The sources of productivity convergence: sectors and structural change

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Abstract

Recent studies have found evidence of productivity convergence across countries, yet these studies 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. Moreover, 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. To this end, Inklaar and Diewert (2016) provide a method for computing comparable productivity estimates which are suited for analysing convergence at the sectoral level and its contribution to aggregate (non-)convergence. We use this method to compute relative price and labour productivity estimates for 9 manufacturing industries and 11 broad non-manufacturing sectors for a sample of 66 developing and developed 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 and financial services, while divergence is found in manufacturing. Furthermore, labour reallocation across sectors plays an important role in driving labour productivity convergence.

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

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

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 9 manufacturing industries and 11 broad non-manufacturing sectors (see Table A1 for an overview of the industries analysed). Furthermore, 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 (Duarte & Restuccia, 2010; McMillan et al., 2014). Yet, convergence studies typically attribute the sources of economy-wide convergence to within-sector productivity dynamics, ignoring the role of structural change herein. Two exceptions here are Paci and Pigliaru (1997, 1999), who estimate the impact that structural change has on labour productivity convergence for a group of Italian and European regions, respectively. They find that structural change has been a key driver of productivity convergence. 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 relative price and labour productivity estimates and analyse productivity convergence for a sample of 66 countries over the period 1990-2018, covering 20 sectors in the economy (See the Appendix for a list of countries and sectors included in our study). 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 business and financial services, productivity levels in manufacturing have diverged. 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 suggests that failing to use the appropriate prices to convert output into a common currency 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 has computed comparative sector relative prices and productivity estimates which are suitable for analysing convergence for a sample of developed and developing countries[2]. Using this data, 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. As mentioned above, the literature recognizes structural change as an important growth driver for developing countries, yet 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.

Overall, 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 divergence in manufacturing and convergence in services suggests that alternative promising development strategies may be available for poor countries. Moreover, the finding of convergence in agriculture suggests that

[2] Herrendorf et al. (2022) has recently published insightful work where they analyse sectoral convergence, and have computed comparative labour productivity estimates as well for 64 countries for the period 1990-2018.

there still might be scope for agriculture-centred policy to promote growth in developing 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 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 more reliable set of productivity estimates, and ultimately lead to more robust findings.

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 $x \gg 0_N$:

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

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. In the Appendix, we describe how this data was collected. 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}:

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

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*:

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

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 in a similar fashion (see Inklaar and Diewert (2016) for an exact description of the steps). 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[3]. Nevertheless, we aim to include TFP estimates 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 sectoral value added PPPs requires data on gross output and intermediate input PPPs (Inklaar & Timmer, 2013; Jorgenson et al., 1987). At the time of writing, data on intermediate inputs was unavailable, and for this paper we computed domestic product PPPs and employed these estimates to proxy for gross output PPPs[4]. We then used these PPPs compute real labour productivity for our convergence analysis; more on this below. For comparison purposes, we also computed alternative labour productivity estimates which were converted into a common currency using GDP PPPs and market exchange rates.

Nevertheless, 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 managed to construct a set of sectoral PPP estimates for a set of 66 countries over the period 1990-2018, based on the Inklaar/Diewert method. The Appendix

[3] Since employment is the only factor input considered in our analysis, we do not compute a primary input quantity index, but simply divide real value added by employment.

[4] The computation of gross output PPPs requires data on domestic product PPPs, but also data on Supply and Use tables (SUTs). We are currently compiling data for the latter; for now we have used domestic product PPPs to proxy for gross output PPPs.

provides more details behind the construction of the sectoral prices, 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:

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

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

$$\mathit{\Gamma}_{jkt}^{IND} = \frac{v_{jkt}/P_{jkt}}{X_{jkt}} \tag{7}$$

Where $\mathit{\Gamma}_{jkt}^{XR}$, $\mathit{\Gamma}_{jkt}^{GDP}$, and $\mathit{\Gamma}_{jkt}^{IND}$ reflect labour productivity estimates $\mathit{\Gamma}_{jkt}$ 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, 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.[5] To measure σ-convergence, we use the productivity dispersion measure below, see e.g., Young et al. (2008):

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

where $\mathit{\Gamma}_{jt}$ reflects the cross-sectional average of labour productivity $\mathit{\Gamma}_{jkt}$ for sector *j* in year *t.* A decreasing value for σ_{jt} indicates convergence, as the dispersion in productivity levels has

[5] 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.

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.

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. First, note that total economy labour productivity for country *k* at time *t* can be written as a weighted sum of labour productivities of *j* sectors:

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

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 P_{kt} the GDP PPP. Similarly, Γ_{jkt} and s_{jkt} reflect sector *j*'s nominal labour productivity and employment share, respectively. We follow Paci and Pigliaru (1997) and analyse the effect of structural change on economy-wide convergence by computing two sets of labour productivity estimates: 1) actual economy-wide labour productivity levels, and 2) counterfactual economy-wide labour productivity estimates based on initial (1990) sectoral value added and employment shares that stay constant over time:

$$\tilde{\Gamma}_{kt} \equiv \sum_{j=1}^{n} \frac{\Gamma_{jkt} \cdot s_{jk1990}}{\tilde{P}_{kt}} \tag{10}$$

Where $\tilde{P}$ reflects the GDP PPP counterfactual, computed using initial (1990) value added shares. The counterfactual labour productivity estimates assume that there has been no labour reallocation between sectors over the period 1990-2018, and thus that structural change is absent. Hence, changes in the dispersion of economy-wide cross-country counterfactual productivity levels reflect the role of within-sector productivity dynamics.

Next, we compute two sets of σ-coefficients: one based on the actual total economy labour productivity level Γ_{kt}, defined as σ_t (see Equation (8)), and another one based on a counterfactual productivity level $\tilde{\Gamma}_{kt}$, which is defined as:

$$\tilde{\sigma}_t \equiv \left[\frac{1}{T}\sum_{k=1}^{K} ln\left(\tilde{\Gamma}_{kt}/\tilde{\Gamma}_t\right)^2\right]^{\frac{1}{2}}; \quad t = 1, \dots, T. \tag{11}$$

Note that changes in productivity dispersion based on actual productivity levels also include the 'productivity effect' of reallocating resources (employment) across sectors. Hence, 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 productivity 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 Implementation and Data

In this paper, we study labour productivity convergence in 20 sectors for a sample of 66 countries over the period 1990-2018. Country and period coverage is based on data availability, i.e., the number of countries for which we were able to compile National Accounts data and compute sectoral PPPs. Table A1 lists the countries and sectors included in the study. As the measurement of productivity requires data on the values and prices of net outputs and primary inputs, we require data on: i) nominal sectoral value added in local currency, ii) deflators (exchange rates, GDP PPPs, and sectoral gross output PPPs), and iii) employment (persons engaged).[6]

