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Industrialization in developing countries: is it related to poverty reduction?

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Abstract: This paper proposes an empirical framework that relates poverty reduction to production growth. We use the GGDC/UNU-WIDER Economic Transformation Database to measure the contribution to growth of productivity improvements within sectors and structural change—the reallocation of workers across sectors—for 42 developing countries from 1990 to 2018. Next, the contributions are used in a regression analysis, which indicates that poverty reduction is significantly related to structural change and productivity growth in manufacturing. An attribution exercise suggests that structural change and agricultural productivity growth account for a substantial share of poverty reduction in developing Asia and sub-Saharan Africa, and that productivity growth in manufacturing accounts for poverty reduction in developing Asia, but not in sub-Saharan Africa.

Key words: poverty, production growth, manufacturing, structural change, developing countries

JEL classification: I32, O11, O47

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1 Introduction

Changes in the sectoral structure of the economy play an important role in shaping growth and poverty reduction. Historically, the reallocation of workers from traditional to modern activities has driven improvements in living standards. When resources shift from traditional agriculture to modern sectors such as manufacturing, aggregate productivity increases. McMillan and Rodrik (2011) call this process 'growth-enhancing' structural change. In the process, workers moving to higher-wage sectors become better off and, as these surplus workers leave rural areas, the average income of those that remain in agriculture rises as well. In the long term, the expansion of modern sectors creates the possibility for sustained growth, further supporting poverty reduction.

However, the impact of structural change on poverty reduction is subject to debate. For instance, the poor are often involved in agriculture, so an expansion of output in modern urban activities need not substantially impact 'the poorest of the poor' (Benfica and Henderson 2021; Christiaensen et al. 2011; Winters 2002). Whether changes in sectoral output relate to poverty reduction depends on (i) the sector's growth performance, (ii) the size of the sector in the aggregate economy, (iii) the indirect impact of those changes on growth in other sectors, and (iv) the extent to which poor people participate in the sector (Christiaensen et al. 2011). When economic production shifts to modern activities, the poor may not be able to move to more productive sectors of the economy due to lack of skills or other barriers. Also, if economic growth is concentrated in sectors that do not benefit the poor, the impact on poverty reduction is likely to be limited (Montalvo and Ravallion 2010). Therefore, the net poverty-reducing impact of structural change is an empirical question, and knowing whether and how changes in the sectoral composition of output relate to poverty reduction is relevant for promoting inclusive and sustainable economic development.

This paper develops an empirical framework that relates poverty reduction to changes in production growth. We start with the semi-elasticity between percentage point changes in the headcount poverty ratio and changes in GDP per capita proposed by Klasen and Misselhorn (2008).[1] GDP per capita is then written as a function of GDP per worker and the number of workers in the population. Subsequently, growth in GDP per worker is split into the contribution from productivity growth within sectors and structural change—the reallocation of workers across sectors—using Stiroh (2002).

For the empirical implementation, poverty data from the World Bank's PovcalNet are combined with the July 2021 release of the GGDC/UNU-WIDER Economic Transformation Database (ETD). We use Atamanov et al. (2019) to create intertemporal consistent poverty changes within each country.[2] The ETD provides consistent time series of employment, and real and nominal value added by 12 sectors of the total economy, including agriculture, manufacturing, and business services, annually for the period 1990–2018. It includes sub-Saharan African, Asian, Latin American, and Middle-East and North African (MENA) economies. Combining ETD with PovcalNet allows us to examine how patterns of poverty reduction and production growth in sub-Saharan Africa (SSA) compare with those in developing Asia.

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[1] See also Benfica and Henderson (2021).

[2] Estimates of poverty in a country are subject to revisions in methodology and sources, which affects the comparability of estimates within countries over time. Atamanov et al. (2019) provide an indicator for comparability of poverty estimates.

We document an increase in the share of manufacturing workers in many developing Asian and SSA countries, starting around 2010 (see also Kruse et al. 2021; Lopes and te Velde 2021; Mensah 2020). The industrialization trend is clearly upward, although manufacturing activity in SSA is below that in developing Asia.

Using Stiroh (2002) we disaggregate labour productivity growth into contributions from individual sectors and worker reallocation across sectors. We find that structural change contributes to growth in developing Asia and SSA. However, the marginal productivity of additional workers in modern activities in SSA is low, holding back productivity growth, especially in manufacturing. This could be due to workers being absorbed in activities characterized by small-scale enterprises and low productivity growth, which is observed for Tanzanian and Ethiopian manufacturing firms by Diao et al. (2021).

Regression results indicate that the poverty-reducing effect of productivity growth is significant, with a semi-elasticity around -0.20. Hence, a 1 per cent increase in GDP per worker is related to about a 0.20 percentage point reduction in the $1.90-a-day headcount poverty ratio on average. This semi-elasticity is comparable to the -0.26 estimated by Benfica and Henderson (2021). An increase in labour force participation also relates to poverty reduction, but is not significant. Once we split GDP per worker into productivity growth within sectors and structural change, we find that poverty reduction is significantly related to productivity growth in manufacturing and to structural change.

In an extension, we also consider more moderate poverty lines, namely the $3.20 and $5.50 a day headcount ratios. We find that productivity growth within business and finance services significantly relates to poverty reduction, and the elasticity increases as more moderate poverty lines are considered. It suggests that for the better-off poor, productivity growth in business and finance activities relates to poverty reduction, which might disproportionally occur in urban areas. For moderate poverty lines, we still find that productivity growth within manufacturing significantly relates to lower poverty.

We then use the regression coefficients and the data in an attribution exercise. This suggests that structural change and agricultural productivity growth account for a major share of poverty reduction in developing Asia and SSA. Also, productivity growth in manufacturing accounts for poverty reduction in developing Asia, but this effect is not observed in SSA.

These findings suggest that industrialization in developing countries is related to poverty alleviation. Growth-enhancing structural change and productivity growth in manufacturing both relate to poverty reduction in developing Asia. The former channel is also observed in SSA, but the latter is not. These results suggest the importance of focusing on measures to realize productivity growth in African manufacturing, which, along with the continued movement of workers to the sector, relates to poverty reduction. More generally, we argue that effective long-run policies to reduce poverty should rely on ensuring that growth is sustained.

This paper closely relates to the literature that examines the contribution of sectoral growth to poverty reduction. The literature typically distinguishes two sectors, namely agriculture and non-agriculture. This is because growth in agriculture appears particularly effective for poverty reduction, as shown for India (Datt and Ravallion 1998) and China (Ravallion and Chen 2007) and through cross-country data (Benfica and Henderson 2021; Christiaensen et al. 2011; Ligon and Sadoulet 2007).

However, it is important to go beyond a two-sector distinction, as the impact of sectoral growth on poverty reduction is not equal across sectors (Dorosh and Thurlow 2018; Ravallion and Datt

1996; World Bank 2000). Sectoral disaggregation allows us to account for heterogeneity in poverty-reducing relations across the various sectors of the economy. Loayza and Raddatz (2010) examine the poverty-reducing impact of sectoral growth, as well as the role of unskilled labour intensity. They find that the largest contribution to poverty reduction comes from the unskilled labour-intensive sectors, namely agriculture, construction, and manufacturing. Our approach and findings are an extension of this literature. In addition to documenting the specific roles of productivity growth within individual sectors, we examine the role of structural change in poverty reduction.

Another strand of literature has examined the elasticity of poverty with respect to inequality (Fosu 2015). Increased income and a more egalitarian income distribution reinforce each other in reducing poverty. That is, lower inequality may help countries achieve more poverty reduction from a given growth in income. We therefore control for changes in inequality in the analysis.

The remainder of the paper is structured as follows. Section 2 sketches a conceptual framework that reviews the various channels by which the sectoral composition of growth is related to poverty reduction. Section 3 presents the empirical framework, which generates testable implications of the various channels. Section 4 present the data and sectoral trends. Section 5 presents a sectoral disaggregation of GDP per capita growth. Section 6 econometrically examines the role of sectoral growth and structural change for poverty reduction. Section 7 uses the regression results in an attribution exercise. Section 8 concludes.

2 Growth, structural change, and poverty reduction: a conceptual framework

The relation between poverty and economic growth receives much attention in the literature (Besley and Burgess 2003; Datt and Ravallion 1992; Dollar and Kraay 2002; Grosse et al. 2008; Kakwani 1993; Kalwij and Verschoor 2007; Ravallion 1995, 2001). Economic growth helps reduce poverty in several ways, such as by raising the income of the poor, creating indirect spillover and trickle-down effects, improving human capital, and fostering the ability of governments to support poverty alleviation programmes.

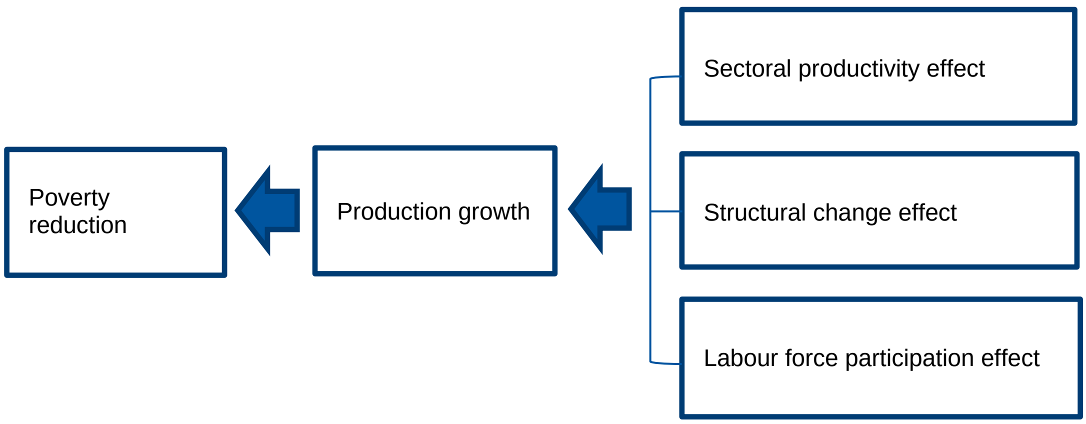
The structure of the economy and the movement of resources across sectors play an essential role in the process of economic growth (Kuznets 1966; Lewis 1954). For instance, in the seminal Lewis model of economic growth, worker movement from farm to non-farm sectors is crucial to the process of economic development (Lewis 1954). Such worker reallocation helps improve the productivity of the agricultural sector and the incomes of workers remaining in the sector. Moreover, it raises the incomes of those who leave the sector if they move to modern activities with higher productivity and thus higher wages. Theoretically, this process facilitates industrialization and the creation of more-productive jobs in the industrial sector, enhancing aggregate economy productivity, economic growth, and incomes. In further stages of development, workers move to services activities (Chenery et al. 1986; Kuznets 1966). The recent literature on structural change extends this idea to include more sectors and views structural transformation as the evolution of an economy's structure from low-productivity to high-productivity activities (de Vries et al. 2012; Erumban et al. 2019; McMillan and Rodrik 2011; Szirmai 2013). Given that worker movements across sectors can enhance productivity and incomes within various sectors, and in the aggregate economy, it is an important channel through which poverty reduction is linked to economic growth (Chen and Ravallion 2004; Kakwani 2000; Loayza and Raddatz 2010; Ravallion 2004).

