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Productivity Convergence Across Sectors:

Are Poor Countries Catching Up with Rich Countries?

Robert Inklaar

(University of Groningen)

Ryan Marapin

(University of Groningen)

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Robert Inklaar

University of Groningen

Ryan Marapin

University of Groningen

Abstract

Existing convergence literature typically uses productivity estimates which are either comparable across countries or over time, but not both, while the study of productivity convergence requires estimates which are comparable across both dimensions. Furthermore, studies analysing developed and developing countries have been unable to trace the sectoral sources of convergence, as this requires a comprehensive accounting of all the sectors that contribute to economy-wide productivity differences. Inklaar and Diewert (2016) provide a method for computing productivity estimates which are suited for analysing convergence at the sectoral level and its contribution to aggregate (non-)convergence. We apply this method to a sample of developed and developing countries and compute agriculture relative prices, as a first step in calculating a complete set of sector relative prices and productivity estimates. Moreover, using sector-level data for 57 developed and developing countries over the period 1990-2018, we find labour productivity convergence at the economy-wide level and in specific sectors of the economy, particularly services. Convergence is strongest in business services, while divergence is found in manufacturing. Furthermore, labour reallocation across sectors plays an important role in driving convergence.

Keywords: Productivity, Index numbers, Purchasing power parities, Convergence

JEL classification: C43, D24, E01, E31, O47

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1 Introduction

The question whether and how fast poor countries are catching up to rich countries has received a great deal of attention in the convergence literature over the past few decades (Barro, 2015; Barro & Sala-i-Martin, 1992). The neoclassical growth model predicts that, given the same preferences and access to identical technologies, poorer countries will grow faster than richer countries. As a result, cross-country per capita incomes will converge to a common level in the long run, regardless of initial conditions (Solow, 1956). However, evidence of low-income countries catching up to high-income countries is scarce. A recent paper by Johnson and Papageorgiou (2020) surveys the convergence literature from the past five decades and concludes that, as a group, poorer countries have not been able to narrow the income gap between them and the richer countries. Whatever evidence of convergence that exists is conditional, i.e., convergence that depends on specific country conditions, such as policies and institutions. Interestingly, recent work by Patel et al. (2021) finds that since the 2000s, developing countries have experienced relatively higher growth rates compared to developed countries, irrespective of initial conditions. However, this has not translated into a decline of the dispersion of per capita incomes across countries, where this convergence in per capita income *levels* is also commonly referred to as σ-convergence.[1]

Moreover, while no evidence is obtained for productivity convergence at the economy-wide level, Rodrik (2013) finds that in manufacturing, productivity levels between developing and developed countries have converged, irrespective of country conditions. Correspondingly, Rodrik (2013) argues that due to manufacturing's growth prospects, policymakers should focus on promoting industrialization in developing countries, as this can significantly help poor countries catch up to rich countries. This then raises an important question, whether manufacturing is "special" in that it exhibits convergence properties, or whether other sectors share these properties as well.

In this article, we tackle this question and analyse productivity convergence across sectors, to uncover whether convergence is a sector-specific phenomenon limited to manufacturing, or whether this is also present in other sectors in the economy. Importantly, current literature has

[1] A negative relation between initial income and subsequent income growth (commonly referred to as β-convergence in the literature, see e.g., Rodrik (2013)) is a necessary but not sufficient condition for σ-convergence. When random shocks to growth are relatively large compared to the initial distribution of incomes, β-convergence may fail to translate into σ-convergence (Young et al., 2008).

not been able to provide a clear answer to this question, as a result of measurement issues relating to the lack of sector-specific prices to compare output across countries and over time (Inklaar & Diewert, 2016). That is, the analysis of convergence requires productivity estimates which are comparable both across countries and over time, while studies typically use productivity estimates which are comparable either across countries or over time, but not both (e.g., Kinfemichael and Morshed, 2019; Rodrik, 2013). Furthermore, studies that investigate convergence in a sample of developed and developing countries typically focus on a specific sector, whereas a complete accounting of the contributions of the different sectors to economy-wide productivity is required to be able to reconcile sector-level evidence with economy-wide trends in productivity differences. This makes it difficult to quantify the relative roles of the different sectors in driving convergence, and uncover whether a sector is indeed "special".

Inklaar and Diewert (2016) provide a method for computing productivity estimates which are comparable across countries and over time, and thus are suited for analysing convergence at the sectoral level and its contribution to (the absence of) aggregate convergence. This approach builds upon the productivity measurement technique pioneered by Diewert and Morrison (1986). We implement this method for a set of developing and developed countries and compute relative prices for the agriculture sector, which we use to compare agricultural output across countries and over time. Due to data limitations, computing relative prices for the other sectors in the economy is beyond the scope of this study; we aim to do this in a future extension of this paper. Nevertheless, we present some descriptive statistics on agriculture prices and discuss how they are computed. This is to illustrate how the productivity measurement approach by Inklaar and Diewert (2016) is applied in practice, as we will rely on this method to compute sectoral productivity estimates which are suitable for analysing convergence.

Furthermore, another limitation of current convergence studies is that they typically attribute the sources of economy-wide convergence to within-sector productivity dynamics, ignoring the role of structural change herein. Yet, the reallocation of resources from low productivity to high productivity activities in the economy is an important source of aggregate productivity growth in developing countries (McMillan et al., 2014). Correspondingly, we examine structural change's role in accounting for convergence, by assessing convergence in two scenarios: one based on actual sector productivity and employment levels, and another one where sector employment shares remain constant throughout the years, i.e., no labour reallocation across the economy has occurred. This allows us to determine whether the transfer of labour resources between sectors has had an effect on the convergence process.

We compute labour productivity estimates and analyse productivity convergence for a sample of 57 countries over the period 1990-2018, covering 20 sectors in the economy. Three key findings emerge. First, while there has been convergence in labour productivity at the aggregate level, large sectoral heterogeneities exist with respect to the presence and pace of convergence. Whereas rapid convergence seems to have occurred in services, e.g., business and financial services, manufacturing and mining have experienced (modest) divergence. Second, the convergence findings are sensitive to the conversion factor used to measure output. Namely, depending on the currency conversion rate used, convergence can be slower or faster, and in some cases is even reversed. This already hints at the fact that failing to use sector prices to measure sectoral output may provide inaccurate productivity estimates, in turn leading to potentially wrong conclusions regarding the convergence process. Finally, structural change has played a key role in driving convergence. Specifically, it has accelerated the pace at which aggregate productivity levels in poor countries have come closer to those in rich countries.

Overall, the contribution of this paper is twofold. First, this paper is, to our knowledge, the first to study the sectoral sources of convergence for a sample of developed and developing countries. This study provides a comprehensive accounting of all sectors that contribute to economy-wide productivity, which allows us to examine which sectors are contributing to convergence, and which ones are hampering it. Second, this paper assesses the role of structural change in driving convergence. Indeed, while the literature recognizes structural change as an important growth driver for developing countries, its role in explaining convergence has been largely ignored. Thus, this paper examines both the role of within-sector productivity convergence as well as the reallocation of labour resources across sectors in jointly contributing to aggregate productivity convergence.

Hence, the implications of this study are that it informs the literature on the circumstances in which convergence occurs and why convergence may fail to aggregate up, advancing academic understanding on what explains cross-country income differences. From a policy perspective, these findings can provide valuable information to policymakers on feasible growth strategies for poor countries, particularly which sectors to strengthen. Whereas industrial policy continues to be prioritized by several policymakers, the evidence of convergence in services suggests that alternative promising development strategies may be available for poor countries. Importantly, this research thus informs the broader debate on growth policies that can help developing countries reduce the income gap with rich countries. Finally, this study provides some preliminary evidence on the importance of theory-based productivity measurement: crude measurements that fail to use appropriate prices to measure output are not suitable for assessing convergence, and may lead to incorrect conclusions and inadequate policy design. Instead, theory-based measurements, while data-intensive, provide a reliable set of productivity estimates, and ultimately lead to more robust conclusions and improved policymaking.