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-

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

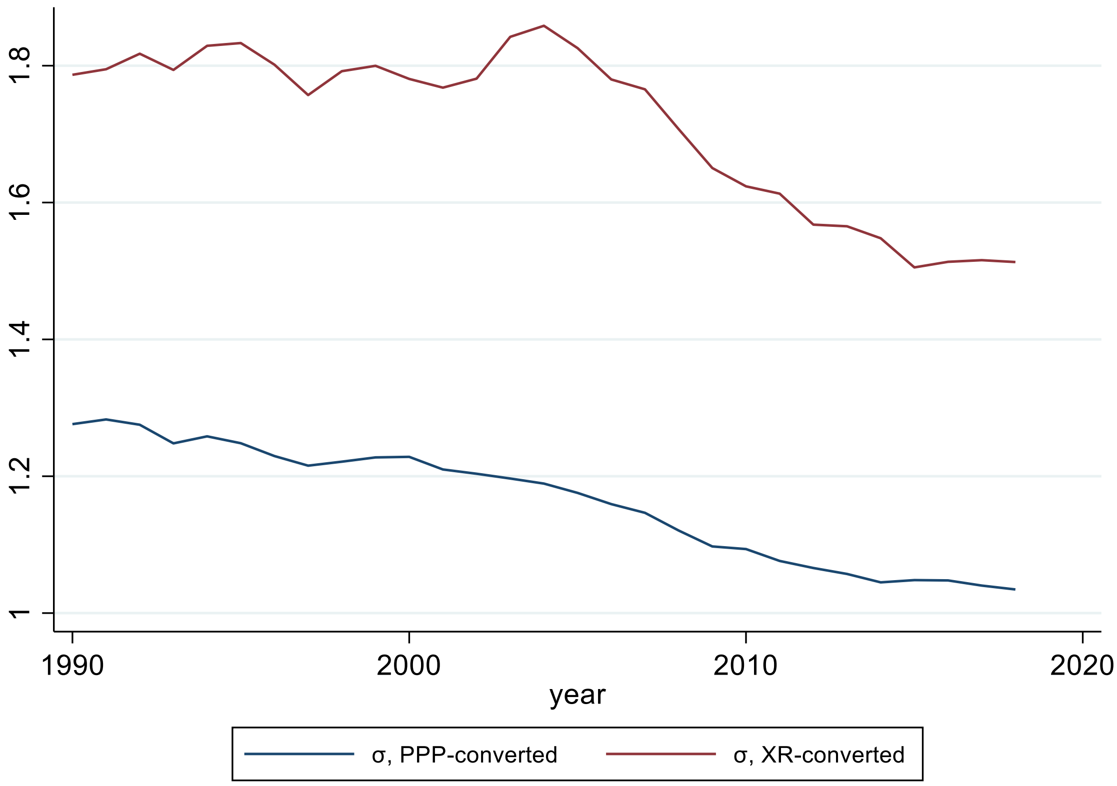
2018, while the STAN database contains detailed industry level (ISIC Rev. 4) data for OECD member countries from 1970 onwards. Moreover, for a future extension of their work, Kruse et al. (2021) have compiled a dataset for 17 2-digit manufacturing industries (ISIC Rev. 4), building upon the work of Pahl 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 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). Given this data, we can construct the labour productivity estimates that are used to assess convergence.

For the computation of the sectoral PPPs, we rely on a variety of sources; a detailed description of the computation of the sectoral PPPs can be found in the Appendix. Essentially, we compute expenditure PPPs (consumption prices), for which we rely on the World Bank PPPs data, produced under the International Comparison Program (ICP) (World Bank, 2020). We utilize data for three benchmark years: 2005, 2011, and 2017. For the remaining years, we rely on interpolation and extrapolation techniques, where we follow the approach used in Penn World Tables 8.0 onwards for extrapolating and interpolating PPPs (Feenstra et al., 2015). More on this is covered in the Appendix.

For two sectors, we are able to compute gross output PPPs using the unit value ratio (UVR) method, due to data availability. Specifically, for the agriculture and mining sector, we estimate output PPPs, where we retrieve this data for the agriculture and the mining sector from FAOSTAT and World Bank, respectively. This is essential, as these sectors produce mainly intermediate inputs, and thus expenditure PPPs are likely to be poor proxies for the output prices of these sectors. We compute product PPPs and use these to proxy for gross output PPPs. The product PPPs should reflect output prices rather than expenditure prices, as expenditure PPPs reflect purchaser prices, which excludes export prices and includes import prices as well as net taxes and trade and transport margins. Hence, we follow Inklaar and Timmer (2013) and adjust the expenditure PPPs by "stripping off" the net taxes and trade and transport margins, and an adjustment is made for international trade prices, since production PPPs cover *produced* goods and thus should include export prices and exclude import prices. In contrast, expenditure PPPs include import prices and exclude export prices. Therefore, we take the expenditure PPPs and net out the margins and net taxes, then add the export prices, and afterwards net out the import prices to compute production PPPs. For the trade prices, we use the quality-adjusted export and import prices constructed by Feenstra and Romalis (2014).

Before turning to the main findings of the paper, 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: Developing and developed countries, where we define developed countries to be those classified as high-income countries according to the World Bank, and the remaining countries are defined as developing countries. Moreover, employment shares have been averaged over each decade. 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.

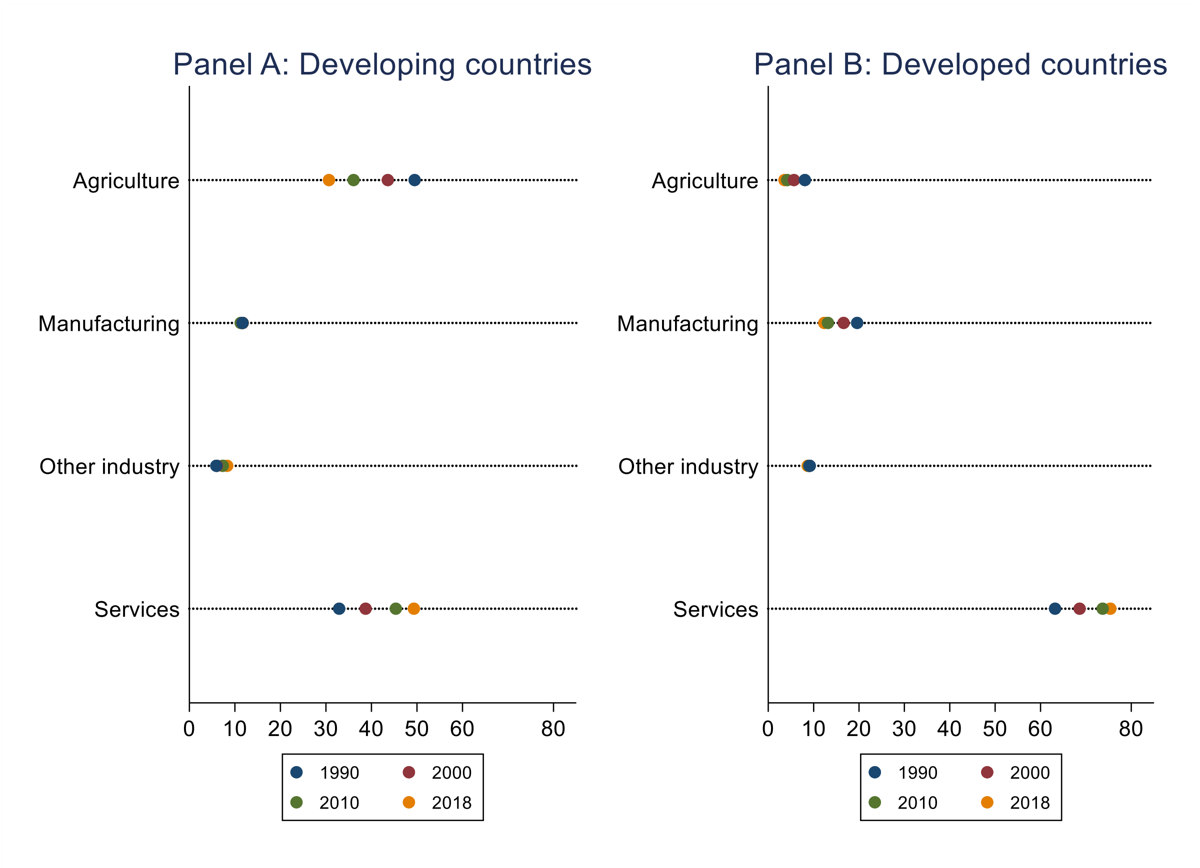
Figure 1. σ-coefficients for the total economy, 1990-2018.