The literature has considered the distinct impact of economic sectors on poverty reduction (Benfica and Henderson 2021; Christiaensen et al. 2011; Datt and Ravallion 1992; Ravallion and

Datt 1996; Suryahadi et al. 2009). For instance, relating changes in poverty to output growth in the three broad sectors of the economy, Ravallion and Datt (1996) observe a poverty-reducing effect from India's primary and tertiary sectors. Ravallion and Chen (2007) observe a poverty-reducing effect of agriculture in China, but not from services. Several subsequent studies have adopted the approach followed by Ravallion and Datt (1996), such as Loayza and Raddatz (2010), Christiaensen et al. (2011), Berardi and Marzo (2017), and Benfica and Henderson (2021). These studies document the direct effect of agricultural growth on poverty reduction and its indirect effect by stimulating growth in other sectors. The poverty-reducing effect of agriculture, however, diminishes as countries become richer (Christiaensen et al. 2011; Dorosh and Thurlow 2018; Ivanic and Martin 2018; Ligon and Sadoulet 2018).[3]

From a structural change perspective, in addition to the direct growth effect of the sector per se, improving productivity in the sector helps release workers to other more productive and income-earning activities, which will have a poverty-reducing effect. Given that most developing countries feature substantial differences in productivity across sectors, the potential poverty-reducing effect of structural change is large. In a nutshell, there are distinct effects of sectoral productivity growth and worker movement across sectors on poverty. They are the direct and indirect effects of sectoral productivity improvements, the effects of worker movements across sectors, and the effects of changes in workforce participation. We consider here a framework that relates poverty reduction to production growth, distinguishing between the three effects shown in Figure 1.

Figure 1: Growth, structural change, and poverty, a conceptual framework



Source: authors' construction.

First, consider improvements in productivity in any given sector, which reduce poverty by raising real wages and incomes of workers (Figure 1: top right). This direct sectoral productivity effect depends on the size and growth rate of the sector. Indeed, productivity improvements within a sector help improve worker incomes—a growth effect. Still, the visibility of its impact on aggregate poverty reduction depends on how large the sector is in the economy—a size effect. For instance, if a large portion of the workforce relies on the agricultural sector and its productivity grows substantially, its direct impact on aggregate growth and poverty reduction is likely large. Moreover, growth of a given sector may create spillover effects to other sectors with which it has linkages, enhancing aggregate poverty reduction. For instance, if productivity growth in agriculture creates

[3] Various studies distinguish between the rural vs. urban composition of poverty in relation to changes in the sectoral structure (e.g. Benfica and Henderson 2021). As expected, rural poverty appears more responsive to agricultural productivity growth (Benfica and Henderson 2021). This paper does not make this distinction, because we lack information to adjust for cost-of-living differences between the urban and rural poor.

additional demand for products and services (final goods or intermediate goods) from other sectors, it enhances jobs, productivity, and incomes in those sectors.

However, if productivity growth is associated with reductions in employment (e.g. because of substitution of labour with capital) rather than an expansion in output (assuming a complementary relation between labour and capital), its impact on poverty at the aggregate level is complex and is crucially linked to reallocation effects. As discussed above, when workers move to sectors with higher productivity, then the income of those that remain in the sector and those that move to sectors may improve, reducing poverty. However, if workers relocate to lower-productivity sectors, poverty reduction due to a within-sector productivity effect can be offset by a structural change effect. Also, if the reduction in sectoral employment leads to unemployment, reflected in lower labour force participation, the impact on poverty reduction will be lower. Finally, as noted earlier, skill constraints of workers may hinder the movement of workers to modern sectors when opportunities in traditional sectors shrink. Therefore, the net poverty-reducing impact of sectoral productivity growth and structural change is an empirical question.

The framework considers worker movements across sectors and changes in labour force participation as two distinct factors that relate poverty to production growth (Figure 1: middle and bottom right). If the shift in production across sectors is associated with productive job creation, it will have a poverty-reducing impact; it will also weaken the impact of aggregate labour force participation on poverty. This is because aggregate participation rates are unlikely to change enough to make any significant poverty impact, as workers are absorbed in sectors where their returns are higher.

The channels we describe above implicitly assume that the benefits of growth have been distributed equally across the population. However, if the benefits of growth are distributed disproportionately to the more affluent, the poverty-reducing effect of growth can be limited. Therefore, it is essential to consider the impact of economic growth on poverty in conjunction with the income distribution (Datt and Ravallion 1992; Ferreira et al. 2010; Fosu 2015; Grootaert 1995; Ravallion 1997). Income inequality may lead to unequal opportunities for part of the population, leading to inefficient resource allocation and deterring the effect of structural change on poverty. In addition, per the Kuznets hypothesis, structural change is not independent from changes in income inequality (Baymul and Sen 2020). Therefore, in our empirical framework (see next section), we consider the effects of structural change, within-sector productivity growth, and labour force participation rates, while also accounting for any impact of income distribution on poverty reduction.

3 Empirical framework

Following the conceptual framework presented in Figure 1, we formulate our empirical model. To start, we define P_c as an indicator of poverty and Q_c as GDP per capita of country c. In its most basic form, the literature posits a relation between poverty and GDP per capita as follows (de Janvry and Sadoulet 2016):

$$\Delta lnP_c = \varepsilon_c \Delta lnQ_c \tag{1}$$

where Δ is a discrete time-difference operator, and the key parameter of interest is ε_c, the GDP-per-capita elasticity of poverty.

We follow Klasen and Misselhorn (2008) in examining the relation between percentage point changes in poverty (ΔP_c) and changes in levels of economic development, so ε_c is a semi-elasticity.[4] Next, note that GDP per capita (Q) can be written as a function of GDP per worker and the number of workers in the population. That is, $Q_c = \frac{Y_c}{L_c}\frac{L_c}{T_c}$, where Y_c is GDP, L_c is persons employed, and T_c is the total population of country c. Hence, we rewrite (1) as:

$$\Delta P_c = \beta \Delta ln\left(\frac{Y_c}{L_c}\right) + \gamma \Delta ln\left(\frac{L_c}{T_c}\right) \quad (2)$$

The first term on the right-hand side relates poverty reduction to growth in GDP per worker ($y_c = Y_c/L_c$) and the second term to changes in Labour Force Participation ($LFP = L_c/T_c$).

In what follows, we show that growth in GDP per worker can be split into the contribution from productivity growth within sectors and the reallocation of workers across sectors using Stiroh (2002).[5] This split is then embedded in (2).

Stiroh (2002) uses a Tornqvist index and defines aggregate value added (GDP) growth as an index of value added growth for the sectors:

$$\Delta lnY_c = \sum_i \bar{\theta}_i \Delta lnY_{ci} \quad (3)$$

where $\bar{\theta}_i$ is the average value added share[6], and Y_{ci} is real value added of sector i in country c.

Let labour productivity of sector i be $y_{ci} = Y_{ci}/L_{ci}$. Aggregate employment is the sum of sectoral employment, $L_c = \sum_i L_{ci}$. Rewriting GDP per worker and sectoral labour productivity as growth rates then yields a decomposition of aggregate labour productivity growth (Stiroh 2002):

$$\Delta lny_c = \sum_i \bar{\theta}_i \Delta lny_{ci} + R_c \quad (4)$$

where the first part of (4) is a 'pure productivity effect', which is a weighted average of labour productivity growth in the sectors. Hence, if productivity in a sector improves, then aggregate productivity rises in proportion to the sector's size. The second term, R, captures the contribution of reallocation to growth. The reallocation effect is positive if workers move to higher-productivity sectors.

[4] Conceptually, consider a 10 percentage point change in the poverty rate, which is substantial. Whether a reduction in the poverty rate by 10 per cent is large depends on the level of headcount poverty ratio. Hence, percentage changes can be large if the headcount ratio is low, whereas in terms of percentage points the changes would not be large. Benfica and Henderson (2021) also examine the relation between percentage point changes in poverty and changes in levels of economic development.

[5] We use Stiroh (2002) because it provides an exact decomposition of the log change in GDP per worker. A similar approach is presented in Timmer and Szirmai (2000), who account for both labour and capital, thus providing a decomposition of the log change in multi-factor productivity. Alternative decompositions, such as those in McMillan and Rodrik (2011) and de Vries et al. (2015), disaggregate changes in levels and not changes in logs, as we do here. We find a positive correlation between the Stiroh (2002) decomposition and alternative decomposition methods proposed by McMillan and Rodrik (2011) and de Vries et al. (2015). The main regression results reported in Section 6.2 are qualitatively similar if we use alternative decomposition methods.

[6] That is, $\bar{\theta}_i$ is the average of the nominal value added share in the initial and final year.

Combining (4) and (2), and writing it as an empirical specification to be tested, gives:

$$\Delta P_c = \alpha + \beta_1(\sum_i \overline{\theta}_i \Delta ln y_{ci}) + \gamma_1 R_c + \gamma_2 \Delta ln\left(\frac{L_c}{T_c}\right) + \varphi_x X_c + \varepsilon_c \qquad (5)$$

where a is a constant, X includes control variables, and ε_c is the error term. Control variables that will be considered include inequality and region dummies, namely a dummy for economies in SSA and in developing Asia (discussed in the next section). We also examine the 'pure productivity effect' of sectors separately, such as agriculture and manufacturing. In that case, β_1 becomes β_i.

Equation 5 is the empirical implementation of the conceptual framework discussed in Section 2 (see Figure 1). The coefficient β_1 captures the effect of productivity growth within the sector ($\Delta ln y_{ci}$) and the relative size of the sector in the economy ($\overline{\theta}_i$) on poverty. The poor tend to be endowed with labour only (Loayza and Raddatz 2010). If an increase in sectoral labour productivity (an increase in the marginal product) translates into rising wages, we expect a reduction in poverty. Improvements in the sector's productivity may also have positive spillover effects on other sectors, which could further lower poverty. That is, sectoral growth may increase demand for goods and services from other sectors and this would also relate to aggregate poverty reduction. γ_1 captures the structural change effect, and is expected to be negative if workers move to sectors where they are better off. In other words, if labour reallocates to more productive sectors with higher wages, poverty falls. Hence, we expect $\beta_1<0$ and $\gamma_1<0$. Higher labour force participation is expected to reduce poverty further, so we expect $\gamma_2<0$. The magnitude of this effect can be affected by structural change, as the employment-to-population ratio can be influenced by how worker reallocation relates to the unemployment rate.

Two remarks are in order. First, the empirical framework is essentially an accounting exercise; we do not mean to imply that these components are independent of each other. Second, the empirical framework presented in this section is premised on the notion that the impact of sectoral growth on poverty reduction is not equal across sectors. Thus, a reduction in poverty depends not just on aggregate production growth but also on its sectoral composition. Therefore, we relate poverty reduction to the size and structure of production growth, and not just to income growth.

4 Data and sectoral trends

This section describes the data we use to examine the relation between poverty reduction and changes in the sectoral structure of the economy. Section 4.1 presents the sectoral dataset and discusses patterns and trends. Section 4.2 discusses poverty measures and inequality.

