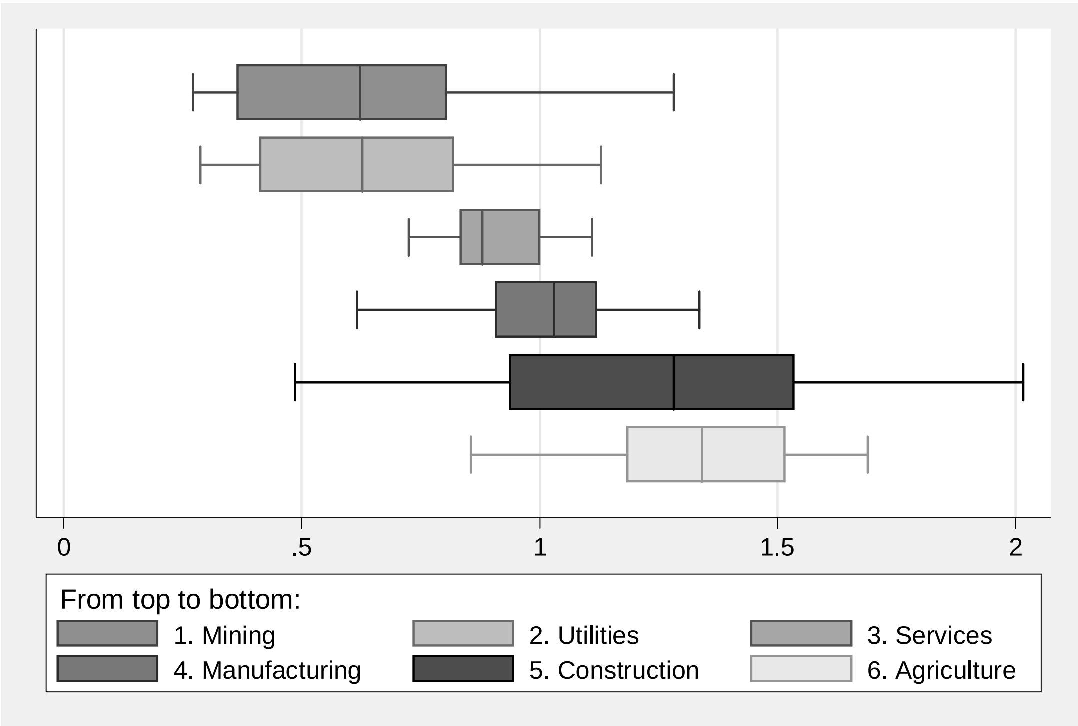
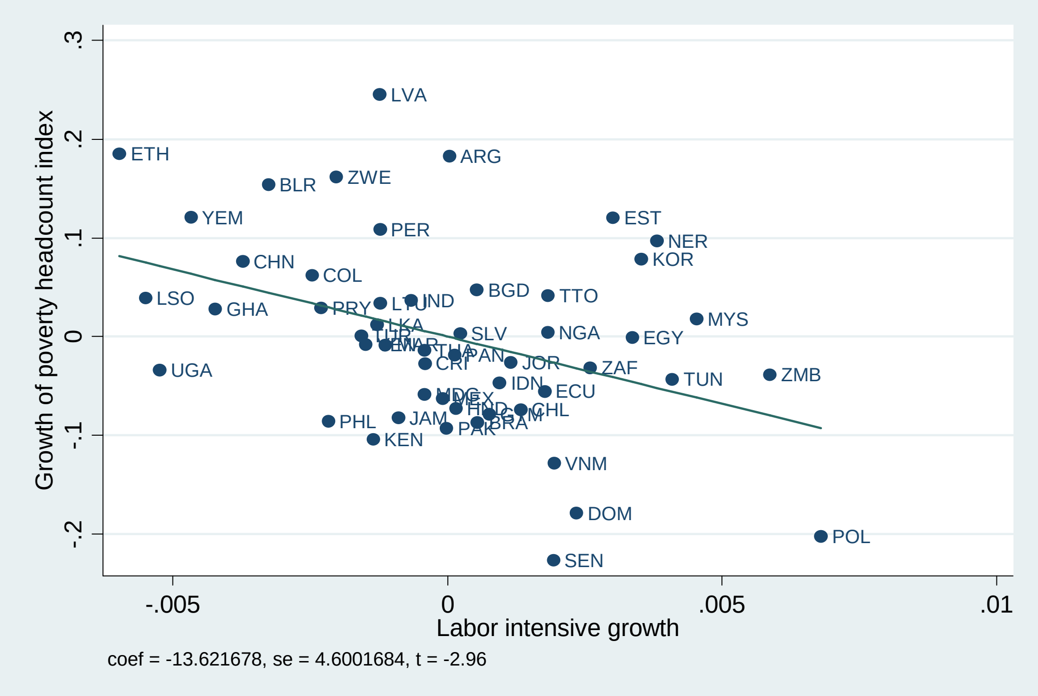