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

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, there has been a large drop in the employment share 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.

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



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, Manufacturing, Other industry (Public Utilities, Construction, Mining), and Services (Business services, Financial services, Trade services, Transport services, Real estate services, Government services, Other services).

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 sectoral PPPs to deflate nominal output, unless stated otherwise. Below, Figure 3 and Table 2 display σ-coefficients for the different sectors in the economy, based on estimating Equation (8). An important finding that follows from this figure and 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 *Petroleum, chemicals, rubber and plastic 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 little to no convergence in productivity levels for total manufacturing, as Figure 4 shows. The lack of convergence in manufacturing is a finding shared by Herrendorf et al. (2022) as well, and is an interesting result given that Rodrik (2013) finds strong evidence of labour productivity convergence in manufacturing.

Figure 3. Percentage change in σ-coefficients between 1990 and 2018, detailed industries.

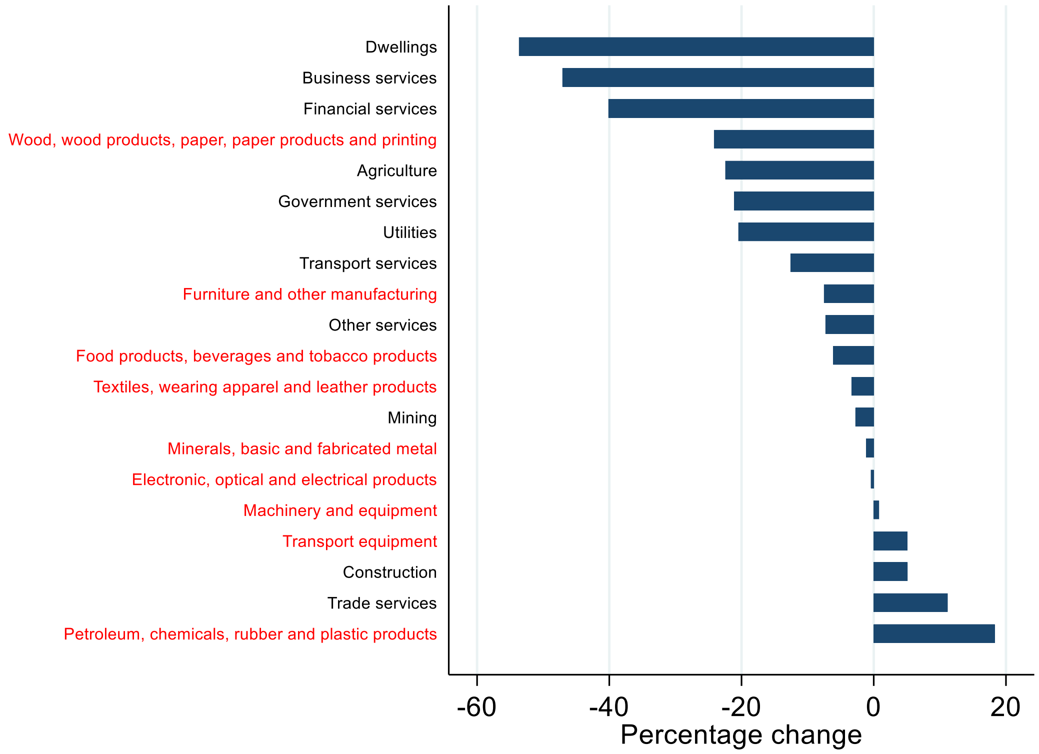
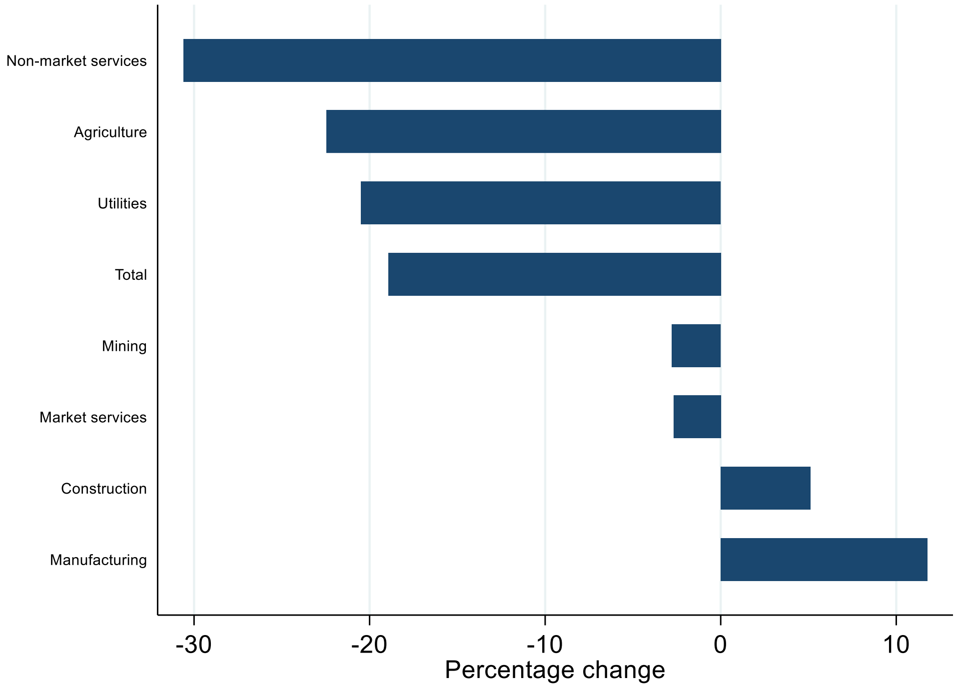


Table 2. σ-coefficients for the different sectors, based on PPP-converted estimates.