4.1 GGDC/UNU-WIDER Economic Transformation Database

Sectoral value added and employment data are obtained from the GGDC/UNU-WIDER Economic Transformation Database (ETD), of which we use the 15 July 2021 release (de Vries et al. 2021). The ETD covers 51 economies. Out of these, we exclude 6 high-income economies, because we are interested in examining how the sectoral composition of growth affects the headcount poverty ratio; those with a negligible fraction of the population below the absolute poverty line have little bearing on this question. Further, Cambodia, Lesotho, and Myanmar are not included in the regressions, because we do not have data on poverty spells in these countries.[7]

[7] Cambodia, Lesotho, and Myanmar are, however, included in the description of sectoral patterns and trends.

The regression analysis thus considers 42 developing countries. Out of these, 17 are countries in SSA, 12 are in developing Asia, and 13 are other developing countries (consisting of 9 from Latin America and 4 from MENA), see Appendix Table A1.[8]

The ETD includes annual sectoral data on gross value added at both real and nominal prices for the period 1990–2018. Data on persons employed are also included such that sectoral labour productivity for each country c and sector i, y_{ci}, can be derived. The database covers the 12 main sectors of the economy as defined in the International Standard Industrial Classification, revision 4 (ISIC rev. 4), namely agriculture (ISIC rev. 4 code A), mining (B), manufacturing (C), public utilities (D+E), construction (F), trade (G+I), transport (H), business services (J+M+N), finance (K), real estate (L), government services (O+P+Q), and other services (R+S+T+U). Together these 12 sectors cover the total economy.

For the decomposition of aggregate labour productivity growth in equation (4) we use all sectors distinguished in the ETD, except real estate.[9] We use the disaggregated sector data in (4), because the contribution of structural change to growth is sensitive to the level of sectoral disaggregation (de Vries et al. 2012). Part of the reallocation of workers, such as from manufacturing to retail trade, would not be captured by the reallocation term 'R' in equation (4) if only two sectors—agriculture and non-agriculture—were considered, as in Christiaensen et al. (2011) and Benfica and Henderson (2021).

Although we implement (4) using disaggregated sector data, we are parsimonious in presenting results. Specifically, we combine mining and public utilities into 'other industry', trade and transport into 'trade & transport services', business and finance into 'business & finance services', and government and other services into 'non-market services'. We show descriptive trends as well as running regressions where these sectors are combined.

Table 1 shows (real and nominal) value added and employment shares by sector for SSA, developing Asia, and the other developing countries in 1990, 2000, 2010, and 2018. The bottom panel shows average annual sectoral labour productivity growth rates for the periods 1990–2000, 2000–10, and 2010–18. The shares and growth rates are computed for each country, and the regional growth rates are obtained as unweighted averages.

Table 1 informs on the expected 'pure productivity effect' and the reallocation effects on changes in GDP per worker. Consider agriculture, the sector in which typically a lot of poor people participate. In SSA, agriculture accounted on average for about 25 per cent of nominal GDP in 1990. This had declined by 5 percentage points to 20 per cent by 2018. In developing Asia, the nominal agricultural share halved from 32 per cent in 1990 to 16 per cent by 2018. The bottom panel reports positive average annual productivity growth rates in agriculture of around 2 per cent in SSA and, depending on the period considered, between 2.4 and 3.9 per cent growth in developing Asia. Since the productivity effect in our framework is a weighted average of labour productivity growth, $\overline{\theta}_i \Delta ln y_{ci}$, the nominal value added shares (θ_i), in combination with positive

[8] These countries account for a major part of output in each region. For SSA, the countries accounted for about 73 per cent of GDP in 2018 (see Kruse et al. 2021 for further discussion of country coverage in the ETD).

[9] Value added from real estate activities consists of rental activities and imputations of owner-occupied housing. The latter imputation is based on an equivalent rent approach and is added to GDP. Imputed income from owner-occupied houses does not have an employment equivalent. Therefore, real estate services are preferably excluded in productivity analysis (Timmer and de Vries 2009).

productivity growth ($\Delta ln y_{ci}$), suggest that agriculture is potentially an important sector for poverty reduction.

Table 1: Value added and employment shares, and labour productivity growth rates

	Sub-Saharan Africa				Developing Asia				Other developing			
	1990	2000	2010	2018	1990	2000	2010	2018	1990	2000	2010	2018
Nominal value added shares												
Agriculture	25	23	22	20	32	26	21	16	13	11	9	8
Manufacturing	17	15	12	11	17	19	20	19	23	21	18	17
Other industry	9	9	9	10	5	6	7	7	8	8	11	9
Construction	5	5	6	7	5	5	6	8	5	6	7	7
Trade & transport services	19	20	22	22	22	23	23	24	23	23	21	22
Business & finance services	9	10	13	13	8	9	10	12	11	13	15	16
Non-market services	16	18	17	18	12	12	12	14	16	19	20	21
Total	100	100	100	100	100	100	100	100	100	100	100	100
Real value added shares												
Agriculture	27	27	22	19	33	26	21	16	11	10	9	9
Manufacturing	14	13	12	12	15	17	19	19	19	20	18	17
Other industry	11	10	9	9	7	8	8	7	9	10	9	8
Construction	4	5	5	7	5	6	6	8	6	6	7	7
Trade & transport services	17	19	22	22	21	22	23	24	22	22	22	22
Business & finance services	8	9	12	13	7	7	10	12	10	11	14	16
Non-market services	19	18	17	18	13	13	14	14	23	22	21	21
Total	100	100	100	100	100	100	100	100	100	100	100	100
Employment shares												
Agriculture	65	62	54	46	62	54	47	39	30	24	19	17
Manufacturing	7	7	7	8	10	11	12	13	15	14	12	12
Other industry	2	1	1	2	1	1	1	1	2	1	2	1
Construction	3	3	4	4	3	4	6	8	6	7	8	9
Trade & transport services	10	12	16	20	12	16	20	23	19	24	26	27
Business & finance services	2	2	4	5	2	2	3	4	4	6	8	9
Non-market services	11	12	14	15	11	11	12	12	24	24	24	25
Total	100	100	100	100	100	100	100	100	100	100	100	100
Average annual labour productivity growth (in percentages)												
		1990-2000	***2000-2010***	***2010-2018***		***1990-2000***	***2000-2010***	***2010-2018***		***1990-2000***	***2000-2010***	***2010-2018***
Agriculture		1.8	2.3	2.1		2.4	3.3	3.9		2.8	2.9	2.9
Manufacturing		1.4	0.8	-0.5		2.2	3.9	3.2		2.0	1.8	1.2
Other industry		2.8	1.0	-1.3		3.7	1.9	4.6		3.6	0.5	0.3
Construction		0.6	1.3	1.5		-1.2	1.3	2.4		-0.1	1.0	0.7
Trade & transport services		0.0	0.9	-0.6		1.0	2.1	3.1		-1.0	0.4	1.6
Business & finance services		-0.5	-1.0	-1.0		1.0	1.9	4.9		-1.4	0.3	1.8
Non-market services		0.3	0.3	0.8		2.6	3.8	3.7		0.2	1.5	1.6
Aggregate economy		1.5	2.9	1.9		3.3	4.0	4.3		0.9	1.6	1.6

Note: shown are the sectoral employment and value added shares of the total economy as well as average annual sectoral labour productivity growth rates. Figures are unweighted averages across regions. Sub-Saharan Africa includes Botswana, Burkina Faso, Cameroon, Ethiopia, Ghana, Kenya, Lesotho, Malawi, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, and Zambia. Developing Asia includes Bangladesh, Cambodia, China, India, Indonesia, Lao People's Democratic Republic, Malaysia, Myanmar, Nepal, Pakistan, Philippines, Sri Lanka, Thailand, and Viet Nam. Other Developing includes countries in Latin America and MENA, namely Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Egypt, Mexico, Morocco, Peru, Tunisia, and Turkey. Real estate is excluded from the analysis.

Source: authors' calculations using the GGDC/UNU-WIDER ETD, release 15 July 2021.

The size of the manufacturing sector commands attention, as economic development is often associated with industrialization (Lewis 1954). Table 1 shows an increase in the manufacturing employment share in SSA from 7 to 8 per cent between 2010 and 2018 (Kruse et al. 2021; Mensah 2020). This is suggestive of a nascent industrialization process in SSA. Diao et al. (2021) argue that workers are absorbed by small unproductive manufacturing firms in SSA. Table 1 seems to support this finding, as it documents a negative labour productivity growth rate (-0.5 per cent) in SSA manufacturing during 2010–18.

The ETD provides disaggregated services sector data; it distinguishes business and finance services, among others. These services have been expanding rapidly in developing countries, their share increasing from 9 to 13 per cent of GDP in SSA, from 8 to 12 per cent in developing Asia, and from 11 to 16 per cent in other developing countries between 1990 and 2018. Non-market services (including government services) also expanded during this period.

A comparison of sectoral value added and employment shares in Table 1 gives an indication of relative productivity differences across sectors. Labour productivity in agriculture is much lower than in services and manufacturing. In 2018, for example, the agricultural value added share in SSA is 20 per cent while the employment share is 46 per cent. This suggests that agricultural labour productivity is about half that of the total economy average. In contrast, the manufacturing value added share is 11 per cent, while the employment share is 8 per cent. Therefore, the labour productivity level in manufacturing is above the economy average.[10] Also, note the high relative productivity levels in several services sectors, such as business and finance services. These sector differences matter in quantifying the labour reallocation effect to changes in GDP per worker, which will be shown in the next section.

4.2 Poverty and inequality data

We use internationally comparable poverty measures from PovcalNet at the World Bank. We focus on headcount ratios, which measure the proportion of the population that lives below the poverty threshold. The threshold is defined on the basis of an 'extreme' absolute poverty line, namely $1.90 per person per day in 2011 purchasing power parity (PPP). In an extension we consider 'moderate' poverty lines, namely $3.20 and $5.50 per person per day in 2011 PPP. In addition, we examine the poverty gap ratio, which is the mean shortfall in income or consumption from the poverty line expressed as a percentage of the poverty line. This measure reflects the depth of poverty as well as its incidence.

The change in poverty between two survey years is denoted a *poverty spell* (Loayza and Raddatz 2010). Two things should be noted regarding poverty spells. First, countries improve their household surveys or change measurement methodologies over time. This may affect the comparability of poverty estimates between the initial and final years of a poverty spell. Within a country, we assume comparability of poverty estimates over time unless there is a known change to survey methodology, measurement, or data structure, as reported in the comparability database by Atamanov et al. (2019). Our regressions exclude poverty spells where there is a break that potentially affects the comparability of poverty estimates in the initial and final years of the

[10] So, if we were to split the static and dynamic effects of structural change, as in de Vries et al. (2015), we would obtain static gains in SSA—workers move to the manufacturing sector, where productivity levels are higher (a static effect)—but the marginal productivity of additional workers would be low, pulling down the productivity growth rate (a dynamic effect).

country's poverty spell.[11] Second, we examine the relation between structural change and poverty reduction. This reallocation of workers across sectors is often a gradual process. To mitigate business cycle effects, we examine poverty spells with a duration of at least four years.[12] In an extension we show that the main results are robust to longer time horizons for poverty spells.

Our key dependent variable, ΔP_c, is defined as the average annual change in a country's poverty headcount ratio between two survey years. The change in poverty is annualized to accommodate spells of different length. Similarly, the contribution to growth in GDP per worker from productivity growth within sectors and the reallocation of workers across sectors during the poverty spell is annualized.