Figure 2. Poverty Change and Labor-Intensive Growth
Partial-regression observations, controlling for per capita GDP growth



Appendix 1. Samples of Countries

WB Code	Country Name	Spell	3-sector data (55-countries)	6-sector data (51-countries)	Non-outliers (47-countries)	Kraay's criteria (32-countries)
ARG	Argentina	1992 - 1998	√	√		
BDI	Burundi	1992 - 1998	√			
BGD	Bangladesh	1984 - 1992	√	√	√	√
BLR	Belarus	1988 - 1995	√	√	√	
BRA	Brazil	1985 - 1998	√	√	√	√
CHL	Chile	1987 - 1998	√	√	√	
CHN	China	1990 - 1998	√	√	√	√
COL	Colombia	1988 - 1998	√	√	√	√
CRI	Costa Rica	1993 - 1996	√	√	√	
DOM	Dominican Republic	1989 - 1998	√	√	√	
DZA	Algeria	1988 - 1995	√			
ECU	Ecuador	1988 - 1995	√	√	√	√
EGY	Egypt	1991 - 1999	√	√	√	√
EST	Estonia	1993 - 1995	√	√		
ETH	Ethiopia	1995 - 2000	√	√	√	√
GHA	Ghana	1987 - 1999	√	√	√	√
GTM	Guatemala	1987 - 1989	√	√	√	
HND	Honduras	1989 - 1998	√	√	√	√
IDN	Indonesia	1987 - 2000	√	√	√	√
IND	India	1983 - 1997	√	√	√	√
JAM	Jamaica	1988 - 2000	√	√	√	
JOR	Jordan	1987 - 1997	√	√	√	
KEN	Kenya	1992 - 1997	√	√	√	√
KOR	Korea, Rep.	1988 - 1993	√	√	√	
LKA	Sri Lanka	1985 - 1995	√	√	√	√
LSO	Lesotho	1986 - 1995	√	√	√	√
LTU	Lithuania	1996 - 2000	√	√	√	
LVA	Lativa	1993 - 1998	√	√		
MAR	Morocco	1985 - 1999	√	√	√	√
MDG	Madagascar	1993 - 1999	√	√	√	√
MEX	Mexico	1989 - 1998	√	√	√	√
MLI	Mali	1989 - 1994	√			
MRT	Mauritania	1988 - 1995	√			
MYS	Malaysia	1984 - 1997	√	√	√	√
NER	Niger	1992 - 1995	√	√	√	
NGA	Nigeria	1985 - 1997	√	√	√	√
PAK	Pakistan	1987 - 1998	√	√	√	√
PAN	Panama	1991 - 1996	√	√	√	√
PER	Peru	1985 - 1994	√	√	√	√
PHL	Philippines	1985 - 2000	√	√	√	√
POL	Poland	1993 - 1998	√	√	√	
PRY	Paraguay	1990 - 1998	√	√	√	√
SEN	Senegal	1991 - 1994	√	√		
SLV	El Salvador	1989 - 1998	√	√	√	√
THA	Thailand	1988 - 2000	√	√	√	√
TTO	Trinidad and Tobago	1988 - 1992	√	√	√	
TUN	Tunisia	1985 - 1990	√	√	√	√
TUR	Turkey	1987 - 2000	√	√	√	
UGA	Uganda	1989 - 1996	√	√	√	√
VEN	Venezuela	1981 - 1998	√	√	√	√
VNM	Vietnam	1993 - 1998	√	√	√	√
YEM	Yemen, Rep.	1992 - 1998	√	√	√	√
ZAF	South Africa	1993 - 1995	√	√	√	
ZMB	Zambia	1991 - 1998	√	√	√	√
ZWE	Zimbabwe	1990 - 1995	√	√	√	