2 Methodology & Data

2.1 Measurement of productivity across space and over time

The analysis of productivity convergence requires input, output, and productivity estimates which are simultaneously comparable across countries and over time. Inklaar and Diewert (2016) put forward an index-number approach for productivity measurement that allows one to construct such estimates, implemented more recently in Freeman et al. (2021). This method, hereinafter referred to as the Inklaar/Diewert method, builds upon the productivity measurement technique pioneered by Diewert and Morrison (1986), a technique that is grounded in production theory. A brief explanation of this method is presented below, followed by a description of the data that is required for implementing this method.

Suppose that a production unit i in country k produces a vector of M net outputs, $y \equiv [y_1, \dots, y_M]$. The production of these net outputs requires a nonnegative N-dimensional vector of primary inputs, $x \equiv [x_1, \dots, x_N]$. A production unit i can produce net outputs conditional upon the technology set S^i, where $i = 1, .. I$. Furthermore, each technology set S^i is a closed convex cone, which implies that the production function of production unit i features constant returns to scale. In line with Diewert and Morrison (1986), consider the following *value added function* or *GDP function* for each strictly positive price vector $p \equiv [p_1, \dots, p_M] \gg 0_M$ and each strictly positive primary input vector $x \gg 0_N$:

$$g^i(p, x) \equiv \max_y \left\{ \sum_{m=1}^{M} p_m y_m : (y, x) \epsilon S^i \right\}; \quad i, = 1, \dots, I. \tag{1}$$

Under the assumption that the value added function has a translog functional form and features constant returns to scale, the Törnqvist–Theil output price and input quantity index can be used to compute input, output, and productivity estimates which are comparable across space and over time. To construct these estimates, we require data on the ‘values’ (in local currency) of net outputs and primary inputs, and a 'prices' (in local currency) dataset corresponding to these net outputs and primary inputs. We define the *value* of net output *m* in country k in year *t* as v_{ktm} for $m = 1, \ldots, M$. Thus, there are *M* net outputs considered, and $v_{ktm} > 0$ implies that net output *m* reflects a commodity that is produced, while $v_{ktm} < 0$ indicates that net output *m* is an intermediate input. The *price or purchasing power parity (PPP)* corresponding to the net output *m* produced in country *k* in year *t* is $p_{ktm} > 0$, where these prices are based on the same unit of measurement for the same commodity between countries. PPPs measure the number of commodities that a single unit of a country's currency can purchase in another country, and are used to compute the *implicit quantity* y_{ktm} of net output *m* for country *k* in year *t* as $y_{ktm} \equiv v_{ktm}/p_{ktm}$ for $m = 1, \ldots, M;\ k = 1, \ldots, K$ and $t = 1, \ldots, T$.

Moreover, the primary input *n* in country *k* in year *t* has a value $V_{ktn} > 0$, and the corresponding *price* or *PPP* is $w_{ktn} > 0$ for $n = 1, \ldots, N$. Again, these prices are based on the same unit of measurement for the same input between countries. In a similar fashion, the *implicit quantity* x_{ktm} of primary input *n* for country *k* and time period *t* is estimated as $x_{ktm} \equiv V_{ktn}/w_{ktn}$ for $n = 1, \ldots, N;\ k = 1, \ldots, K$ and $t = 1, \ldots, T$. Having defined our inputs and outputs, we next sum over the net outputs to estimate *total value added* v_{kt} for each country *k* in year *t*:

$$v_{kt} \equiv \sum_{m=1}^{M} v_{ktm}\ ; k = 1, \ldots, K; t = 1, \ldots, T. \tag{2}$$

Afterwards, we compute productivity estimates Γ_{kt} for country *k* in year *t* by dividing the aggregate output level Y_{kt} by the aggregate input level X_{kt}:

$$\begin{aligned} &\Gamma_{kt} = Y_{kt}/X_{kt}; \\ &\quad k = 1, \ldots, K; t = 1, \ldots, T. \end{aligned} \tag{3}$$

Where Y_{kt} reflects our set of *real* value added estimates, calculated by dividing nominal value added by the *value added* PPP deflator for country *k* at time *t*:

$$Y_{kt} \equiv [v_{kt}/P_{kt}]; \quad k = 1, \ldots, K; t = 1, \ldots, T. \tag{4}$$

Moreover, the value added PPP deflator P_{kt} and the aggregate quantity of primary input X_{kt} are a Törnqvist-Theil output price and input quantity index, respectively, and we compute these indexes by following the steps described in Inklaar and Diewert (2016). This provides us with a set of input, output, and productivity estimates which are comparable across countries and over time.

Ideally, our measure of productivity used to assess convergence is total factor productivity (TFP). Yet, data limitations cause that computing TFP estimates is beyond the scope of this paper. Thus, this paper focuses instead on assessing labour productivity convergence, where labour productivity is computed as value added per worker. Nevertheless, TFP remains the preferred measure, and TFP estimates will be included in an extension of this paper. Another data scarcity issue we encounter in this paper relates to the measurement of sectoral prices, which are needed to make sectoral output comparable across countries and over time. Particularly, the deflation of sector value added is based on a double deflation procedure. That is, the construction of value added PPPs requires data on sectoral gross output and intermediate input PPPs (Inklaar & Timmer, 2013; Jorgenson et al., 1987), which at the time of writing was unavailable. Hence, due to data limitations with respect to sector prices, we stick to the available measures commonly used in the literature to convert value added estimates at national prices into a common currency, namely GDP PPPs and market exchange rates.

Also here, our aim is to construct sector value added PPPs, which we will do in a future extension of this paper. This is important, because relying on aggregate PPPs or exchange rates to measure sectoral real output, i.e. output that is comparable across countries and over time, may lead to inaccurate productivity estimates (Inklaar & Timmer, 2009; Van Biesebroeck, 2009). Nevertheless, we have so far managed to construct a set of agriculture PPP estimates for a set of 71 countries over the period 1991-2017, based on the Inklaar/Diewert method. Section 2.4 presents some more details behind the construction of the agriculture prices as well as some descriptive statistics, to provide the reader with an idea of how the Inklaar/Diewert method is applied in practice. Overall, the following sectoral labour productivity measures are used in this paper:

$$\Gamma_{jkt}^{XR} = \frac{v_{jkt}/XR_{kt}}{X_{jkt}} \tag{5}$$

$$\Gamma_{jkt}^{GDP} = \frac{v_{jkt}/P_{kt}}{X_{jkt}} \tag{6}$$

$$\Gamma_{jkt}^{IND} = \frac{v_{jkt}/P_{jkt}}{X_{jkt}} \tag{7}$$

Where Γ_{jkt}^{XR}, Γ_{jkt}^{GDP}, and Γ_{jkt}^{IND} reflect labour productivity estimates Γ_{jkt} for sector *j* in country *k* at time *t*, where real output is measured using different currency conversion rates. Specifically, these estimates are computed by deflating sector value added v_{jkt}, using market exchange rates (XR), GDP PPPs, and sector PPPs (only available for agriculture in this paper), respectively.