Appendix Table A2 provides an overview of countries (by region) and poverty spells. We have a total of 119 spells/observations from 42 countries spanning the period 1990–2018. The overall average spell length is approximately 5 years.

The regressions control for inequality using the Gini coefficient from the UNU-WIDER World Income Inequality Database (WIID, UNU-WIDER 2021). We use the variable named *gini_std* in WIID. This variable includes estimates based on the originally reported values that have been adjusted for comparability over time and across countries. Sometimes Gini coefficient estimates are not available for the initial or final year of the poverty spell, but are available for adjacent years. To avoid losing these poverty spells in the regression analysis, we linearly interpolate Gini estimates.

5 Sectoral disaggregation of growth in GDP per capita

Following equation (2), we split per capita income into labour productivity and labour force participation. Figure 2 provides the results for SSA, developing Asia (Asia), and the remaining developing economies in our sample (Rest), for three time periods, 1990–2000, 2000–10, and 2010–18.

We document two important trends in per capita income growth. First, despite the global financial crisis around 2008, the period 2000–10 records the highest per capita income growth in all three regions. Although developing Asian economies are the best performers in the 1990s and 2000s, SSA also experienced substantial growth during this period. Second, during the 2010s, growth eased everywhere, but more in SSA than in developing Asia and the Rest. Yet, growth rates in the 2010s remain higher than in the 1990s.

Regarding the role of labour productivity and labour force participation, productivity growth appears to be the main contributor, particularly in developing Asia. Productivity growth was

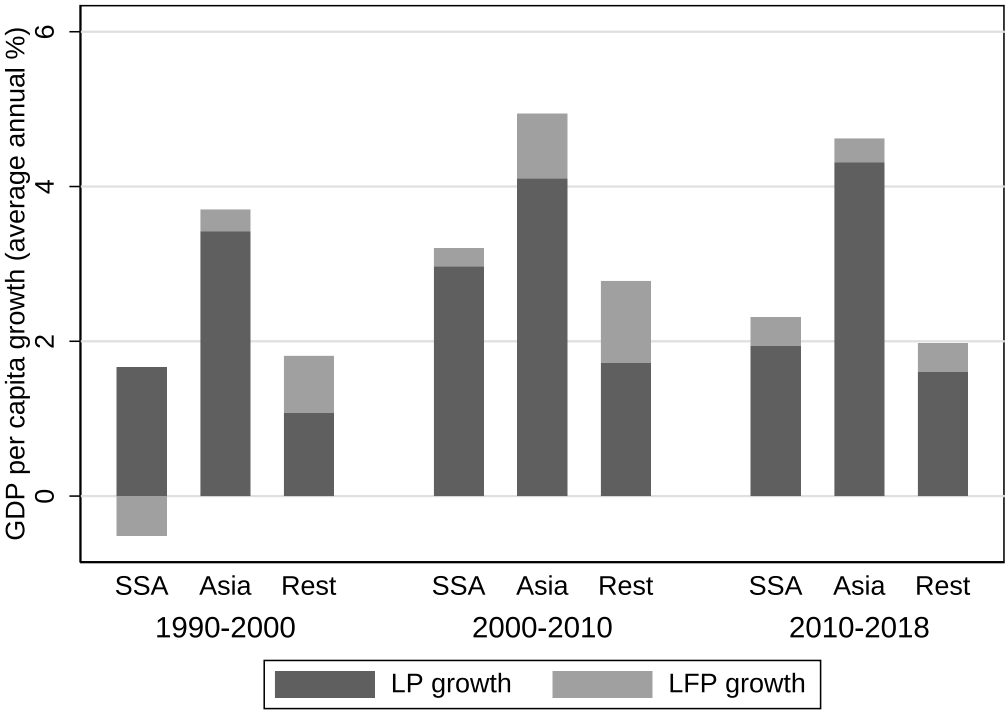
[11] Intertemporal comparability of the headcount poverty ratio is an important issue, which might have been ignored in previous studies that look at the cross-country relation between poverty reduction and production growth. Comparability issues lead us to exclude 63 of the original 172 poverty spells. Consider China. The comparability database indicates that the decline in the headcount ratio from 6.5 to 1.9 between 2012 and 2013 is due to a break in the series. If a poverty spell were to include these years, it would wrongly interpret the change as a substantial fall in poverty.

[12] In addition, the identification of poverty spells is backward-looking. For example, PovcalNet provides annual poverty data for Argentina from 1991 to 2018. Our approach thus identifies six poverty spells for Argentina, namely 1994–98, 1998–2002, 2002–06, 2006–10, 2010–14, and 2014–18. The (Excel) tool to identify poverty spells with a minimum number of years between the initial and final year is provided in the replication package.

relatively weaker in the rest of developing countries group in the 1990s, and that group continued to perform relatively poorly in subsequent periods. In developing Asian economies, productivity had its best performance in the 2010s. In contrast, in the 2010s, productivity growth was lower in SSA than in the 2000s.

We observe a decline in the participation rate in SSA in the 1990s, which is an exception to the regions and time periods considered in Figure 2. It is unclear whether this is an indicator of underutilization of productive potential. This is because in developing economies, if youth remain longer in education and training, the employment/population ratio is likely to fall, which is, in fact, desirable for long-term productivity. Participation rates improved everywhere in the 2000s, with a rapid increase in developing Asia and the Rest, as well as rising participation in SSA.

Figure 2: GDP per capita growth and its components, by region and period



Note: growth is split into growth in labour productivity (LP) and labour force participation (LFP). Regional growth rates are unweighted country averages.

Source: authors' calculations using the GGDC/UNU-WIDER ETD, release 15 July 2021.

Overall, productivity growth accounts for the majority of changes in GDP per capita. Changes in the participation rate are comparable across regions. Productivity growth in SSA remains below developing Asia, and it decelerated in the 2010s. Next, we account for the contributions of sectoral productivity growth and worker movements across sectors.

The top rows in Table 2 show the decomposition of per capita income growth into the contributions from productivity and labour force participation. Using equation (5), productivity is further disaggregated into the contributions of individual sectoral productivity growth and inter-sectoral worker reallocation in subsequent rows. Note that the sectoral disaggregation is obtained using disaggregated sector data. However, for ease of exposition, we provide results at a higher level of aggregation. For example, mining and construction are considered separately in our disaggregation but are combined into one sector group, 'other industry', in Table 2.

Table 2: GDP per capita decomposition into changes in labour force participation and aggregate labour productivity

	Sub-Saharan Africa			Developing Asia			Other developing		
	90–00	**00–10**	**10–18**	**90–00**	**00–10**	**10–18**	**90–00**	**00–10**	**10–18**
GDP per capita	1.15	3.20	2.31	3.70	4.94	4.62	1.81	2.78	1.98
Labour force participation	-0.51	0.24	0.37	0.28	0.84	0.31	0.73	1.06	0.37
Aggregate labour productivity	1.67	2.96	1.94	3.42	4.10	4.31	1.08	1.72	1.60
of which:									
Reallocation	*0.60*	*1.88*	*1.54*	*1.47*	*1.28*	*1.13*	*0.35*	*0.47*	*-0.02*
Productivity within sectors	*1.07*	*1.08*	*0.40*	*1.96*	*2.82*	*3.18*	*0.73*	*1.25*	*1.63*
of which:									
Agriculture	*0.42*	*0.61*	*0.61*	*0.66*	*0.85*	*0.69*	*0.29*	*0.29*	*0.27*
Manufacturing	*0.17*	*0.08*	*-0.07*	*0.61*	*0.85*	*0.62*	*0.46*	*0.35*	*0.22*
Other industry	*0.33*	*0.09*	*-0.07*	*0.26*	*0.08*	*0.19*	*0.33*	*0.08*	*0.11*
Construction	*0.11*	*0.04*	*0.15*	*-0.07*	*0.06*	*0.13*	*0.01*	*0.06*	*0.05*
Trade & transport services	*0.12*	*0.21*	*-0.11*	*0.18*	*0.49*	*0.68*	*-0.23*	*0.07*	*0.34*
Business & finance services	*-0.05*	*-0.10*	*-0.19*	*0.04*	*0.10*	*0.38*	*-0.20*	*0.14*	*0.29*
Non-market services	*-0.03*	*0.15*	*0.08*	*0.28*	*0.39*	*0.50*	*0.07*	*0.26*	*0.34*

Note: using Stiroh (2002), aggregate labour productivity is split into the contribution from the reallocation of workers to higher productivity sectors and the direct contribution of sectoral value added productivity growth. Unweighted country averages by region are shown (see Appendix Table A1 for the countries included).

Source: authors' calculations using the GGDC/UNU-WIDER ETD, release 15 July 2021.

The contribution of worker reallocation to productivity growth in SSA is comparable with that in developing Asia and even slightly higher in the 2010s. However, productivity growth within sectors is substantially lower and even negative in several sectors, including manufacturing, trade, and transport services. Within-industry productivity growth contributes about one-fifth of aggregate labour productivity in SSA, whereas close to three-quarters of all productivity in developing Asia is due to within-sector improvement. Apparently, while SSA seems to be witnessing productivity-enhancing worker reallocation, it is lagging behind in keeping the marginal product of reallocated workers high. Previous studies have also pointed at the importance of worker reallocation in combination with weak productivity growth in SSA (de Vries et al. 2015; McMillan and Rodrik 2011), which is here confirmed using more recent data.[13]

As noted in Section 4, there appears to be nascent industrialization in SSA, but productivity growth is low. This contrasts with the high manufacturing productivity growth in developing Asia. This implies that the contribution of SSA's manufacturing renaissance to poverty reduction is likely limited—which is examined in Section 7.

6 Regression results

This section examines empirically the relation between poverty reduction and the sectoral composition of growth. Section 6.1 shows the correlation between poverty reduction and our key

[13] The regional average decomposition results for the periods 1990–2000 and 2000–10 are similar to de Vries et al. (2015) if we use their approach (cf. figure 1 and table 2 in de Vries et al. 2015). Country-specific decomposition results are occasionally substantially different, likely due to recent revisions of the national accounts that have been incorporated in the ETD (de Vries et al. 2021).

variables of interest. Section 6.2 presents the main regression results. Section 6.3 explores various extensions and the robustness of the results.