Appendix 2. Descriptive Statistics for 51-Country Sample

Poverty Reduction and Sectoral Growth

(a) Univariate

variable	mean	median	min	max	sd
Growth in headcount poverty index	-0.014	-0.028	-0.279	0.267	0.106
Industry growth	0.008	0.004	-0.018	0.070	0.014
Agriculture growth*	0.000	0.000	-0.004	0.005	0.002
Mining growth*	0.000	0.000	-0.014	0.016	0.004
Manufacturing growth*	0.005	0.003	-0.006	0.046	0.009
Utilities growth*	0.001	0.001	-0.002	0.009	0.002
Construction growth*	0.002	0.001	-0.003	0.016	0.003
Services growth*	0.010	0.009	-0.018	0.033	0.011

(b) Bivariate Correlation

variable	Growth in head-count poverty index	Industry growth	Agricul-ture growth*	Mining growth*	Manu-facturing growth*	Utilities growth*	Construc-tion growth*	Services growth*
Growth in headcount poverty index	1.00							
Industry growth	-0.32	1.00						
Agriculture growth*	-0.28	0.42	1.00					
Mining growth*	-0.12	0.58	0.41	1.00				
Manufacturing growth*	-0.31	0.91	0.31	0.32	1.00			
Utilities growth*	-0.11	0.61	0.23	0.17	0.56	1.00		
Construction growth*	-0.20	0.52	0.05	0.15	0.41	0.40	1.00	
Services growth*	-0.13	0.60	0.14	0.32	0.57	0.30	0.57	1.00

Note: * All sectoral growths are per capita value added in that sector (weighted by the share of its value added in total GDP).

Appendix 3. Descriptive Statistics for 51-Country Sample

Poverty Reduction and Labor Intensive Growth

(a) Univariate

variable	mean	median	min	max	sd
Growth in headcount poverty index	-0.014	-0.028	-0.279	0.267	0.106
Proportional change in poverty gap	-0.006	-0.027	-0.316	0.310	0.138
Proportional change in squared poverty gap	0.013	-0.020	-0.513	1.291	0.269
Proportional change in Watt's poverty index	0.005	-0.025	-0.463	0.888	0.222
GDP per capita growth	0.018	0.016	-0.061	0.091	0.026
Labor intensive growth	-0.001	-0.001	-0.007	0.006	0.003
Gini coefficient	43.61	43.19	21.78	66.25	10.49
Survey mean growth	0.011	0.016	-0.416	0.301	0.090
Mean component of Pov. change	-0.020	-0.028	-0.279	0.266	0.103
Distribution component of Pov. change	-0.024	-0.038	-0.252	0.262	0.098

(b) Bivariate Correlation

variable	Growth in head-count poverty index	Propor-tional change in poverty gap	Propor-tional change in squared poverty gap	Propor-tional change in Watt's poverty gap	GDP per capita growth	Labor intensive growth	Gini coeffi-cient	Survey mean growth	Mean component of Pov. growth	Distribution component of Pov. growth
Growth in headcount poverty index	1.00									
Proportional change in poverty gap	0.96	1.00								
Proportional change in squared poverty gap	0.90	0.90	1.00							
Proportional change in Watt's poverty index	0.93	0.95	0.99	1.00						
GDP per capita growth	-0.45	-0.37	-0.48	-0.46	1.00					
Labor intensive growth	-0.25	-0.20	-0.19	-0.19	-0.21	1.00				
Gini coefficient	-0.01	0.07	-0.03	0.01	-0.13	0.06	1.00			
Survey mean growth	-0.62	-0.53	-0.46	-0.49	0.33	0.19	0.24	1.00		
Mean component of Pov. change	1.00	0.96	0.90	0.93	-0.46	-0.25	-0.01	-0.62	1.00	
Distribution component of Pov. change	0.73	0.61	0.50	0.54	-0.46	-0.25	-0.17	-0.87	0.73	1.00