2.2 Measuring productivity convergence and sectoral contributions to aggregate productivity differences

For our main measure of productivity convergence, we analyse the dispersion of cross-country sectoral labour productivity levels around the cross-country mean sectoral labour productivity in each year, more commonly known as σ-convergence.[2] To measure σ-convergence, we use the productivity dispersion measure below, see e.g., Young et al. (2008):

$$\sigma_{jt} \equiv \left[\frac{1}{T}\sum_{k=1}^{K} ln\left({}^{\Gamma_{jkt}}\!/_{\Gamma_{jt}}\right)^2\right]^{\frac{1}{2}}; \quad t = 1, \ldots, T. \tag{8}$$

where Γ_{jt} reflects the cross-sectional average of labour productivity Γ_{jkt} for sector *j* in year *t.* A decreasing value for σ_{jt} indicates convergence, as the dispersion in productivity levels has decreased. Generally, a value of zero for σ_{jt} would indicate complete convergence, as each Γ_{jkt} would equal Γ_{jt} in year *t.* In other words, all country productivity levels would be the same for the respective sector.

Having examined sectoral convergence, we then undertake a regression-based sectoral decomposition of cross-country productivity differences to assess the role of the different sectors in explaining aggregate productivity differences between countries, and how this has evolved over time. That is, total economy labour productivity for country *k* at time *t* can be written as a weighted sum of labour productivities of *j* sectors:

[2] Another commonly used measure of convergence in the literature is β-convergence (e.g., Rodrik, 2013). However, the Inklaar/Diewert method uses a simultaneous weighting of countries and years to construct a panel dataset of productivity estimates which are comparable both across countries and over time. Meanwhile, β-convergence involves regressing productivity growth rates on initial productivity levels, and thus makes a distinction between within-country growth and relative income levels. Thus, it is less sensible to estimate such *growth-initial level* regressions using a panel of country-year weighted productivity estimates, particularly since we are most interested in analysing the dispersion of cross-country sectoral labour productivity levels.

$$\Gamma_{kt} = \sum_{j=1}^{n} \frac{Y_{jkt}}{X_{jkt}} \cdot \frac{X_{jkt}}{X_{kt}} \equiv \sum_{j=1}^{n} \Gamma_{jkt} \cdot s_{jkt} \tag{9}$$

Where Y_{jkt} and X_{jkt} reflect value added and employment in sectors *j=1,2,3…n* in country *k* for year *t*, $X_{kt} = \sum_{j=1}^{n} X_{jkt}$ reflects total employment in country *k* in year *t*, and similarly Γ_{jkt} and s_{jkt} reflect sector *j*'s labour productivity and employment share, respectively. Next, we regress the weighted labour productivity term of each sector *j* in country *k* at time *t* on total economy labour productivity in country *k* at time *t*:

$$\Gamma_{jkt} \cdot s_{jkt} = \beta_{jt}\Gamma_{kt} + \varepsilon_{jkt} \tag{10}$$

As the sum of the weighted sector productivities equals total economy productivity, this then implies that the sum of the dependent variables equals the independent variable, therefore providing us with a set of *β*-coefficients that sum up to one. Correspondingly, each coefficient can be interpreted as the contribution of each industry in explaining labour productivity differences across countries.

Furthermore, an important aim of this study is to assess the role of structural change in influencing the economy-wide convergence process, and we do this as follows. We compute two sets of σ-coefficients: one based on the actual total economy labour productivity level $\Gamma_{kt} \equiv \sum_{j=1}^{n} \Gamma_{jkt} \cdot s_{jkt}$, defined as σ_t, and another one based on a counterfactual productivity level $\tilde{\Gamma}_{kt} \equiv \sum_{j=1}^{n} \Gamma_{jkt} \cdot s_{jk\tau}$, which is defined as $\tilde{\sigma}_t$. Here, the counterfactual productivity levels are based on initial period τ employment shares that remain constant over time. In other words, actual sectoral labour productivities are weighted by initial employment shares, implying that there has been no labour reallocation between sectors over the period 1990-2018. Hence, changes in the dispersion of economy-wide cross-country counterfactual productivity levels reflect the role of within-sector productivity dynamics. In contrast, changes in productivity dispersion based on actual productivity levels also include the 'productivity effect' of reallocating resources (employment) across sectors. By comparing the trends of these two estimates of productivity dispersion σ_{jt} and $\tilde{\sigma}_{jt}$ over time, this sheds light on whether structural change has had any effect on driving (or hampering) aggregate convergence. For example, if σ_{jt} declines at a faster rate over time compared to $\tilde{\sigma}_{jt}$, then this implies that structural change has accelerated aggregate convergence in labour productivity.

2.3 Data

In this paper, we study labour productivity convergence in 20 sectors for a sample of 57 countries over the period 1990-2018. Country and period coverage is based on data availability and the list of countries for which agriculture PPPs are also available, in order to have a consistent dataset. Table A1 (see Appendix) lists the countries and sectors included in the study. As mentioned above, while the measurement of productivity requires data on the values and prices of net outputs and primary inputs, due to data limitations we focus in this study on measuring labour productivity using GDP PPPs and market exchange rates. Thus, for the construction of our labour productivity estimates, we require data on: i) nominal sectoral value added in local currency, ii) deflators (exchange rates, GDP PPPs, and agriculture PPPs), and iii) employment (persons engaged).[3]

Ideally, the measure for labour inputs would be the number of hours worked, as the average number of hours worked per adult differs tremendously across countries. Specifically, average hours worked per adult are found to be significantly higher in poor countries compared to rich countries (Bick et al., 2018). This implies that labour productivity differences between developing and developed countries are understated when employment is measured using persons engaged rather than hours worked. However, as this data is not available, the number of persons engaged is used instead as our employment measure. For data on sectoral value added and employment, we rely on two key databases. Data for developing countries is retrieved from the Economic Transformation Database (ETD) (de Vries et al., 2021), and data for developed countries from the OECD Structural Analysis (STAN) database. The ETD contains data for 12 sectors (ISIC Rev. 4) for 51 developing countries over the period 1990-2018, while the STAN database contains detailed industry level (ISIC Rev. 4) data for OECD member countries from 1970 onwards.

Moreover, for a future extension of their work, Kruse et al. (2021) have compiled a dataset for 17 2-digit manufacturing industries (ISIC Rev. 4), building upon the work of Pahl and Timmer (2019). The primary source of the manufacturing industries data is the United Nations Industrial Development Organization (UNIDO) Industrial and Statistics Database (UNIDO, 2020). We consult this dataset to compute value added and employment shares for the manufacturing industries, covering 40 countries. The original number of manufacturing

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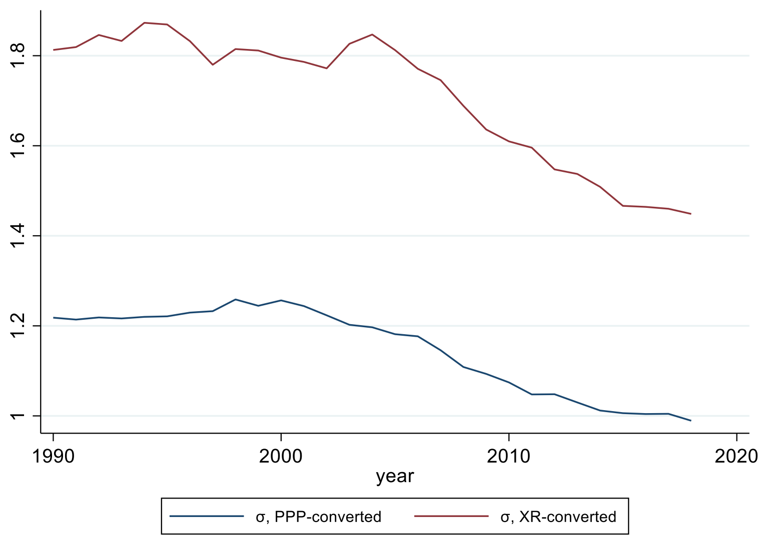
[3] As labour is the only input considered, we do not require data on prices and values but simply use employment data.

industries in the dataset is 17, so we aggregate over industries to arrive at the desired final number of manufacturing industries (9) for our study. These shares are then multiplied with manufacturing value added data from the ETD to obtain scaled estimates such that total manufacturing estimates are consistent with the national accounts data. Furthermore, data on GDP PPPs and market exchange rates is obtained from the Penn World Tables (PWT) (Feenstra et al., 2015). The construction of the agriculture PPPs is discussed in the next section. Given this data, we can construct the labour productivity estimates that are used to assess convergence. See Table A2 in the Appendix for an overview of the variables used in this study.