6.1 Correlations and descriptive statistics

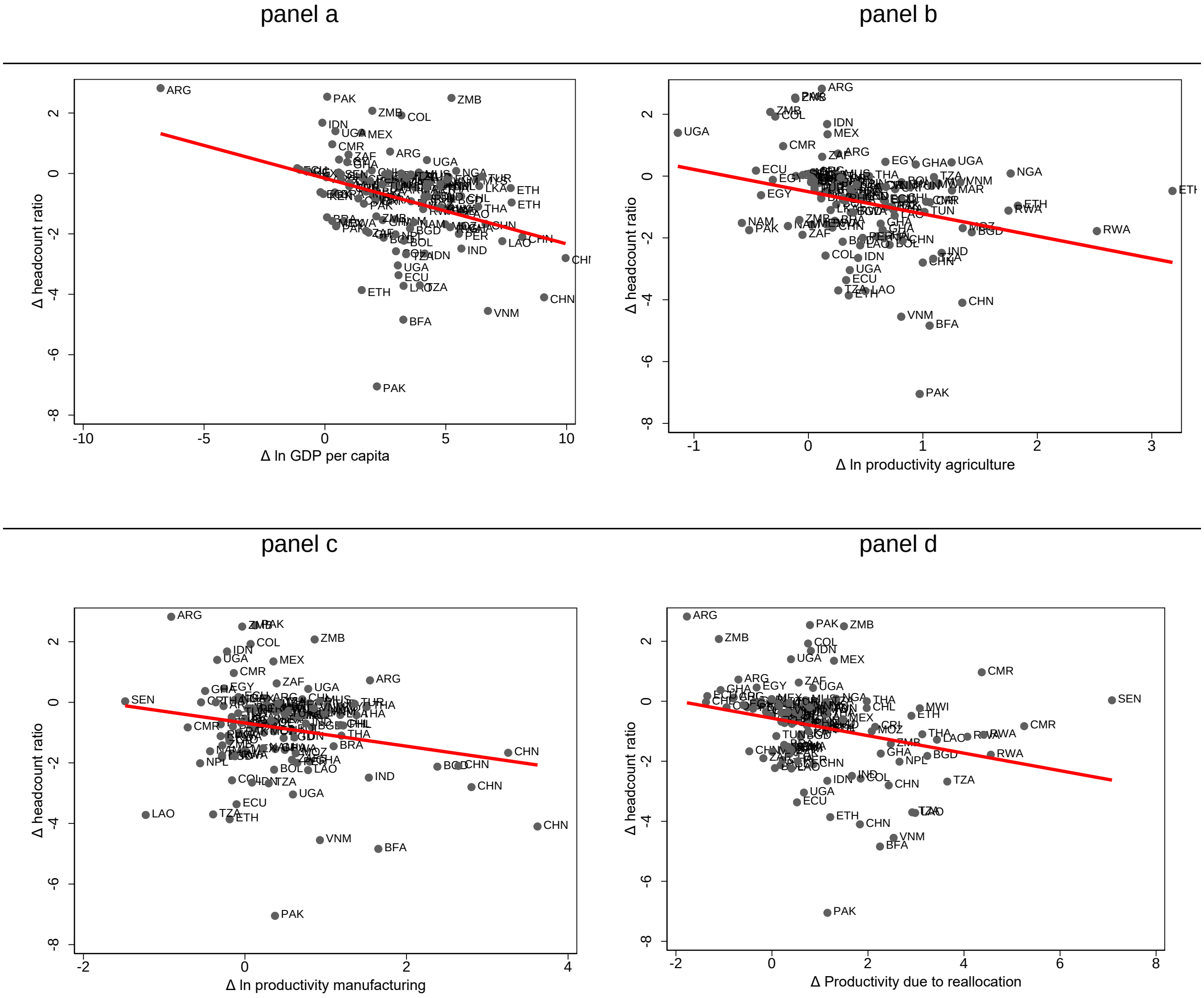
Appendix Table A3 presents descriptive statistics for the dependent and independent variables. The statistics refer to the 119 poverty spells across 42 developing countries for which we have data.

On average, the $1.90-a-day headcount ratio fell by 0.84 percentage points annually during the spells considered.[14] Hence, on average, we observe a reduction in poverty. This average, however, conceals wide variation between individual countries. For example, in Burkina Faso, the headcount ratio fell by 4.84 percentage points annually between 1998 and 2003; and in Viet Nam, by an average annual 4.55 percentage points between 2002 and 2006. For some country spells, on the other hand, the headcount ratio increased. For example, between 1998 and 2002, Argentina experienced an economic crisis during which its $1.90 headcount ratio increased on average annually by 2.83 percentage points.

Figure 3 provides scatter plots and linear fits between our key dependent variable (changes in the $1.90 headcount ratio) and the main independent variables for each of the 119 poverty spells. The change in poverty is related to the change in GDP per capita (panel a), agricultural productivity (panel b), manufacturing productivity (panel c), and productivity due to the reallocation of workers across sectors (panel d). The downward sloping linear fits indicate that each independent variable relates to poverty reduction. This relation is more formally tested in the next subsection.

[14] On average, the $3.20 and $5.50 a day headcount ratios and the poverty gap ratio also fell.

Figure 3: Correlation between poverty reduction, growth, and structural transformation



Note: average annual percentage point change in the \$1.90-a-day headcount ratio is related to the average annual percentage change in: GDP per capita (panel a), agricultural productivity (panel b), manufacturing productivity (panel c), and productivity due to the reallocation of workers across sectors (panel d) during each poverty spell (n=119). The solid red line is the linear fit. The slope of the linear fit is -0.22, -0.72, -0.38, and -0.29 in panels a–d, respectively. The slope coefficients are significant at the 1% level, except for panel c, where the coefficient is significant at the 5% level.

Source: authors' calculations.

6.2 Main regression results

Table 3 provides baseline regression results. The dependent variable is the average annual change in the \$1.90 a day headcount ratio.[15] To start, column 1 considers dummies for poverty spells in SSA and developing Asia. This helps explore whether poverty reduction in these regions is different from the excluded category, namely developing countries in Latin America and MENA. The coefficients for both dummies are significant and negative. It suggests that in our data set, poverty falls more rapidly in SSA and developing Asia compared with other developing countries.

[15] We consider poverty spells with a minimum duration of four years. As a result, we typically have one or only a few observations per country. Therefore, we do not control for country-fixed effects in the regressions, but we do cluster standard errors by country.

Further, the size of the coefficients suggests that poverty reduction proceeds at a faster pace in developing Asia than in SSA.

Table 3: Baseline regressions

	(1)	(2)	(3)	(4)
Δ ln GDP per capita		-0.176***	-0.179***	
		(-3.29)	(-3.69)	
Δ ln Aggregate labour productivity				-0.196***
				(-4.08)
Δ ln Labour force participation				-0.0615
				(-0.45)
Δ Gini coefficient			0.627***	0.635***
			(2.94)	(3.04)
Dummy SSA	-0.523*	-0.387	-0.522*	-0.433*
	(-1.72)	(-1.40)	(-2.00)	(-1.71)
Dummy developing Asia	-1.029***	-0.633**	-0.787**	-0.701**
	(-3.53)	(-2.20)	(-2.43)	(-2.21)
Constant	-0.336***	0.0710	0.173	0.152
	(-6.59)	(0.56)	(1.47)	(1.21)
Observations	*119*	*119*	*119*	*119*
$\overline{R^2}$	0.068	0.131	0.184	0.186

Note: dependent variable is the average annual percentage point change in the $1.90-a-day headcount ratio during the poverty spell (for poverty spells with a minimum duration of 4 years). GDP per capita, aggregate labour productivity (GDP per worker), and labour force participation are measured in average annual percentage changes. Δ Gini coefficient is the average annual absolute change in the Gini coefficient. Robust t-statistics in parentheses. Standard errors are clustered by country. Bottom row reports the adjusted R-squared. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Source: authors' calculations.

Column 2 includes the growth rate of GDP per capita. This model is similar to equation (1) in Benfica and Henderson (2021), except that we have added region dummies. Since changes in poverty are regressed on the growth rate of income per capita, the estimated coefficient can be interpreted as a semi-elasticity (Klasen and Misselhorn 2008). The results suggest that growth has a significant poverty-reducing effect. A 1 per cent increase in GDP per capita is related to a 0.18 percentage point reduction in poverty on average. This semi-elasticity is close to the -0.26 reported by Benfica and Henderson (2021).[16]

In column 3, we include income inequality, measured using the Gini coefficient, to account for the effect of changes in the income distribution on poverty. The semi-elasticity remains largely unchanged from column 2 and is significant at the 1 per cent level. The added variable, income inequality, has a positive coefficient of 0.63, and is significant at the 1 per cent level. This suggests that poverty is aggravated if inequality rises, which could imply that any poverty-reducing effects from growth can be outweighed by rising income inequality. A more unequal income distribution would then impede growth to benefit the entire population, defying the poverty-reducing effect of rising GDP per capita.

[16] If we exclude region dummies, the coefficient is -0.22, which is even closer to the -0.26 found by Benfica and Henderson (2021).

In column 4, we split growth into changes in labour productivity and changes in labour force participation (using equation 2). The poverty-reducing effect of labour productivity is significant and slightly more pronounced than GDP per capita. That is, the semi-elasticity of productivity is -0.20 compared with a semi-elasticity of GDP per capita of -0.18. Changes in labour force participation relate to poverty reduction, but the relation is not significant. The coefficient and significance for the relation between poverty and inequality remains. The model's explanatory power increases as we incorporate more control variables, which is reflected in the higher adjusted R^2, although a substantial fraction of poverty reduction remains unexplained.[17]

In columns 1 and 2 of Table 4, we have the two components of growth as before, namely labour productivity growth, and changes in the labour force participation rate. But the former is now split into a within-industry productivity component and a component that measures the contribution to growth from the reallocation of workers across sectors (using equation 4). The difference between columns 1 and 2 is that we include interaction terms between region dummies and structural change in column 2, to study whether the relation between structural change and poverty differs across regions. In columns 3 and 4, within-sector productivity growth is split into the contribution of each sector, such as agriculture, manufacturing, and business and finance services. Recall that we implement equation 4 using data for 11 sectors. For ease of exposition, we aggregate within-sector productivity growth for each sector i into seven broad sectors before running the regressions.[18]

In the regressions, the impact of the income distribution is positive and significant at the 1 per cent level. While the region dummy for SSA is negative, it is not significant in any of the models, indicating no significant difference between SSA and other developing countries in terms of poverty reduction. On the other hand, developing Asia shows a faster reduction, but significant only in columns 1 and 3, at the 5 per cent level.

Looking at the variables of interest, we note that labour productivity growth within industries is related to poverty reduction. The coefficient is significant in columns 1 and 2 and the semi-elasticity is around -0.17. The coefficient for structural change is also significant and negative, indicating that structural change relates to poverty alleviation. It suggests that workers moving to more productive sectors help lower poverty, whereby workers moving to higher wage sectors become better off and the average income of those that remain in the sector rises as well. The findings suggest that a 1 per cent higher worker reallocation relates to a 0.4 percentage point drop in poverty.

Finally, consider the interaction between structural change and region dummies. The coefficient for this interaction term is positive for SSA, suggesting that the impact of structural change on poverty is lower than in other developing countries. In developing Asia, the coefficient is negative, suggesting a relatively faster poverty reduction related to structural change. Although the coefficients for the interaction terms are insignificant, the F-statistics reported in the bottom rows of Table 4 suggest that the combined impact of the interaction and the main effect is significant.

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[17] There is a debate in the literature on the empirical identification of the income–poverty elasticity (Bourguignon 2003). In this debate, the elasticity originates from log–log relations, where an identity links poverty to mean income and change in the distribution of income. This paper does not relate to that debate. It examines the sign and significance of the semi-elasticity between production growth and percentage point changes in poverty.

[18] We also ran regressions using within-sector productivity growth for each of the 11 sectors distinguished. We did this in order to check the sign of the coefficients, to ensure that aggregation to broad sectors is adequate.