Sector	1990	2018	Difference (%)
Agriculture	2.16	1.67	-22%
Mining	1.81	1.76	-3%
Manufacturing	1.14	1.27	12%
Food products, beverages and tobacco products	1.09	1.02	-6%
Textiles, wearing apparel and leather products	1.43	1.38	-3%
Wood, wood products, paper, paper products and printing	1.20	0.91	-24%
Petroleum, chemicals, rubber and plastic products	1.17	1.38	18%
Minerals, basic and fabricated metal	1.16	1.15	-1%
Electronic, optical and electrical products	2.00	1.99	0%
Machinery and equipment	1.86	1.88	1%
Transport equipment	1.77	1.86	5%
Furniture and other manufacturing	1.57	1.45	-8%
Utilities	1.09	0.87	-20%
Construction	0.83	0.87	5%
Trade services	0.90	1.00	11%
Transport	0.89	0.78	-13%
Business services	1.30	0.69	-47%
Financial services	1.43	0.86	-40%
Real estate	1.82	0.84	-54%
Government services	0.82	0.64	-21%
Other services	1.09	1.01	-7%

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

Figure 4. Percentage change in σ-coefficients between 1990 and 2018, major sectors.



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.

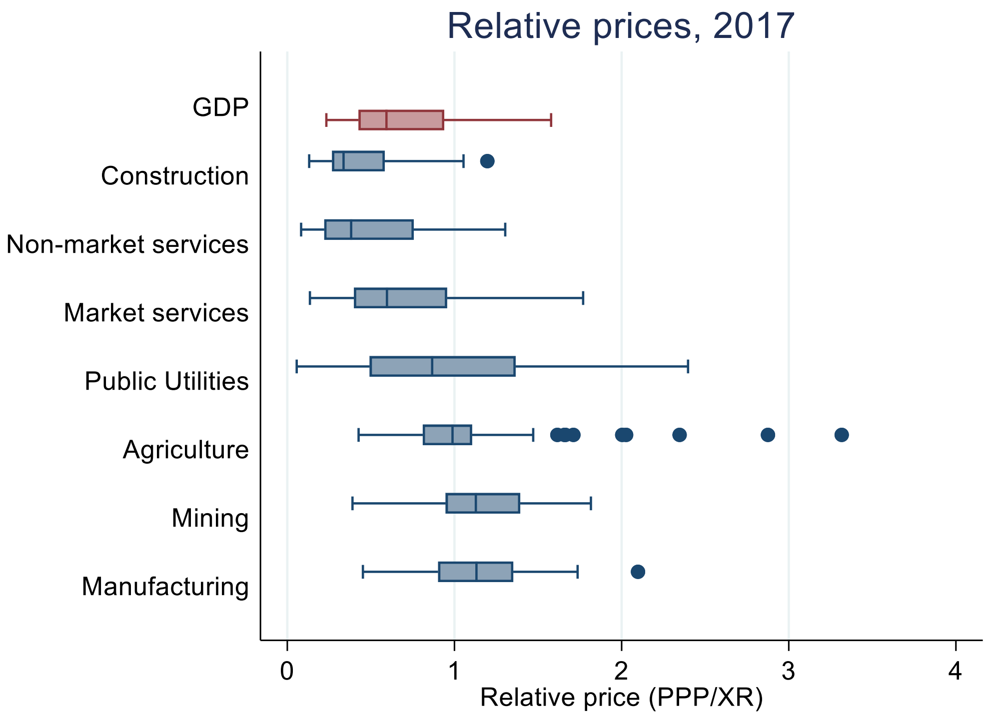
To assess how these results depend on the currency conversion factor used to deflate nominal value added, Table 3 shows the percentage change in the dispersion of cross-country sector labour productivity levels between 1990 and 2018. Three cases are compared: the case where labour productivity is estimated using sectoral PPPs, GDP PPPs, and market exchange rates. Table 3 makes clear that the convergence coefficients are sensitive to the currency conversion rate used for output. This finding is also not surprising, given that there exists quite some variation in sector relative prices (Inklaar and Timmer, 2014). Indeed, Figure 5 compares the sector relative prices with the relative price of GDP for the benchmark year 2017, and illustrates the price differences that exist across sectors. This highlights the importance of using sectoral PPPs to measure sectoral output, as failing to use sector prices to measure sectoral real output may provide inaccurate productivity estimates, and lead to wrong conclusions regarding convergence.

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 PPP vs XR
Agriculture	-22%	-19%	-17%	-5
Mining	-3%	2%	-5%	2
Manufacturing	12%	1%	2%	10
Food products, beverages and tobacco products	-6%	-15%	-10%	4
Textiles, wearing apparel and leather products	-3%	-15%	6%	-10
Wood, wood products, paper, paper products and printing	-24%	-15%	-14%	-10
Petroleum, chemicals, rubber and plastic products	18%	12%	14%	4
Minerals, basic and fabricated metal	-1%	-13%	-9%	8
Electronic, optical and electrical products	0%	21%	15%	-16
Machinery and equipment	1%	8%	5%	-4
Transport equipment	5%	3%	-1%	6
Furniture and other manufacturing	-8%	-11%	-7%	-1
Utilities	-20%	-18%	-16%	-4
Construction	5%	-1%	-7%	12
Trade services	11%	4%	0%	11
Transport	-13%	-5%	-5%	-8
Business services	-47%	-36%	-18%	-29
Financial services	-40%	-36%	-16%	-24
Real estate	-54%	-39	-22%	-31
Government services	-21%	-27	-21%	0
Other services	-7%	-1	-5%	-2
Average change				

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

Figure 5. Relative prices for the different sectors, 2017.

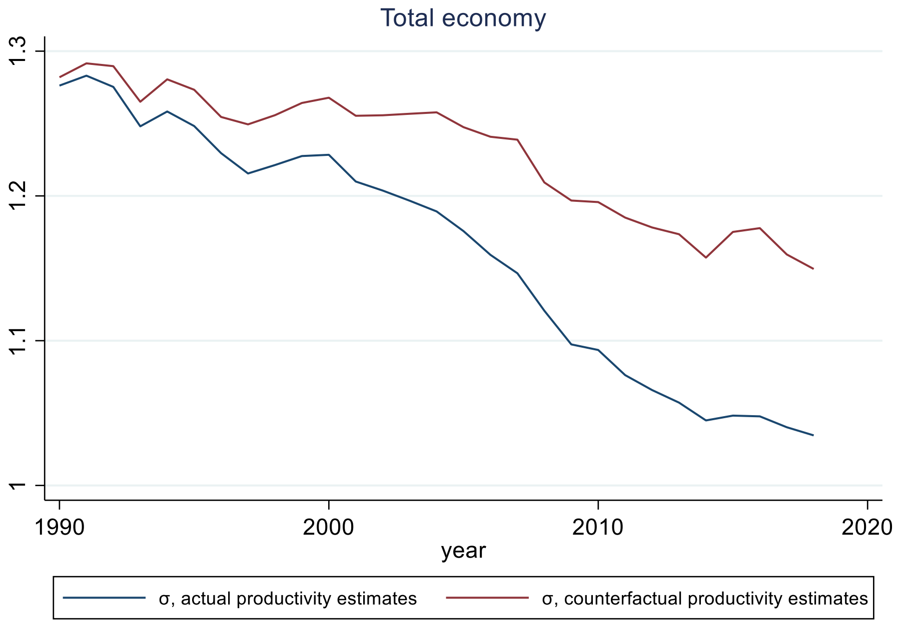


Note: Relative prices are computed by dividing PPPs by the market exchange rate (XR). We follow Inklaar and Timmer (2014) and define non-market services as government services, and dwellings, and market services as trade, transport, finance, business, and other services.