Before turning to the discussion on how the agriculture PPPs were computed, it is fruitful to present some descriptive statistics that can be helpful when discussing the results later on. Figure 1 presents σ-coefficients for the total economy, based on estimating Equation (8). It shows that at the economy-wide level, there has been a steady decline in the dispersion of cross-country labour productivity after 2000, which implies that there has been a convergence in total economy labour productivity over the period 1990-2018. Moreover, the convergence process starts earlier when using the PPP-converted labour productivity estimates rather than the exchange rate-converted estimates. Turning to the employment data, Figure 2 presents sector employment shares for two country groups: 1) Low income & lower middle income countries, and 2) Higher middle income countries & high income countries. Employment shares have been averaged over each decade.

Figure 1. σ-coefficients for the total economy, 1990-2018.

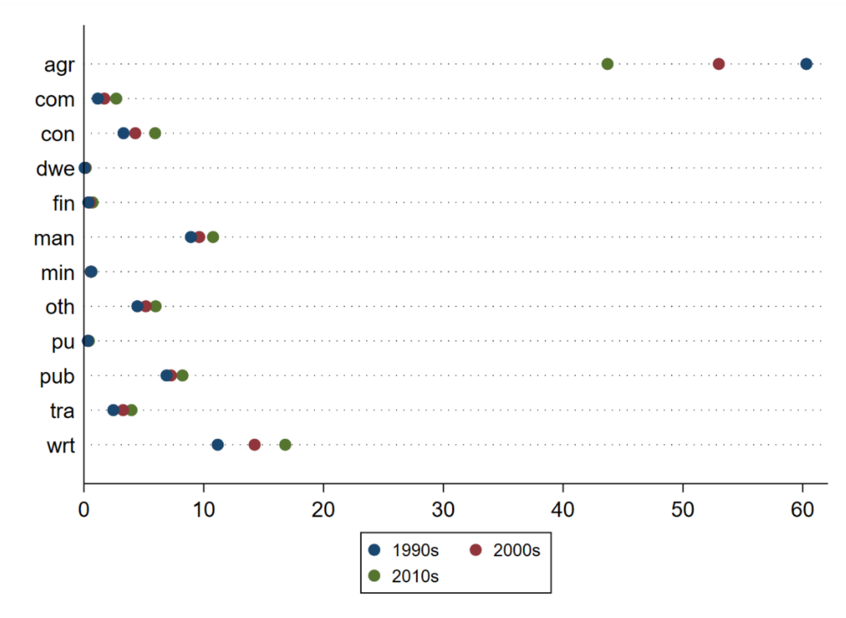


Note: Figure shows the dispersion of economy-wide labour productivity σ_t, based on estimating Equation (8).

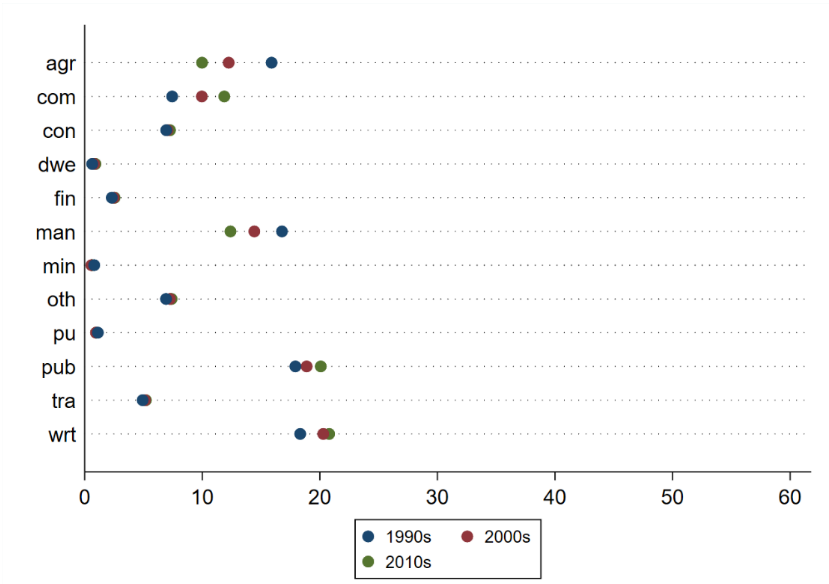
The purpose of this figure is to illustrate the difference in the structure of the economy between poor and rich countries, and how this has changed over time.

Figure 2. Evolution of the sector employment shares over the years.

Panel A: Low income & lower middle income countries



Panel B: Upper middle income & high income countries



Note: Sector employment shares are computed as averages over each decade, for each income group. Country income groups are based on the World Bank country income classification. Employment shares are presented for the following sectors: Agriculture (agr), Mining (min), Manufacturing (man), Utilities (pu), Construction (con), Trade services (wrt), Transport (tra), Business services (com), Financial services (fin), Real estate (dwe), Government services (pub), Other services (oth).

Two key findings stand out from the figure. First, over the past two decades, poorer countries on average seem not to have deindustrialized, but in fact the opposite. This is in line with the finding by Kruse et al. (2021) of employment industrialization in the developing world. Second, with respect to the poorer countries, the largest change in employment share over the past two decades has been for agriculture, a sector where labour productivity is relatively low compared to the rest of the economy (Restuccia et al., 2008). This illustrates how structural change could play a positive role in driving convergence, namely through the reallocation of employment from a low-productive sector (agriculture) to other, more productive sectors in the economy.

2.4 Agriculture PPPs

For the agricultural labour productivity estimates, we draw upon the agriculture PPPs that we have constructed to deflate agricultural value added, where the PPPs were computed as follows. We constructed a 'values' dataset for gross outputs, and a 'prices' dataset corresponding to these gross outputs. We computed gross output PPPs, as there was no data available on the intermediate inputs used in the agriculture sector, and thus we could not compute value added PPPs. We collected data on 151 agricultural products which cover crops and primary livestock, for 71 countries over the period 1991-2017. To compute the PPPs, we retrieved data on producer prices and gross output values from the FAOSTAT database from the Food and Agriculture Organization (FAO) of the United Nations (FAO, 2019).

Importantly, when using the Inklaar/Diewert method to compute the PPPs, we assume that the value added function from Equation (1) has a translog functional form and features constant returns to scale, and a corollary that follows from this is that this method requires a complete set of prices for each commodity and country. In our sample, not every commodity is produced in each country, which causes that there are goods with no producer prices in certain countries. We refer to these commodities as the *zero-production* cases. Moreover, there are several agricultural goods that are produced but for which no price data is reported by FAOSTAT, which we refer to as the *missing-price* cases. In order to obtain a complete set of prices, we impute prices for both cases in the following way.