Table 4: Regression results, accounting for changes in the sectoral structure

	(1)	(2)	(3)	(4)
Δ ln Productivity within sectors	-0.173***	-0.164***		
	(-3.31)	(-3.33)		
Productivity growth within:				
Agriculture (agr)			-0.448	-0.440
			(-1.45)	(-1.45)
Manufacturing (man)			-0.382**	-0.439**
			(-2.19)	(-2.54)
Other industry (min & pu)			-0.0186	0.00327
			(-0.11)	(0.02)
Construction (con)			-0.469	-0.429
			(-0.93)	(-0.94)
Trade and transport services (mser)			0.364*	0.396*
			(1.85)	(1.89)
Business and finance services (bfser)			-0.305	-0.223
			(-1.49)	(-1.07)
Government and other services (nmser)			-0.239	-0.285
			(-1.09)	(-1.31)
Reallocation effects:				
Δ ln Productivity due to reallocation	-0.379***	-0.424***	-0.295**	-0.263
	(-3.98)	(-2.95)	(-2.24)	(-1.35)
Δ ln Productivity due to reallocation * Dummy SSA		0.142		0.0866
		(0.72)		(0.49)
Δ ln Productivity due to reallocation * Dummy developing Asia		-0.223		-0.375
		(-0.79)		(-1.26)
Other variables:				
Δ ln Labour force participation	-0.0250	-0.0197	-0.0978	-0.116
	(-0.19)	(-0.15)	(-0.70)	(-0.80)
Δ Gini coefficient	0.653***	0.637***	0.741***	0.727***
	(3.11)	(2.93)	(3.41)	(3.25)
Dummy SSA	-0.142	-0.310	-0.307	-0.527
	(-0.48)	(-0.88)	(-0.96)	(-1.42)
Dummy developing Asia	-0.546*	-0.233	-0.591*	-0.158
	(-1.81)	(-0.64)	(-1.75)	(-0.38)
Constant	0.0917	0.0817	0.231	0.248
	(0.66)	(0.62)	(1.29)	(1.47)
Observations	*119*	*119*	*119*	*119*
Test reallocation effect developing Asia is zero (F-value)		7.99***		5.65**
Test reallocation effect sub-Saharan Africa is zero (F-value)		4.94**		1.63
$\overline{R^2}$	0.210	0.210	0.228	0.236

Note: dependent variable is the average annual percentage point change in the $1.90-a-day headcount ratio during the poverty spell (for poverty spells with a minimum duration of 4 years). GDP per capita, aggregate labour productivity (GDP per worker), and labour force participation are measured in average annual percentage changes. Δ Gini coefficient is the average annual absolute change in the Gini coefficient. Robust t-statistics in parentheses. Standard errors are clustered by country. Bottom row reports the adjusted R-squared. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Source: authors' calculations.

Columns 3 and 4 split within-sector productivity growth into the individual contribution of sectors. Only two sectors show a statistically significant relation to poverty reduction. These are manufacturing and distributive trade and transport services. Productivity growth in the other sectors, including agriculture, relates to poverty reduction but the coefficient estimates are insignificant. This aligns with Benfica and Henderson (2021), who find that the non-agricultural sector significantly relates to poverty reduction. Our more detailed sector estimates elucidate the role of manufacturing. Benfica and Henderson (2021) also find an insignificant effect for agriculture, which appears to contrast to literature that emphasizes the importance of agricultural development for poverty reduction in developing countries (Berardi and Marzo 2017; Dorosh and Thurlow 2018; Ligon and Sadoulet 2018; Ravallion and Datt 1996). Note that, although the coefficient for agriculture is insignificant, the attribution exercise in Section 7 suggests that agricultural productivity growth accounts for a major share of poverty reduction in developing Asia and SSA due to its relative size in the economy.[19]

The relation between poverty and structural change remains significant in column 3, although the coefficient size is smaller. Column 4 includes the interaction terms again and now the structural change coefficient becomes insignificant, although the sign and size of the coefficient are similar to column 3. The F-statistics reported in the bottom rows suggest that in developing Asia the combined impact of the interaction and the main effect is significant.

6.3 Extensions and robustness analysis

This subsection relates the sectoral composition of output growth to alternative poverty measures. We consider more moderate poverty headcount ratios and poverty gap ratios. Furthermore, we examine sensitivity of the results to poverty spells with a duration of at least 5 and of at least 6 years.

Table 5 presents regression results using the $3.20 and $5.50 a day headcount ratios as dependent variables. The results suggest that structural change and productivity growth within sectors significantly relate to poverty reduction for these more 'moderate' absolute poverty lines. This suggests that structural change and within-sector productivity growth relate to poverty reduction whatever the poverty line considered, although reallocation appears less strongly related to poverty reduction among the better-off poor in developing Asia.

The semi-elasticity for productivity growth within sectors is higher for the $3.20 and $5.50 than for the $1.90 headcount ratio. That is, the semi-elasticity is -0.25 for the $3.20 headcount ratio (see column 1) and -0.27 for the $5.50 headcount ratio (column 4), compared with -.17 for the $1.90 headcount ratio (cf. column 1 of Table 4).

This stronger poverty-reducing effect from within-sector productivity growth might be due to the better-off poor living in urban areas. Columns 3 and 6 indicate that for agriculture, the semi-elasticity reduces in size as more moderate poverty lines are considered. That is, agriculture appears relatively more strongly related to reducing poverty among the poorest of the poor, who are more likely to live in rural areas (Christiaensen et al. 2011), although the coefficient estimate is still insignificant.

Indeed, for productivity growth within sectors, several different results are observed compared with regressions using the $1.90 headcount ratio. For construction, the semi-elasticity increases to -0.99 for the $5.50 headcount ratio and is significant at the 10 per cent level. Productivity growth within business and finance services significantly relates to poverty reduction and the elasticity

[19] If we include observations where there are issues of comparability in the headcount poverty ratio between the initial and final years of the poverty spell, we do observe a significant negative relation between productivity growth in agriculture and poverty reduction.

increases as higher poverty lines are considered. This suggests that for the better-off poor, productivity growth in business and finance activities relates to poverty reduction and this might disproportionally occur in urban areas.

Table 5: Regressions using $3.20 and $5.50 a day headcount ratios

	$3.20 headcount ratio			$5.50 headcount ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ln Productivity within sectors	-0.250***	-0.231***		-0.267***	-0.236***	
	(-5.24)	(-5.34)		(-4.53)	(-5.09)	
Productivity growth within:						
Agriculture (agr)			-0.335			-0.220
			(-1.65)			(-1.17)
Manufacturing (man)			-0.387***			-0.366**
			(-3.09)			(-2.61)
Other industry (min & pu)			-0.195			-0.172
			(-1.06)			(-1.10)
Construction (con)			-0.644			-0.986*
			(-1.64)			(-1.96)
Trade and transport services (mser)			0.176			0.0876
			(1.01)			(0.49)
Business and finance services (bfser)			-0.461**			-0.530**
			(-2.14)			(-2.24)
Government and other services (nmser)			-0.215			-0.122
			(-0.88)			(-0.45)
Reallocation effects:						
Δ ln Productivity due to reallocation	-0.360***	-0.669***	-0.354***	-0.341***	-0.962***	-0.374**
	(-3.34)	(-3.48)	(-2.76)	(-2.83)	(-3.76)	(-2.59)
Δ ln Productivity due to reallocation * SSA		0.416*			0.744**	
		(1.82)			(2.69)	
Δ ln Productivity due to reallocation * developing Asia		0.288			0.877***	
		(1.07)			(3.20)	
Other variables:						
Δ ln Labour force participation	-0.306**	-0.267**	-0.327**	-0.366***	-0.286**	-0.334**
	(-2.42)	(-2.08)	(-2.47)	(-2.71)	(-2.29)	(-2.52)
Δ Gini coefficient	0.708***	0.669***	0.780***	0.874***	0.806***	0.942***
	(3.87)	(3.79)	(4.53)	(3.81)	(3.70)	(4.53)
Dummy SSA	0.0860	-0.133	0.0352	0.602*	0.314	0.673*
	(0.25)	(-0.32)	(0.09)	(1.82)	(0.88)	(1.92)
Dummy developing Asia	-0.733***	-0.784**	-0.719***	-0.0697	-0.531*	-0.0287
	(-2.99)	(-2.32)	(-2.85)	(-0.23)	(-1.78)	(-0.09)
Constant	0.0722	0.0771	0.120	-0.204	-0.182	-0.254
	(0.30)	(0.38)	(0.49)	(-0.60)	(-0.69)	(-0.82)
Observations	*119*	*119*	*119*	*119*	*119*	*119*
Test reallocation effect SSA zero (F-value)		3.53*			3.08*	
Test realloc. effect dev. Asia zero (F-value)		4.47**			0.72	
$\overline{R^2}$	0.337	0.343	0.338	0.351	0.406	0.356

Note: dependent variable is the average annual percentage point change in the $3.20-a-day headcount ratio in columns (1)–(3) and $5.50-a-day headcount ratio in columns (4)–(6). GDP per capita, aggregate labour productivity, productivity within sectors, productivity growth due to reallocation, and labour force participation are measured in average annual percentage changes. Gini coefficient is the average annual change in inequality. Robust t-statistics in parentheses. Standard errors are clustered by country. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Source: authors' calculations.

For moderate poverty lines, productivity growth within manufacturing continues to significantly relate to lower poverty. The semi-elasticity is similar regardless of the poverty line considered. Finally, changes in the labour force participation rate now also significantly relate to poverty reduction. This suggests that workforce participation relates to a reduction in poverty among the better-off poor.

In Appendix Table A4 we use the poverty gap ratio as dependent variable. Our key coefficients of interest are qualitatively similar. That is, growth in GDP per worker significantly relates to a reduction in the poverty gap. Productivity growth within sectors relates to a reduction in poverty, except for the $1.90-a-day poverty gap ratio. Structural change significantly relates to lower poverty regardless of the poverty gap ratio that is used. Also here, the semi-elasticity for productivity growth within sectors is higher for the $3.20 and $5.50 poverty gap ratios than for the $1.90 poverty gap ratio.

In Table 6, the dependent variable is again the $1.90-a-day poverty headcount ratio. Poverty spells with a duration of at least 5 years (columns 1 and 2) and of at least 6 years (columns 3 and 4) are considered. The use of longer poverty spells may further mitigate potential business cycle effects. It does, however, reduce the number of observations and therefore the degrees of freedom in the regressions. The number of observations falls from 119 to 91 for poverty spells of at least 5 years, and to 71 for poverty spells of at least 6 years.

Encouragingly, an increase in GDP per worker still significantly relates to poverty reduction. The coefficient is comparable with the baseline regression (cf. column 4 in Table 3). Also, structural change and within-sector productivity growth are significantly related to poverty reduction. As before, worsening inequality relates to higher poverty. This effect is significant for poverty spells of at least 5 years. For spells that last at least 6 years, the coefficient for inequality appears less precisely measured.