Finally, to assess how structural change has contributed to the economy-wide convergence process, we compute two sets of σ-coefficients: one based on actual labour productivity estimates σ_t using Equation (8), and the other one based on the counterfactual productivity levels $\tilde{\sigma}_t$ using Equation (9). 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. The change in the σ-coefficient based on actual labour productivity levels is 19 percent, compared to 10 percent in the case of counterfactual labour productivity levels, highlighting the major contribution of structural change to convergence. 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).

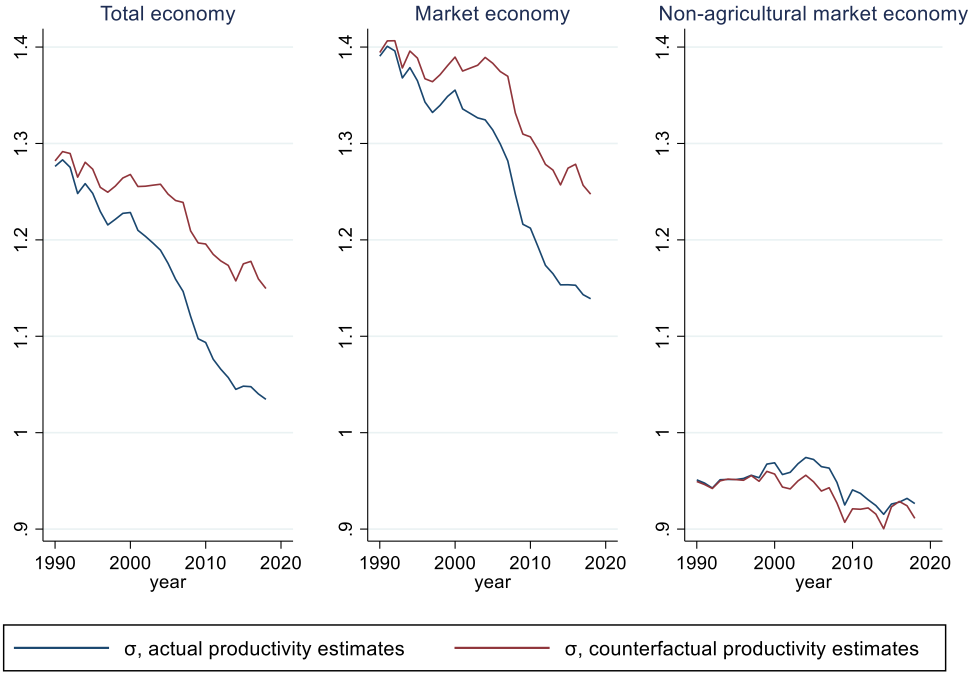
Moreover, we repeat this exercise again for the market economy and non-agricultural market economy, where the market economy excludes the real estate and public sector, and the non-agricultural market omits the agriculture sector as well. Figure 7 shows that the structural change effect has occurred in the market economy, i.e. it has been the reallocation of resources out of agriculture that has been crucial in explaining the contribution of structural change.

Figure 6. σ-coefficients based on actual and counterfactual labour productivity estimates, 1990-2018.



Note: σ-coefficients estimated using Equation (8) and Equation (11). Counterfactual productivity levels based on initial (1990) sector employment shares.

Figure 7. σ-coefficients based on actual and counterfactual labour productivity estimates for the total, market, and non-agricultural market economy, 1990-2018.



Note: σ-coefficients estimated using Equation (8) and Equation (11). Counterfactual productivity levels based on 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 66 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, divergence is found in manufacturing, a finding in contrast to Rodrik (2013) who finds evidence of strong convergence in this sector. In a recent paper, Herrendorf et al. (2022) also fail to find evidence of convergence in manufacturing. 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, further adjustments are required to compute the appropriate sectoral 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 are currently collecting data to improve our estimates of sector relative prices. Moreover, we are compiling the necessary data to compute TFP estimates, and we will use the improved sectoral PPPs and TFP estimates to build on our current analysis of productivity convergence and its sectoral sources.

5 References

Barro, R. J. (2015). Convergence and Modernisation. *The Economic Journal*, 125(585), 911–942. https://doi.org/10.1111/ecoj.12247

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, 100(2), 223–251. https://doi.org/10.1086/261816

Bick, A., Fuchs-Schündeln, N., & Lagakos, D. (2018). How Do Hours Worked Vary with Income? Cross-Country Evidence and Implications. *American Economic Review*, 108(1), 170–199. https://doi.org/10.1257/aer.20151720 de Vries, G., Arfelt, L., Drees, D., Godemann, M., Hamilton, C., Jessen-Thiesen, B., Ihsan Kaya, A., Kruse, H., Mensah, E., & Woltjer, P. (2021). The Economic Transformation Database (ETD): Content, Sources, and Methods. *WIDER Technical Note 2/2021*. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/WTN/2021-2

Diao, X., McMillan, M., & Rodrik, D. (2019). The Recent Growth Boom in Developing Economies: A Structural-Change Perspective. In M. Nissanke & J. A. Ocampo (Eds.), *The Palgrave Handbook of Development Economics* (pp. 281–334). Springer International Publishing. https://doi.org/10.1007/978-3-030-14000-7_9

Diewert, W. E., & Morrison, C. J. (1986). Adjusting Output and Productivity Indexes for Changes in the Terms of Trade. *The Economic Journal*, 96(383), 659–679. https://doi.org/10.2307/2232984

Duarte, M., & Restuccia, D. (2010). The Role of the Structural Transformation in Aggregate Productivity. Quarterly Journal of Economics, 125(1), 129–173. https://doi.org/10.1162/qjec.2010.125.1.129

FAO. (2019). FAOSTAT Online Statistical Service. *Food and Agriculture Organization of the United Nations*. http://faostat.fao.org

Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The Next Generation of the Penn World Table. *American Economic Review*, 105(10), 3150–3182. https://doi.org/10.1257/aer.20130954

Feenstra, R. C., & Romalis, J. (2014). International prices and endogenous quality. *The Quarterly Journal of Economics*, *129*(2), 477-527.