To impute prices for commodities that are not produced, we follow Freeman et al. (2021) and identify a *Hicksian reservation price* (Hicks, 1940). The *Hicksian reservation price* reflects the price that is sufficiently high such that demand reaches zero. In this setting, we specifically define a *producer Hicksian reservation price,* which is the price where production of the agricultural commodity *m* in country *k* drops to zero. While computing a *reservation price* is formally possible, this entails estimating complicated econometric equations which is beyond the scope of this paper. Instead, we estimate this price based on a similar reasoning by Freeman et al. (2021). Consider the setting where each country *k* faces the choice of producing or importing an agricultural commodity *m*. Producing the good *m* costs C_m^k, while importing it costs W_m. If the production costs C_m^k are higher than the world (import) price W_m, then a country imports rather than produces that good. In contrast, if C_m^k is lower than W_m, then that good is produced domestically and sold at the domestic price p_m^k. In the limit, the good is not produced if a good's production costs equal the (world) import price, i.e., $C_m^k = W_m$. In this case, the good is instead imported and the *Hicksian reservation price* equals the (world) import price W_m. Correspondingly, the price for agricultural commodity *m* in country *k* is defined as follows:

$$\omega_m^k = \begin{cases} p_m^k & if\ W_m > C_m^k \\ W_m & if\ W_m \leq C_m^k \end{cases} \tag{11}$$

As production costs are not observed when a commodity is not produced, Equation (11) is depicted as $\omega_m^k = min(p_m^k, W_m)$. Having defined the *producer reservation price*, this ensures that all agricultural commodities in the sample have a strictly positive price[4]. Thus, for the *zero-production* cases, all prices are initially based on the country's import price. If this price is unavailable, the maximum global import price and cross-country average producer price in a year is implemented, respectively.

For the price imputations of the *missing-price* cases, we first use export prices and import prices, respectively, to approximate the producer price when this is missing. These prices are retrieved from FAOSTAT as well. When these prices are also unavailable for a country in a certain year, we rely on price deflators from previous or subsequent years to impute the price. Finally, for the remaining commodities that have missing prices, we use the cross-country average producer price in that year to approximate the price. Table 1 presents an overview of the role of each of these prices in approximating the commodity prices for the *zero-production* and *missing-price* cases.

[4] This requires the assumption that the commodity is traded internationally and has an import price, and this assumption indeed holds for our sample.

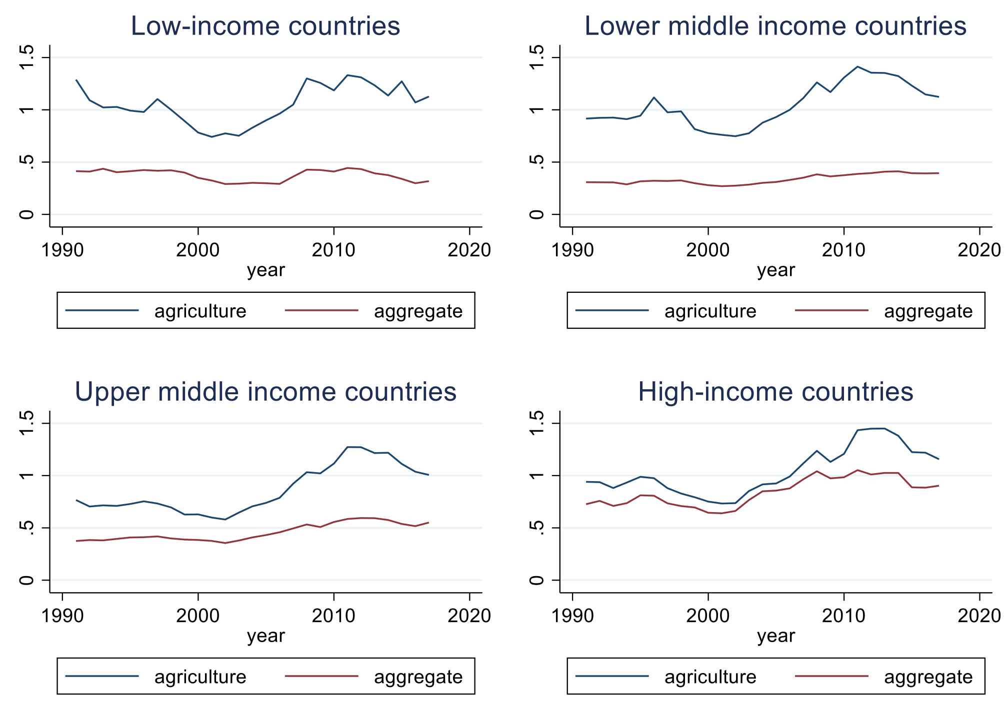
Table 1. Overview of the prices used in the agriculture PPP computation.

Variable used for price imputation	% of prices imputed using this variable	
	Missing-price cases	*Zero-production cases*
Producer price	91	0
Export price	3	0
Import price	1	39
Max global import price	0	30
Price deflator	2	0
Cross-country average producer price	3	31
Total	100	100
N (observations)	131,672	157,795
Total sample *N (observations)*		289,467

Next, we use these agriculture PPPs to highlight the importance of using sector-specific prices in measuring sectoral output. Figure 3 shows that agriculture prices are typically higher than economy-wide (aggregate) prices, and that these prices do not grow in tandem over time (high-income countries appear to be the exception here). That agriculture prices are typically higher than average economy-wide prices, is a finding shared by Hassan (2016) as well. Therefore, this serves as preliminary evidence that using GDP PPPs may not be appropriate for measuring real agricultural output levels.

Additionally, to gauge the reliability of the computed agriculture output PPPs based on the Inklaar/Diewert method, we compare these estimates with other PPPs computed in different studies. While data on GDP PPPs is quite abundant, very few studies have estimated PPPs for the agriculture sector. Fortunately, we are able to consult the studies by Inklaar and Timmer (2009, 2014) who have calculated sector PPPs for 1997 and 2005, respectively. While they analyse mostly developed countries, their data still serve as a useful check that the method used here is a valid one. For the 1997 estimates, the correlation between our estimates and that of Inklaar and Timmer (2009) is 0.998, whereas this is 0.978 for the 2005 estimates from Inklaar and Timmer (2014). This shows that the computed agriculture PPPs are in line with other constructed PPPs found in the literature, and provides some comfort with respect to its reliability.

Figure 3. The evolution of agriculture and aggregate relative prices over time.



Note: Relative prices are computed by dividing PPPs by the market exchange rate.

3 Results

Earlier above, we presented evidence of σ-convergence in labour productivity at the economy-wide level. In this section, we take a sectoral perspective to analyse convergence. Labour productivity is estimated using GDP PPPs to deflate nominal output, unless stated otherwise. Below, Table 2 provides σ-coefficients for the different sectors in the economy, based on estimating Equation (8). An important finding that follows from this table, is that there exists significant heterogeneity in the convergence process at the sectoral level. For example, while business and financial services have experienced significant convergence in labour productivity, the opposite has occurred in the *Textiles, wearing apparel and leather products* manufacturing industry, namely divergence. More generally, within manufacturing there seems to have been both converging and diverging processes occurring, ultimately leading to that there has been a slight divergence in productivity levels for total manufacturing. This is an interesting result, given that Rodrik (2013) finds that manufacturing productivity levels in developing countries have caught up to those of developed countries; more on this below.

Table 2. σ-coefficients for the different sectors.

Sector	1990	2018	Difference (%)
Agriculture	1.467	1.241	-15%
Mining	1.465	1.628	11%
Manufacturing	0.974	1.027	6%
Food products, beverages and tobacco products	0.983	0.857	-13%
Textiles, wearing apparel and leather products	0.994	1.325	33%
Wood, wood products, paper, paper products and printing	1.282	1.122	-13%
Petroleum, chemicals, rubber and plastic products	1.059	1.213	14%
Minerals, basic and fabricated metal	1.042	0.947	-9%
Electronic, optical and electrical products	1.167	1.431	23%
Machinery and equipment	1.222	1.371	12%
Transport equipment	1.298	1.371	6%
Furniture and other manufacturing	1.415	1.242	-12%
Utilities	0.944	0.864	-8%
Construction	0.906	0.885	-2%
Trade services	0.936	0.932	0%
Transport	0.885	0.899	2%
Business services	1.034	0.619	-40%
Financial services	0.985	0.679	-31%
Real estate	1.478	0.911	-38%
Government services	0.966	0.706	-27%
Other services	1.301	1.214	-7%

Note: Table shows the dispersion of sectoral labour productivity levels σ_{jt}, based on estimating Equation (8).