Table 6: Regressions semi-elasticity poverty reduction, other minimum duration poverty spells

	Poverty spells of at least 5 years		**Poverty spells of at least 6 years**	
	(1)	**(2)**	**(3)**	**(4)**
Δ ln Aggregate labour productivity	-0.169***		-0.216***	
	(-3.12)		(-3.29)	
Δ ln Productivity within sectors		-0.155**		-0.207***
		(-2.56)		(-3.01)
Δ ln Productivity due to reallocation		-0.285***		-0.285***
		(-3.43)		(-3.42)
Δ ln Labour force participation	0.147	0.142	-0.155	-0.153
	(0.94)	(0.91)	(-0.94)	(-0.92)
Δ Gini coefficient	0.600**	0.635**	0.236	0.251
	(2.22)	(2.45)	(1.05)	(1.09)
Constant	-0.428*	-0.321	-0.128	-0.0764
	(-1.91)	(-1.34)	(-0.56)	(-0.32)
Observations	*91*	*91*	*71*	*71*
$\overline{R^2}$	0.129	0.146	0.139	0.138

Note: dependent variable is the average annual percentage point change in the $1.90-a-day headcount ratio, where the poverty spell is at least 5 years in columns (1)–(2) and at least 6 years in columns (3)–(4). Aggregate labour productivity, productivity within sectors, productivity growth due to reallocation, and labour force participation are measured in average annual percentage changes. Gini coefficient is the average annual change in inequality. Robust t-statistics in parentheses. Standard errors are clustered by country. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Source: authors' calculations.

7 Industrialization and poverty reduction: attribution exercise

This section aims to examine how sectoral trends relate to poverty reduction in SSA, developing Asia, and other developing countries. As in Benfica and Henderson (2021), we use the regression results to explore the contribution of changes in the sectoral structure of the economy and other variables for poverty reduction. We use the region-specific results in column 4 of Table 4. The coefficient estimates and the data are used to predict the change in poverty due to a given source. For each poverty spell and each variable, we first calculate the variables' predicted reduction in poverty. Next, we calculate the unweighted average annual contribution for each variable in each poverty spell, by region.

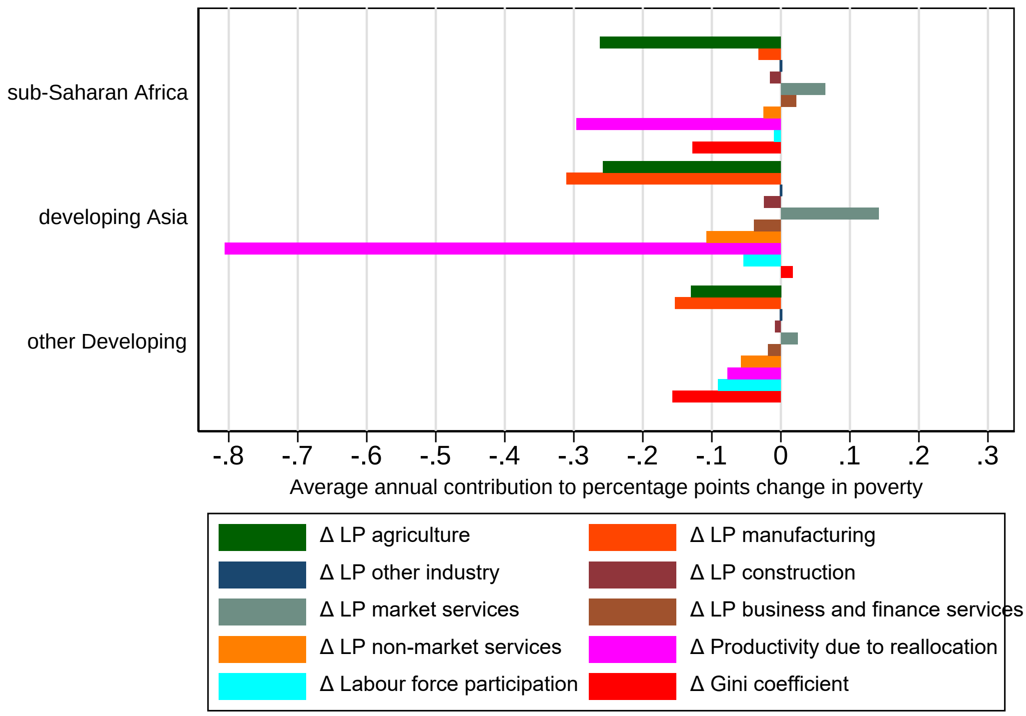
Note that this attribution exercise examines relations, so no causal interpretation should be made. In addition, we attribute poverty reduction to various variables, including sectoral patterns of growth. However, these sectoral patterns are themselves driven by policies and other underlying determinants that are outside the scope of this paper. Also, some coefficient estimates, such as those for productivity growth in agriculture and market services, are insignificant, so one should not draw firm conclusions about their attribution to poverty reduction.

Figure 4 presents the results from the attribution exercise. Clearly, the contribution of variables to poverty reduction differs across regions. In SSA, poverty reduction appears mainly accounted for by productivity growth within agriculture, the reallocation of workers across sectors, and a reduction in income inequality. This confirms the importance of agriculture for poverty reduction (Christiaensen et al. 2011), which relates to the sector's large employment share (see Table 1). The findings also point at the role of structural change—the movement of workers to higher-productivity, higher-wage sectors—in poverty reduction. Finally, in the descriptive analysis we found that productivity growth in SSA manufacturing was weak, and this is reflected in the limited contribution of manufacturing productivity growth to poverty reduction.

The latter observation contrasts with developing Asia, where manufacturing productivity growth did contribute to poverty reduction. In addition, the contribution of structural change to poverty reduction is more pronounced. Agricultural productivity growth in developing Asia also contributed to poverty reduction, just as in SSA.

In other developing countries, productivity growth in agriculture and manufacturing and improvements in the income distribution appear to be the main factors accounting for poverty reduction.

Figure 4: Contribution to poverty reduction



Note: predicted effects are calculated using the data in combination with the coefficient estimates shown in column 4 of Table 4. For each poverty spell and each variable, we first calculate the predicted relation to poverty reduction; then we take the unweighted average contribution for each variable in each poverty spell by region.

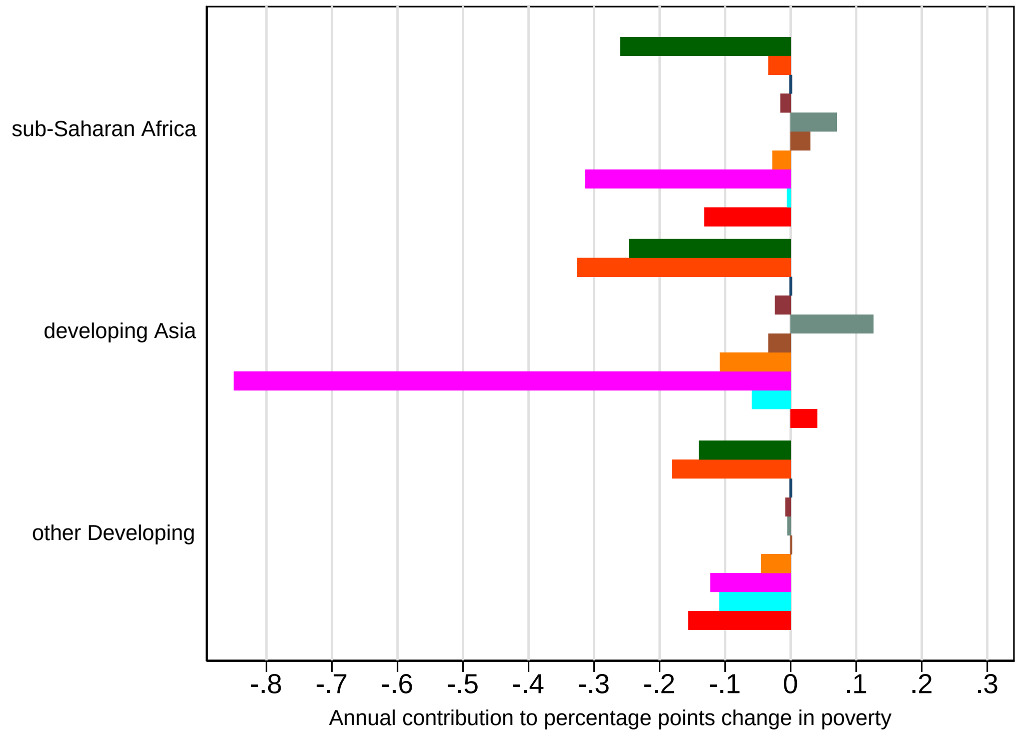
Source: authors' calculations.

Figure 5 presents results from the attribution exercise for two time periods. Poverty spells are split between those that started before 2010 (panel a) and those that started after 2009 (panel b). This split is used to explore whether industrialization in developing countries in the 2010s is related to poverty reduction. It also allows us to explore whether the contribution of structural change to poverty reduction is different across different time periods.

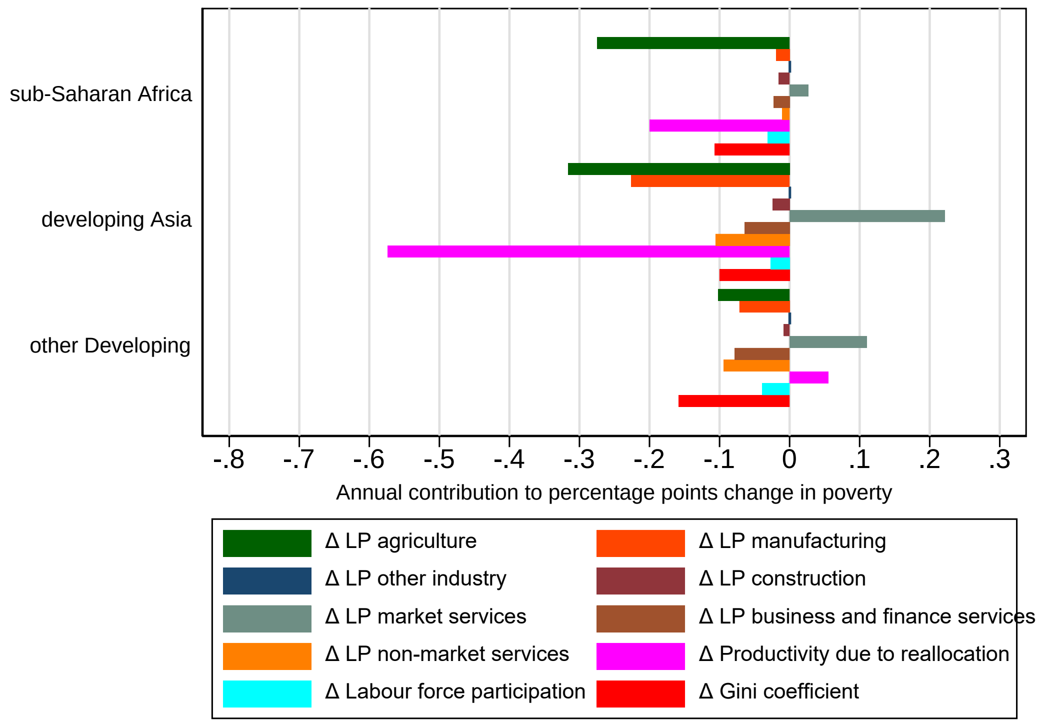
The results suggest that in SSA the same factors—agricultural productivity growth, structural change, and a more equal income distribution—account for the majority of poverty reduction in both periods. However, the contribution of structural change to poverty reduction appears larger in the pre-2010 period. This might relate to a reduction in sectoral productivity gaps and therefore to smaller wage differentials between sectors. Yet, the differences are small and subject to uncertainty, so it is difficult to draw firm conclusions.