Freeman, D., Inklaar, R., & Diewert, W. E. (2021). Natural Resources and Missing Inputs in International Productivity Comparisons*. *Review of Income and Wealth*, 67(1), 1–17. https://doi.org/10.1111/roiw.12451

Hassan, F. (2016). The price of development: The Penn–Balassa–Samuelson effect revisited. *Journal of International Economics*, 102, 291–309. https://doi.org/10.1016/j.jinteco.2016.07.009

Herrendorf, B., Rogerson, R., & Valentinyi, Á. (2022). New Evidence on Sectoral Labor Productivity: Implications for Industrialization and Development (No. w29834). National Bureau of Economic Research.

Hicks, J. R. (1940). The Valuation of the Social Income. *Economica*, 7(26), 105–124. JSTOR. https://doi.org/10.2307/2548691

Inklaar, R., & Diewert, W. E. (2016). Measuring industry productivity and cross-country convergence. *Journal of Econometrics*, 191(2), 426–433. https://doi.org/10.1016/j.jeconom.2015.12.013

Inklaar, R., & Timmer, M. P. (2009). PRODUCTIVITY CONVERGENCE ACROSS INDUSTRIES AND COUNTRIES: THE IMPORTANCE OF THEORY-BASED MEASUREMENT. *Macroeconomic Dynamics*, 13(S2), 218–240. Cambridge Core. https://doi.org/10.1017/S1365100509090117

Inklaar, R., & Timmer, M. P. (2013). Using Expenditure PPPs for Sectoral Output and Productivity Comparisons. In *Measuring the Real Size of the World Economy* (pp. 617–644). https://doi.org/10.1596/9780821397282_CH24

Inklaar, R., & Timmer, M. P. (2014). The Relative Price of Services. *Review of Income and Wealth*, 60(4), 727–746. https://doi.org/10.1111/roiw.12012

Johnson, P., & Papageorgiou, C. (2020). What Remains of Cross-Country Convergence? *Journal of Economic Literature*, 58(1), 129–175. https://doi.org/10.1257/jel.20181207

Jorgenson, D., Kuroda, M., & Nishimizu, M. (1987). Japan-U.S. Industry-Level Productivity Comparisons, 1960-1979. *Journal of the Japanese and International Economies*, 1(1), 1–30.

Kinfemichael, B., & Morshed, A. K. M. M. (2019). Unconditional convergence of labor productivity in the service sector. *Journal of Macroeconomics*, 59, 217–229. https://doi.org/10.1016/j.jmacro.2018.12.005

Kruse, H., Mensah, E., Sen, K., & de Vries, G. (2021). A manufacturing renaissance? Industrialization trends in the developing world. *WIDER Working Paper 2021/28*. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2021/966-2

McMillan, M., Rodrik, D., & Verduzco-Gallo, Í. (2014). Globalization, Structural Change, and Productivity Growth, with an Update on Africa. *World Development*, 63, 11–32. https://doi.org/10.1016/j.worlddev.2013.10.012

Paci, R., & Pigliaru, F. (1997). Structural change and convergence: An Italian regional perspective. Structural Change and Economic Dynamics, 8(3), 297–318. https://doi.org/10.1016/S0954-349X(96)00077-X

Paci, R., & Pigliaru, F. (1999). Is dualism still a source of convergence in Europe? Applied Economics, 31(11), 1423–1436. https://doi.org/10.1080/000368499323300

Pahl, S., & Timmer, M. P. (2019). Patterns of vertical specialisation in trade: Long-run evidence for 91 countries. *Review of World Economics*, 155(3), 459–486. https://doi.org/10.1007/s10290-019-00352-3

Patel, D., Sandefur, J., & Subramanian, A. (2021). The new era of unconditional convergence. *Journal of Development Economics*, 152, 102687. https://doi.org/10.1016/j.jdeveco.2021.102687

Restuccia, D., Yang, D. T., & Zhu, X. (2008). Agriculture and aggregate productivity: A quantitative cross-country analysis. *Journal of Monetary Economics*, 55(2), 234–250. https://doi.org/10.1016/j.jmoneco.2007.11.006

Rodrik, D. (2013). Unconditional Convergence in Manufacturing *. *The Quarterly Journal of Economics*, 128(1), 165–204. https://doi.org/10.1093/qje/qjs047

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, 70(1), 65–94.

Temurshoev, U., & Timmer, M. P. (2011). Joint estimation of supply and use tables. Papers in Regional Science, 90(4), 863–882. https://doi.org/10.1111/j.1435-5957.2010.00345.x

Timmer, M. P., & Ypma, G. Productivity Levels in Distributive Trades: A New ICOP Dataset for OECD Countries. GGDC Research Memorandum, GD-83, Groningen Growth and Development Centre, University of Groningen, 2006.

Timmer, M., Ypma, G., & van Ark, B. (2007). PPPs for industry output: a new dataset for international comparisons. Groningen Growth and Development Centre.

United Nations Industrial Development Organization (UNIDO). (2020). *INDSTAT 2 Industrial Statistics Database*. Vienna. Available from http://stat.unido.org

Van Biesebroeck, J. (2009). Disaggregate productivity comparisons: Sectoral convergence in OECD countries. *Journal of Productivity Analysis*, 32(2), 63–79. https://doi.org/10.1007/s11123-009-0132-z

Vollrath, D. (2009). How important are dual economy effects for aggregate productivity? *Journal of Development Economics*, 88(2), 325–334. https://doi.org/10.1016/j.jdeveco.2008.03.004

World Bank (2020) Purchasing Power Parities and the Size of World Economies: Results from the 2017 International Comparison Program. World Bank, Washington, D.C. https://openknowledge.worldbank.org/handle/10986/33623.

Young, A. T., Higgins, M., & Levy, D. (2008). Sigma Convergence versus Beta Convergence: Evidence from U.S. County-Level Data. *Journal of Money, Credit and Banking*, 40(5), 1083–1093. https://doi.org/10.1111/j.1538-4616.2008.00148.x

6 Appendix

In this section, we describe in more detail the data behind the construction of sectoral PPPs, which are used to compute real value added estimates which are comparable across countries and over time. Labour productivity is then computed as real value added per worker. We analyse convergence in labour productivity at the sectoral (see Table A1 for an overview of the sectors covered in our study) and economy-wide level. For our analysis of economy-wide labour productivity convergence, we retrieve data on nominal GDP, GDP PPPs (used to compute real GDP), and employment levels from the Penn World Table (Feenstra et al., 2015). For the sectoral analysis, we rely on the Economic Transformation Database (ETD) (de Vries et al., 2021) and the OECD STAN database for sectoral nominal value added and employment data. Regarding real value added estimates, one of the main contributions of this paper is the construction of a dataset on sectoral PPPs for a broad sample of developed and developing countries, which is notably scarce.

Table A1. List of sectors included in the study.