Additionally, agriculture, recognized in the literature as a sector with large cross-country labour productivity differences (Restuccia et al.,2008), has experienced convergence over the past two decades. However, the strongest convergence has been in the services sectors, namely business services. This finding is in line with the recent evidence of unconditional convergence in services industries by Kinfemichael and Morshed (2019), who argue that the increasing tradability of services activities has led to increased competition and technology adoption. In turn, this has strongly boosted productivity levels.

To assess how these results depend on the currency conversion factor used to deflate nominal value added, Table 3 shows the percentage change in the dispersion of cross-country sector labour productivity levels between 1990 and 2018. Two cases are compared: the case where labour productivity is estimated using GDP PPPs to measure real output, and market exchange rates (XRs). Additionally, for agriculture, labour productivity estimates are presented which are computed using agricultural PPPs. Table 3 makes clear that depending on the currency conversion rate used, different conclusions follow regarding the convergence process that a sector has experienced in the past two decades.

Table 3. σ-coefficients for the sectors, PPP-converted versus market exchange rate (XR)-converted productivity estimates.

%-change in σ-coefficients, 1990-2018				
Sector	Sector PPP	GDP PPP	XR	Difference in change GDP PPP vs XR
Agriculture	-15	-15	-19	4
Mining		11	-5	16
Manufacturing		6	-4	10
Food products, beverages and tobacco products		-13	-14	1
Textiles, wearing apparel and leather products		33	12	21
Wood, wood products, paper, paper products and printing		-13	-15	2
Petroleum, chemicals, rubber and plastic products		14	4	10
Minerals, basic and fabricated metal		-9	-13	4
Electronic, optical and electrical products		23	10	13
Machinery and equipment		12	-2	14
Transport equipment		6	0	6
Furniture and other manufacturing		-12	-14	2
Utilities		-8	-16	8
Construction		-2	-9	7
Trade services		0	-7	7
Transport		2	-8	10
Business services		-40	-27	-13
Financial services		-31	-24	-7
Real estate		-38	-26	-12
Government services		-27	-26	-1
Other services		-7	-12	5
Average change		-5	-10	5

Note: Table shows the dispersion of sectoral labour productivity levels σ_{jt}, based on estimating Equation (8). The data for Agriculture PPPs covers 49 countries of our sample over the period 1990- 2017, therefore the %-change in σ-coefficients for Agriculture in the Sector PPP column is based on a sample of 49 countries over the period 1991-2017. The rest of the Sector PPP column is empty, as no PPPs have yet been computed for the other sectors.

Most striking are the cases where the percentage change switches from sign, like in the case of mining and transport. Furthermore, whereas for trade and transport services convergence seems to be present when using exchange rates to measure output, convergence is slower for the business and financial services sectors. Reconciling this with the evidence of large differences in relative prices across services industries (Inklaar & Timmer, 2014) this suggests once again that failing to use sector prices to measure sectoral real output may provide inaccurate productivity estimates, and lead to wrong conclusions regarding convergence.

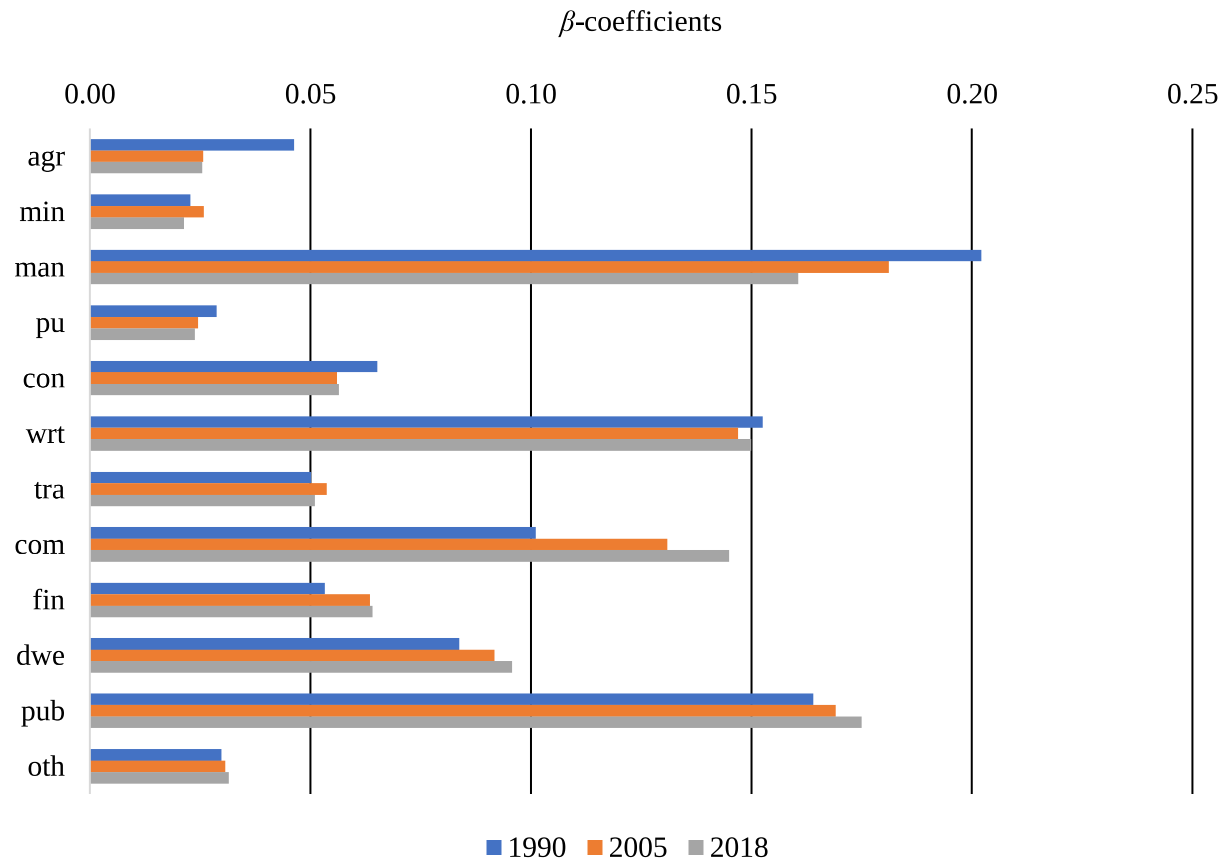
However, as GDP PPPs also are not the appropriate PPP conversion rates to measure sector real value added, an important upcoming exercise remains to see how these results hold when computing sector labour productivity estimates using sector-specific prices. In the case of agriculture, not much difference exists between the differently measured productivity estimates. Nevertheless, the overall sensitivity of the findings to the currency conversion rate used stresses the importance of using appropriate prices to measure real output.

Next, to obtain a better understanding of how sector labour productivity convergence relates to the aggregate economy, a fruitful analysis is to provide a comprehensive accounting of the sectoral contributions to aggregate productivity differences between countries. Correspondingly, we decompose total economy labour productivity into the contributions of weighted sector labour productivities (see Equation (9)). This way, it becomes clear what role the different sectors play in explaining cross-country aggregate productivity differences, and how this has evolved over time. Figure 4 below presents β-coefficient estimates obtained from a regression-based decomposition of cross-country productivity differences, i.e., based on estimating Equation (10). A decreasing β-coefficient implies that a particular sector, weighted by its employment share, plays a less important role in explaining aggregate productivity differences between countries. What Figure 4 then makes clear, is that the role of manufacturing in explaining productivity differences, while large, has steadily diminished over the years. Moreover, trade and government services appear to play an important role in explaining cross-country productivity differences, and this role has remained stable throughout the years. Finally, the business services sector has seen its role rise over the years.