Figure 5: Contribution to poverty reduction, by period

(a) Poverty spells starting before 2010



(b) Poverty spells starting after 2009



Note: predicted effects are calculated using the data in combination with the coefficient estimates shown in column 4 of Table 4 for poverty spells that started before 2010 (panel a) and after 2009 (panel b). For each poverty spell and each variable, we first calculate the predicted relation to poverty reduction. Then we take the unweighted average contribution for each variable in each poverty spell by region.

Source: authors' calculations.

In developing Asia, we also observe the same factors as before—agricultural and manufacturing productivity growth, and structural change—accounting for the majority of poverty reduction in both periods. Here, the attribution exercise suggests that the contribution of structural change and manufacturing productivity growth to poverty reduction is larger in the pre-2010 period. This might relate to a reduction in sectoral productivity gaps, and a slowdown in manufacturing productivity growth in recent years.

Overall, the attribution exercise suggests that manufacturing productivity growth is related to poverty reduction in developing Asia, but hardly so in SSA. This regional difference originates from weak productivity growth in manufacturing in SSA. Structural change does account for poverty reduction in both developing Asia and SSA, although the contribution is more pronounced in the former.

8 Concluding remarks

This paper proposed an empirical framework that relates poverty reduction to the various channels of production growth. We considered the semi-elasticity between percentage point changes in the headcount poverty ratio and productivity growth within sectors and the reallocation of workers across sectors. The GGDC/UNU-WIDER Economic Transformation Database was used to measure the contribution of productivity growth within sectors and structural change to growth for 42 developing countries from 1990 to 2018.

We document evidence for industrialization in developing Asian and sub-Saharan African countries in recent years. Developing Asia has a relatively larger manufacturing presence than SSA. The contribution of structural change—the movement of workers across sectors—to aggregate labour productivity growth was found comparable in SSA and developing Asia. However, productivity growth within sectors is substantially lower and even negative in several sectors in SSA, including manufacturing, trade, and transport services. The expansion of manufacturing jobs in SSA countries appears not to be accompanied by productivity improvements, perhaps because workers are absorbed in low-productivity activities within the sector (Diao et al. 2021). Regression results suggest that aggregate labour productivity growth in developing countries is related to poverty reduction, with a semi-elasticity of around -0.20, which is close to previous estimates (Benfica and Henderson 2021). Results also indicate that poverty reduction is significantly related to structural change in the economy and productivity growth within manufacturing sector. An attribution exercise then suggested that structural change and agricultural productivity growth account for a major share of poverty reduction in developing Asia and SSA. Productivity growth in manufacturing accounts for poverty reduction in developing Asia, but not in SSA, as the region displays weak productivity growth in manufacturing.

These results may suggest the importance of focusing on productivity growth in African manufacturing, which, along with the continued movement of workers to the sector, could help alleviate poverty. Changes in poverty are related to what happens to mean income and the distribution of income, so one could focus on either growth or redistribution as a poverty-reduction strategy. Since there is a limit to redistributing income, one could argue that effective long-run policies to reduce poverty should rely on ensuring that growth is sustained (Bourguignon 2003). This necessitates an ongoing process whereby workers relocate from traditional to modern activities, and the creation of productive jobs.

We are careful not to attribute a causal interpretation to our regression results. The analysis was conducted in differences, which helps control for country-specific structural factors that affect both poverty and the sectoral composition of growth. However, poverty reduction may influence growth from the demand and supply side, for instance due to the accumulation of human capital, thus making the analysis in differences also subject to endogeneity issues.

Further, productivity growth within sectors is unlikely to be independent from structural change. For example, productivity growth in agriculture may occur because workers are moving out of agriculture into more productive sectors. We observed an insignificant effect for productivity growth in agriculture and a significant effect for structural change, so the nature of our analysis was such that structural change was attributed to poverty reduction. Clearly, the sectoral composition of growth arises from linkages to other sectors, government interventions, and fundamental causes of growth. Since the analysis is not based on a structural model and does not account for long-run effects, it does not provide ground for sector-specific policies. Such issues need further consideration in future work.

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Appendix

Table A1: Content of the GGDC/UNU-WIDER Economic Transformation Database

Countries in:		
Sub-Saharan Africa (18)	**Developing Asia(14)**	**Other developing countries (13)**
Botswana	Bangladesh	Argentina
Burkina Faso	Cambodia	Bolivia
Cameroon	China	Brazil
Ghana	India	Chile
Ethiopia	Indonesia	Colombia
Lesotho	Lao P.D.R.	Costa Rica
Kenya	Malaysia	Ecuador
Malawi	Myanmar	Mexico
Mauritius	Nepal	Peru
Mozambique	Pakistan	Egypt
Namibia	Philippines	Morocco
Nigeria	Sri Lanka	Tunisia
Rwanda	Thailand	Turkey
Senegal	Viet Nam	
South Africa		
Tanzania		
Uganda		
Zambia		
Sector coverage:		
Agriculture (International Standard Industrial Classification, revision 4 code A), mining (B), manufacturing (C), public utilities (D+E), construction (F), trade (G+I), transport (H), business services (J+M+N), finance (K), real estate (L), government services (O+P+Q), and other services (R+S+T+U). Together these 12 sectors cover the total economy.		
Time period: 1990–2018		
Variables:		
Gross value added at constant (2015) prices (national currency in millions)		
Gross value added at current prices (national currency in millions)		
Persons employed (in thousands)		

Source: adapted from information provided at https://www.wider.unu.edu/project/etd-economic-transformation-database.

Table A2: Overview of countries (by region) and poverty spells

Region	Number of spells	Number of countries	Average spell length	Minimum spell length	Maximum spell length
Sub-Saharan Africa	36	17	5.78	4	10
Developing Asia	33	12	5.15	4	11
Other developing countries	50	13	4.3	4	7
Total	119	42	4.98	4	11

Note: see main text for a description of the data. Statistics refer to country-specific poverty spells with a minimum of four years between the initial and final year.

Source: World Bank's PovcalNet.

Table A3: Descriptive statistics

Variable	Average	Standard deviation	Minimum	Median	Maximum
Headcount ratio ($1.90)	-0.84	1.47	-7.05	-0.60	2.83
Δ ln GDP per capita	3.15	2.38	-6.80	3.15	9.96
Δ ln Aggregate labour productivity	2.62	2.41	-5.81	2.42	10.06
Δ ln Productivity within sectors	1.67	2.43	-7.20	1.81	7.63
Δ ln Productivity due to reallocation	0.96	1.42	-1.77	0.60	7.08
Δ ln Labour force participation	0.52	1.05	-2.61	0.55	2.90
Δ Gini coefficient	-0.12	0.58	-3.08	-0.08	1.93
Changes in Gini coefficient in:					
Developing Asia	*0.004*	*0.47*	*-1.46*	*0.10*	*0.84*
Other developing	*-0.25*	*0.64*	*-3.08*	*-0.23*	*1.23*
sub-Saharan Africa	*-0.04*	*0.57*	*-1.53*	*0.04*	*1.93*
Δ ln Productivity Agriculture (agr)	0.47	0.60	-1.14	0.36	3.18
Δ ln Productivity Manufacturing (man)	0.42	0.78	-1.48	0.36	3.62
Δ ln Productivity Other industry (min & pu)	0.16	0.75	-2.90	0.18	2.96
Δ ln Productivity Construction (con)	0.08	0.29	-0.79	0.07	1.13
Δ ln Productivity Trade and transport services (mser)	0.24	0.72	-1.80	0.30	2.28
Δ ln Productivity Business and finance services (bfser)	0.07	0.70	-3.89	0.11	1.61
Δ ln Productivity Government and other services (nmser)	0.22	0.57	-1.70	0.16	2.02
Δ headcount ratio ($3.20)	-1.11	1.47	-5.02	-1.08	4.45
Δ headcount ratio ($5.50)	-1.11	1.45	-5.22	-0.80	5.50
Δ poverty gap ratio ($1.90)	-0.26	0.70	-3.86	-0.06	1.78
Δ poverty gap ratio ($3.20)	-0.41	0.84	-4.08	-0.23	2.32
Δ poverty gap ratio ($5.50)	-0.50	0.81	-3.18	-0.40	1.93

Note: number of observations for each variable is 119. Statistics refer to country-specific poverty spells with a minimum duration of 4 years. Average annual percentage point change in the $1.90-, $3.20-, and $5.50-a-day poverty headcount ratio and poverty gap ratio are shown. GDP per capita, aggregate labour productivity, productivity within sectors, productivity growth due to reallocation, and labour force participation are measured in average annual percentage changes. Δ Gini coefficient is the average annual absolute change in the Gini coefficient.

Source: World Bank's PovcalNet, GGDC/UNU-WIDER ETD, and UNU-WIDER World Income Inequality Database (UNU-WIDER 2021).

Table A4: Regressions using poverty gap ratios

	Poverty gap ratio, $1.90 a day		Poverty gap ratio, $3.20 a day		Poverty gap ratio, $5.50 a day	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Δ ln Aggregate labour productivity	-0.0491*		-0.0885**		-0.120***	
	(-1.83)		(-2.65)		(-3.44)	
Δ ln Productivity within sectors		-0.0385		-0.0767**		-0.110***
		(-1.31)		(-2.17)		(-3.13)
Δ ln Productivity due to reallocation		-0.134**		-0.183***		-0.203***
		(-2.41)		(-2.86)		(-3.06)
Δ ln Labour force participation	0.101	0.118	0.0317	0.0506	-0.0623	-0.0459
	(1.23)	(1.47)	(0.37)	(0.60)	(-0.81)	(-0.59)
Δ Gini coefficient	0.165	0.173	0.158	0.167	0.186	0.194*
	(1.21)	(1.26)	(1.14)	(1.21)	(1.61)	(1.70)
Dummy SSA	-0.367**	-0.231	-0.412**	-0.262	-0.318	-0.187
	(-2.06)	(-1.50)	(-2.08)	(-1.21)	(-1.50)	(-0.72)
Dummy developing Asia	-0.145	-0.0726	-0.324	-0.243	-0.362*	-0.292
	(-0.84)	(-0.44)	(-1.41)	(-1.09)	(-1.79)	(-1.42)
Constant	-0.0102	-0.0154	0.0401	0.0342	0.0660	0.0609
	(-0.15)	(-0.23)	(0.42)	(0.39)	(0.46)	(0.46)
Observations	*119*	*119*	*119*	*119*	*119*	*119*
$\overline{R^2}$	0.108	0.130	0.124	0.142	0.184	0.197

Note: dependent variable is the average annual percentage point change in the $1.90-, $3.20-, and $5.50-a-day poverty gap ratio in columns (1)–(2), (3)–(4), and (5)–(6), respectively. Aggregate labour productivity (GDP per worker), productivity within sectors, productivity growth due to reallocation, and labour force participation are measured in average annual percentage changes. Δ Gini coefficient is the average annual absolute change in the Gini coefficient. Robust t-statistics in parentheses. Standard errors are clustered by country. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Source: authors' calculations.