Sectors	
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

As mentioned above, for the construction of the sectoral PPPs, we require data on the 'values' (in local currency) of net outputs, and 'prices' (in local currency) corresponding to these net outputs. For the 'values' data, we rely on our sectoral value added estimates, while the 'prices' dataset is constructed using a variety of sources, see Table A2 for a brief overview of the sources. This 'values' and 'prices' dataset on net outputs is then used in the Inklaar-Diewert method to construct sectoral PPPs, and the USA is chosen as the base country, so PPP=1 for USA in each year. Before going further into the PPPs construction, two key implementation issues must be mentioned: 1) the estimation of output PPPs vs expenditure PPPs, and 2) the computation of single versus double deflated value added estimates. In the literature, PPPs have been typically measured from the expenditure side or from the production side. PPPs measured from the production side reflect output prices, while the expenditure approach relies on data on prices of expenditures to compute PPPs.

As Inklaar and Timmer (2013) point out, for appropriate international comparisons of output and productivity levels, PPPs should be measured from the production side, i.e., PPPs should reflect output prices rather than expenditure prices. Expenditure PPPs reflect purchaser prices, which excludes export prices and includes import prices as well as net taxes and trade and transport margins. Moreover, expenditure PPPs do not cover intermediate inputs. One way production PPPs can be computed is by using data on producer prices. Another approach is to use the unit value ratio (UVR) method to estimate production PPPs, which involves utilizing output values and quantities data to compute unit value ratios. Yet, this data is scarce, particularly for developing countries. As a result, limited data for output PPPs often imply that expenditure PPPs are used in practice to proxy producer prices, where efforts are taken to adjust the expenditure prices for the issues listed above. In particular, correcting for export and import prices, as well as trade and transport margins and net taxes. Additionally, expenditure PPPs reflect prices of consumer goods and services, and need to be mapped to the output prices of industries, which is based on a subjective exercise as the literature does not delineate a formal approach for doing this.

Secondly, as value added reflects the difference between gross output and intermediate inputs, it is straightforward that the deflation of nominal value added to compute real value added should be based on a double deflation procedure, involving both gross output and intermediate inputs PPPs. However, as data on intermediate inputs is typically scarce and introduces additional measurement error due to crudely measured input prices, the literature typically opts for gross output PPPs to deflate value added, also known as single deflation. The choice of single deflation can lead to imprecise price estimates, as it suffers from substitution and terms-of-trade biases, and this measurement error increases with the share of intermediate inputs in gross output. Currently, we do not have data on intermediate inputs and thus we compute solely gross output PPPs. For an extension of this paper, additional data is being collected which will allow us to compute value added PPPs.

Table A2. Data sources for the sectoral PPP computations.

Sector ISIC Rev. 4 code	Sector name	Data source	Note
A	Agriculture	FAOSTAT	
B	Mining	World Bank	
C10-12, C13-15, C16-18, C19-22, C23-25, C26-27, C28, C29-30, C31-33 (9 industries)	Manufacturing	World Bank - International Comparison Program (ICP) OECD STAN (margins data) Asian Development Bank (ADB) Individual country-level sources: *AGR, PER, ECU* (margins data)	Data on margins is collected from Supply and Use Tables (SUTs); discussed in more detail below
D+E	Public Utilities	World Bank- ICP	
F	Construction	World Bank- ICP	
G+I	Trade	World Bank- ICP OECD STAN (margins data) Asian Development Bank (ADB) Individual country-level sources: *AGR, PER, ECU* (margins data)	Data on margins is collected from Supply and Use Tables (SUTs); discussed in more detail below
H	Transport	World Bank- ICP	
J,M+N	Business	World Bank- ICP	
K	Finance	World Bank- ICP IMF IFS (margins data) MIR (margins data)	Data on margins is collected from Bank lending and deposit rates data, discussed in more detail below
L	Real estate	World Bank- ICP	
O+P+Q	Public services	World Bank- ICP	
R+S+T+U	Other services	World Bank- ICP	

For the computation of the sectoral PPPs, we rely on a variety of sources; a detailed description of the computation of the sectoral PPPs can be found in the Appendix. Essentially, we compute expenditure PPPs (consumption prices), for which we rely on the World Bank PPPs data, produced under the International Comparison Program (ICP) (World Bank, 2020). We utilize data for three benchmark years: 2005, 2011, and 2017. For the remaining years, we rely on interpolation and extrapolation techniques, where we follow the approach used in Penn World Tables 8.0 onwards for extrapolating and interpolating PPPs (Feenstra et al., 2015). More on this is covered in the Appendix below.

For two sectors, we are able to compute gross output PPPs using the unit value ratio (UVR) method, due to data availability. Specifically, for the agriculture and mining sector, we estimate output PPPs, where we retrieve this data for the agriculture and the mining sector from FAOSTAT and World Bank, respectively. This is essential, as these sectors produce mainly intermediate inputs, and thus expenditure PPPs are likely to be poor proxies for the output prices of these sectors. As mentioned above, we compute production PPPs and use these to proxy for gross output PPPs. The production PPPs should reflect output prices rather than expenditure prices, as expenditure PPPs reflect purchaser prices, which excludes export prices and includes import prices as well as net taxes and trade and transport margins. Hence, we follow Inklaar and Timmer (2013) and adjust the expenditure PPPs by "stripping off" the net taxes and trade and transport margins, and an adjustment is made for international trade prices, since production PPPs cover *produced* goods and thus should include export prices and exclude import prices. In contrast, expenditure PPPs include import prices and exclude export prices. Therefore, we take the expenditure PPPs and net out the margins and net taxes, then add the export prices, and afterwards net out the import prices to obtain production PPPs. We use quality-adjusted export and import prices for goods, which have been constructed by Feenstra and Romalis (2014). We treat manufacturing as a tradable sector which feature margin industries (more on this below), and compute adjusted expenditure PPPs for the manufacturing industries. For the remaining sectors for which expenditure PPPS are estimated, no adjustment is made for the expenditure PPPs.

Moreover, we follow the procedure of Inklaar and Timmer (2014) to map the expenditure basic heading PPPs from the ICP data to the relevant sectors, based on the name of the basic heading. Within each sector, the mapped basic headings reflect then the commodities that will be used to compute the sectoral PPP.