Having analysed the sectoral sources of convergence and the sectoral contributions to aggregate productivity differences between countries, we examine how structural change has played a role in affecting aggregate productivity differences and convergence. As mentioned above, we do this by computing counterfactual labour productivity estimates, which is based on initial (1990) sector employment shares that remain constant throughout the years. This counterfactual labour productivity estimate essentially tells us what the total economy labour productivity would be had there been no labour reallocation across sectors in the economy.

Interestingly, when doing the regression-based decomposition of cross-country productivity differences using the counterfactual productivity levels, a rather different picture emerges.

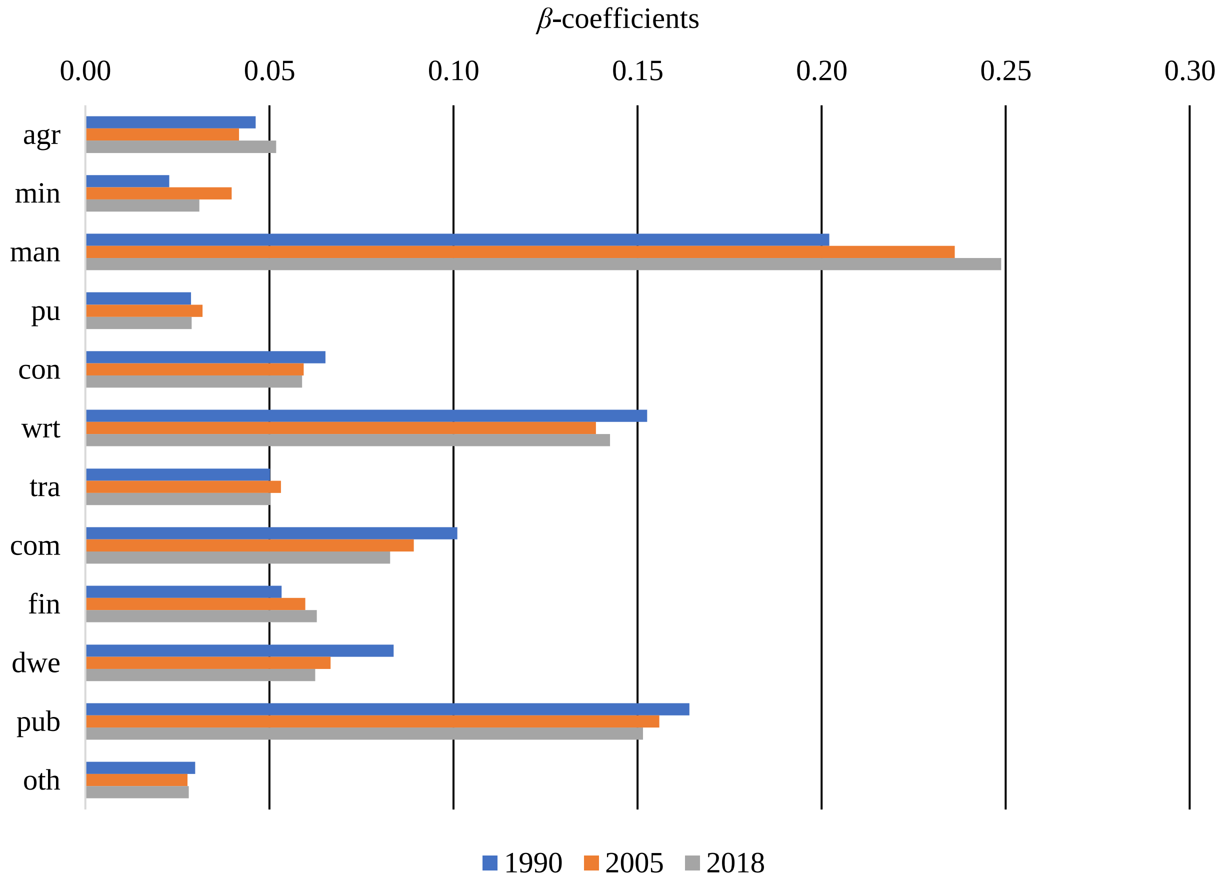
Figure 4. β-coefficients of regression-based decomposition of productivity differences.



Note: β-coefficients computed by estimating Equation (10), and are presented for the following sectors: Agriculture (agr), Mining (min), Manufacturing (man), Utilities (pu), Construction (con), Trade services (wrt), Transport (tra), Business services (com), Financial services (fin), Real estate (dwe), Government services (pub), Other services (oth). β-coefficients sum up to one in each year.

Now, manufacturing sees its role in explaining aggregate productivity differences grow steadily over the years (see Figure 5), practically the opposite of what Figure 4 reports. Moreover, agriculture's role has slightly increased. This highlights the role that structural change plays in accounting for aggregate cross-country productivity differences.

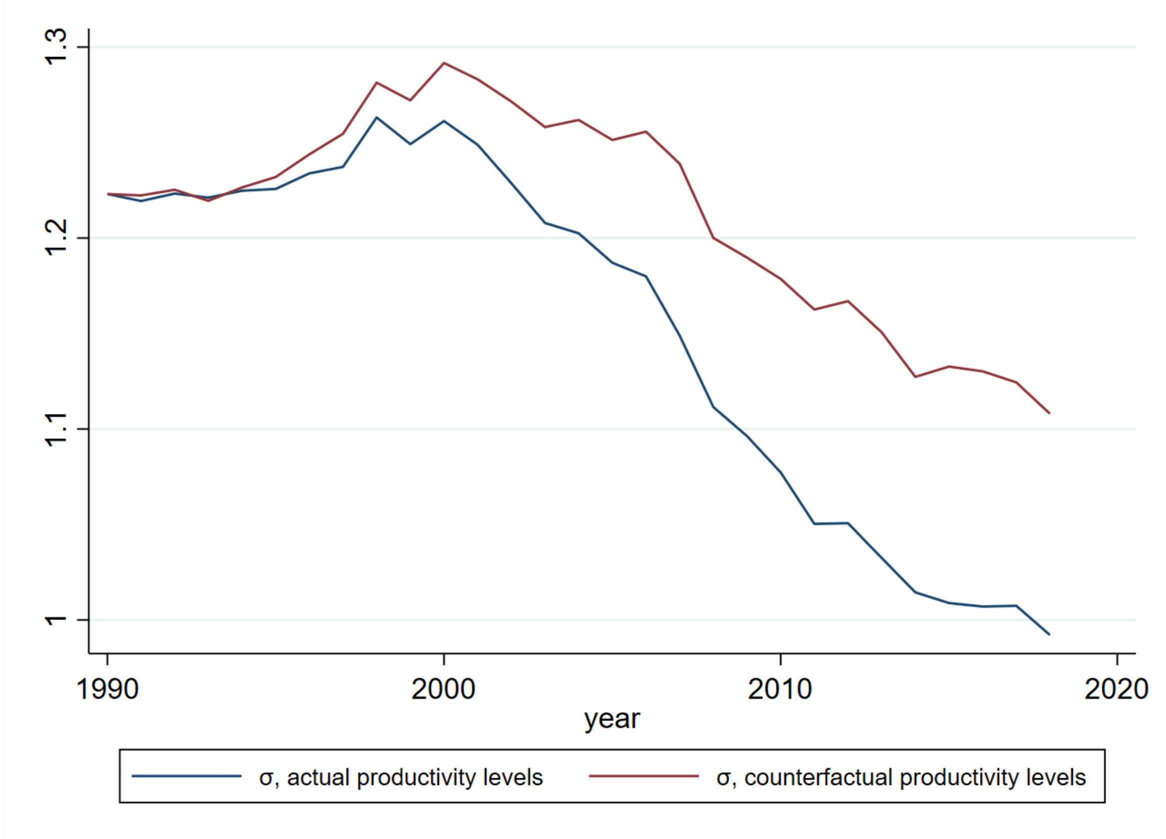
Figure 5. β-coefficients of the regression-based decomposition of productivity differences: counterfactual productivity levels.



Note: β-coefficients computed by estimating Equation (10), and are presented for the following sectors: Agriculture (agr), Mining (min), Manufacturing (man), Utilities (pu), Construction (con), Trade services (wrt), Transport (tra), Business services (com), Financial services (fin), Real estate (dwe), Government services (pub), Other services (oth). β-coefficients sum up to one in each year. Counterfactual productivity levels are computed based on assuming constant initial (1990) sector employment shares.

Finally, to assess how structural change has contributed to the economy-wide convergence process, we compute two sets of σ-coefficients using Equation (8): one based on actual labour productivity estimates σ_t, and the other one based on the counterfactual productivity levels $\tilde{\sigma}_t$ described above. Next, we examine whether the assumption of no labour reallocation across sectors within countries has any effects on economy-wide productivity convergence. Figure 6 illustrates the important role structural change has played in driving convergence: based on the counterfactual productivity levels, convergence occurs at a noticeably slower pace compared to the case of actual productivity levels. In other words, labour reallocation across sectors has played a key role in reducing the dispersion of total economy labour productivity across countries, indicating that not only within-sector dynamics but also between-sector dynamics are important for explaining productivity differences across countries. This result is in line with studies that find that structural change plays an important role in raising aggregate productivity levels in developing countries (Diao et al., 2019; McMillan et al., 2014; Vollrath, 2009).

Figure 6. σ-coefficients, 1990-2018. Based on actual and counterfactual productivity levels.



Note: σ-coefficients estimated using Equation (8). Counterfactual productivity levels based on constant initial (1990) sector employment shares.

4 Conclusion

What role do the different sectors in an economy play in narrowing the labour productivity gap between poor and rich countries? And how does the reallocation of labour between the different sectors affect this process? Answering these questions are highly relevant from an academic viewpoint for advancing our understanding on what explains cross-country income differences. From a policy perspective, it is crucial that policymakers are aware of the sectors that contribute to economic growth, and which serve as a drag on development. Currently, scholars continue to argue that manufacturing remains an important growth engine for poor countries, due to its relatively high productivity levels and convergence properties. Is manufacturing “special” in this regard, or are there other sectors in the economy that also share these characteristics? Evidence of convergence in other sectors would imply that alternative promising growth strategies may be available for poor countries to catch up with rich countries, besides industrialization. Moreover, if structural change contributes to convergence, then this suggests that a more efficient use of factor inputs in the economy can also reduce aggregate productivity differences between countries.

Using data for 57 countries over the period 1990-2018, this study finds evidence of labour productivity convergence in different parts of the economy, particularly in services, which ultimately translates to convergence at the economy-wide level as well. Interestingly, manufacturing is found to exhibit divergence, in contrast to Rodrik (2013) who finds convergence. This contradictory result may be (partially) explained due to the difference in currency conversion rate used to measure output: when using market exchange rates like Rodrik (2013), convergence, albeit modest, is found in manufacturing. Obviously, GDP PPPs are not appropriate either for measuring manufacturing real output, but the main message here is that convergence findings are sensitive to how productivity is estimated. This emphasizes the importance of using appropriate prices to measure sectoral real output. Another key finding of this paper is that not only within-sector, but also between-sector dynamics play an important part in driving aggregate convergence. That is, the reallocation of labour across sectors has been key in reducing the gap in productivity levels between poor and rich countries. This reiterates the importance of policymakers focusing on reallocating activities from less productive to more productive activities in the economy.

While we find encouraging signs regarding the growth prospects of poor countries in this paper, we note that this study faces an important limitation with respect to the measurement of output and productivity. That is, except for agriculture, we lack relative price estimates for the sectors in the economy. More generally, we require data on the values and prices of sector gross outputs and intermediate inputs to compute the appropriate (value added) sector PPPs, which are needed to measure sector real value added. Furthermore, due to a lack of data on inputs, we are unable to assess convergence in TFP across sectors. To tackle this limitation, for a future extension of this paper we will collect the necessary data to compute estimates of sector relative prices and TFP, and build on our current analysis of productivity convergence and its sectoral sources.

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6 Appendix

Table A1. Countries and industries included in the study.

Countries			
Argentina	Germany	Italy	Philippines
Australia	Denmark	Japan	Poland
Austria	Ecuador	Kenya	Senegal
Belgium	Egypt	Korea	Singapore
Bangladesh	Spain	Sri Lanka	Thailand
Bolivia	Ethiopia	Morocco	Tunisia
Brazil	Finland	Mexico	Turkey
Botswana	France	Myanmar	Tanzania
Canada	United Kingdom	Mauritius	Uganda
Switzerland	Ghana	Malawi	United States
Chile	Greece	Malaysia	Vietnam
China	Hungary	Namibia	South Africa
Cameroon	Indonesia	Nigeria	
Colombia	India	The Netherlands	
Costa Rica	Israel	Peru	

Industries	
ISIC Rev. 4	*Sector description*
A	Agriculture, forestry, fishing
B	Mining and quarrying
C10-C12	Food products, beverages and tobacco products
C13-C15	Textiles, wearing apparel and leather products
C16-C18	Wood, wood products, paper, paper products and printing
C19-C22	Petroleum, chemicals, rubber and plastic products
C23-C25	Minerals, basic and fabricated metal
C26-C27	Electronic, optical and electrical products
C28	Machinery and equipment
C29-C30	Transport equipment
C31-C33	Furniture and other manufacturing
D-E	Electricity, gas, steam and air conditioning supply; Water supply; sewerage, waste management and remediation activities
F	Construction
G+I	Wholesale and retail trade; repair of motor vehicles and motorcycles; Accommodation and food service activities
H	Transportation and storage
J+M+N	Information and communication; Professional, scientific and technical activities; Administrative and support service activities
K	Financial and insurance activities
L	Real estate activities
O+P+Q	Public administration and defence; compulsory social security; Education; Human health and social work activities
R+S+T+U	Other services

Note: C10-C33 reflect manufacturing industries.

Table A2. Variables used in the study and their sources.

Variable	Countries	Source	Notes
Value added (in current national prices) and employment (persons engaged) data	40 (developing)	Economic Transformation Database (ETD)	Value added data: primary source is national accounts (NA) data from National Statistical Institutes (NSIs); employment data: primary source is census and labour force survey (LFS) data
		Manufacturing dataset: data on 17 2-digit manufacturing industries (ISIC Rev. 4), compiled by Kruse et al. (2021) for a future extension of their work	Primary source of manufacturing industries data is United Nations Industrial Development Organization (UNIDO) Industrial and Statistics Database (UNIDO, 2020)
	17 (developed)	OECD STAN database	STAN database primarily based on member countries' NA data
Market exchange rates	57 countries	Penn World Tables (PWT) version 10.0	
GDP PPPs	57 countries	Penn World Tables (PWT) version 10.0	
Agriculture PPPs	71 countries	FAOSTAT	Agriculture PPPs have been constructed using the Inklaar/Diewert method for 71 countries, which represents the maximum number of countries for there was sufficient data available to compute PPPs