This allows us to compute PPPs for the benchmark year 2005, 2011, and 2017. For the remaining years, we rely on interpolation and extrapolation methods, where we follow the approach used in the Penn World Tables version 8.0 onwards for estimating PPPs in non-benchmark years. The interpolation of sectoral PPPs between two benchmarks for country *k* at time *t* looks as follows:

$$PPP_k^t = \left[PPP_k^1 \cdot \frac{\frac{P_k^t}{P_k^1}}{\frac{P_{USA}^t}{P_{USA}^1}} \right]^{1-w^t} \cdot \left[PPP_k^T \cdot \frac{\frac{P_k^t}{P_k^T}}{\frac{P_{USA}^t}{P_{USA}^T}} \right]^{w^t} \quad ; k = 1,2 \ldots, M; t = 2, .. T-1 \qquad (12)$$

where $w^t = \frac{t-1}{T-1}$ and P_k^t the National Accounts (NA) deflator. For the PPPs, the U.S. is the base country, hence why price changes relative to the U.S. is considered here as well. Similarly, for the extrapolation of PPPs, we apply the difference in sectoral price changes between the respective country and the USA (base country) to the benchmark PPP estimate. For example: if the PPP conversion factor for country A in 2017 is 1.50, and the change in the deflator ($\frac{P_t}{P_{t-1}}$) between 2017 and 2018 is 1.05 in country A and 1.02 in the USA, then 1.50*1.05/1.02 would be the extrapolated PPP for country A in 2018. Using this method, we are able to compute PPPs for the period 1990-2018 for the respective industries. Taking this altogether, final country and period coverage is based on data availability from the different sources which we rely on to compute labour productivity estimates. This ultimately has led to our final sample of 66 countries which are analysed for the period 1990-2018 (See Table A3).

Three sectors here require extra attention, namely trade, manufacturing, and finance. Within the trade sector, wholesale and retail trade industries are treated as margin industries in National Accounts, i.e. firms in these industries earn their income by charging a margin on the products they sell to their customers. Similarly, within the finance sector, interest margins are a key source of income in banking activities, and thus when measuring the real value of bank output this needs to be accounted for. Furthermore, we distinguish nine manufacturing industries that produce consumption and/or investment goods, which in turn are purchased by the wholesale and retail industries. The manufacturing PPPs that are estimated using the ICP expenditure PPPs data include margins, and thus we adjust the manufacturing PPPs as well to correct for this. We describe these adjustments in more detail below. More generally, in the following section we will describe in more detail how we computed PPPs for the different sectors. We start with a detailed focus on how agricultural PPPs were computed, particularly to provide the reader with an idea on the data requirements behind the sectoral PPPs construction using the UVR method.

Table A3. Countries included in the study.

ARG	DNK	JPN	PHL
AUS	ECU	KEN	POL
AUT	EGY	KOR	PRT
BEL	ESP	LKA	SEN
BGD	ETH	LUX	SGP
BOL	FIN	MAR	SVK
BRA	FRA	MEX	SWE
BWA	GBR	MMR	THA
CAN	GHA	MUS	TUN
CHE	GRC	MWI	TUR
CHL	HUN	MYS	TZA
CHN	IDN	NAM	UGA
CMR	IND	NGA	USA
COL	IRL	NLD	VNM
CRI	ISL	NOR	ZAF
CZE	ISR	NZL	
DEU	ITA	PER	

Agriculture

For the computation of agricultural PPPs, we relied on the UVR method to compute output PPPs. 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 agricultural products which cover crops and primary livestock, for the period 1991-2018. The PPP for 1990 was estimated using the aforementioned extrapolation technique. 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[7]. Thus, for the *zero-production* cases, all prices are initially based on the country's import price. If this price is

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

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.

Mining

In a similar fashion to the computation of Agriculture PPPs, we relied here on the UVR method to compute mining PPPs. We construct PPPs for the mining sector by using data on prices and production of subsoil assets (e.g., gold, oil, gas), which we retrieved from the World Bank. We computed gross output PPPs, as there was no data available on the intermediate inputs used in the mining sector, similar to the agriculture PPPs computation. Also here, we relied on *Hicksian reservation prices* for assets which are not produced. As the period coverage of this data only goes until 2014, we imputed PPPs for the years 2015-2018 using the extrapolation method discussed earlier above.

Manufacturing

We use the World Bank PPPs to estimate expenditure PPPs for nine manufacturing industries, where Table A5 shows the number of basic headings from the ICP 2017 round mapped to each industry. As mentioned above, for the manufacturing industries we make an adjustment to the expenditure PPP. Particularly, we "peel off" the domestic margins and net taxes (trade costs) from the expenditure PPPs, and net-out the import price and add the export price to arrive at output prices. We compute the domestic trade costs as the ratio of consumption expenditures in purchaser prices divided by consumption expenditures at basic prices (which excludes margins and net taxes on products). We compile the required data to compute this ratio from Supply and Use Tables for the countries in our sample where available.

Table A5. Number of basic headings covered per industry

ISIC Rev. 4.	Number of basic headings
10t12	34
13t15	6
16t18	2
19t22	6
23t25	4
26t27	5
28	3
29t30	6
31t33	7

Trade

Measurement

Wholesale and retail trade industries are a margin industry, i.e., firms earn their income by charging a margin on the products they sell to their customers:

$$M_i = S_i - C_i = m_i S_i, \text{for } i \in w, r;\ w = 1, \dots, W; r = 1 \dots R \qquad (1)$$

Let M_i be the gross margin (i.e., the gross output) of an industry in wholesale trade (indexed by w) or retail trade (indexed by r), S_i the sales of that industry, C_i the cost of goods sold and m_i the margin-to-sales ratio, M_i/S_i; M_i, C_i and S_i are all expressed at current prices.

The challenge in comparing output prices for margin industries is that we do not observe the margin price. In the United States producer price index (PPI) for wholesale and retail trade, these margins are surveyed and used to construct a margin price index, but in absence of such data, we follow the conceptual approach of Timmer and Ypma (2007) and define the margin PPP for industry i as:

$$PPP_{j,k}^{Y_i} = \frac{m_{i,j}}{m_{i,k}} PPP_{j,k}^{S_i} \qquad (2)$$

Here, $PPP_{j,k}^{S_i}$ is the PPP for the sales of product i in country j relative to country k. This sales PPP is multiplied by the relative margin-to-sales ratio in the two countries, $\frac{m_{i,j}}{m_{i,k}}$, to arrive at the margin PPP for that industry. The final step is to aggregate $PPP_{j,k}^{Y_i}$ using shares of M_i in total output of wholesale and retail trade to arrive at the PPP for the broader industry.

Implementation: margin rates

In our dataset, we distinguish nine goods-producing industries. As this is the most granular data available, we let each of these correspond to a wholesale industry and a retail industry, so $W = R = 9$.[8] A challenge is that we do not observe wholesale and retail margins separately. Instead, for each of the 9 goods-producing industries, we observe total margins, $M_w + M_r$ from the Supply table.

Yet using this total margin number is problematic because wholesale margin rates tend to be much lower than retail margin rates, which will lead to compositional bias. Assume two countries have exactly the same margin rates in wholesale and retail trade, $m_{w,j} = m_{w,k}$ and $m_{r,j} = m_{r,k}$. Also assume that in country j, wholesale makes up a larger share of the total industry, so $\frac{M_{w,j}}{M_{w,j}+M_{r,j}} > \frac{M_{w,k}}{M_{w,k}+M_{r,k}}$. In this stylized example, the joint margin rate for country j would be lower than for country k: $\frac{M_{w,j}+M_{r,j}}{S_{w,j}+S_{r,j}} < \frac{M_{w,k}+M_{r,k}}{S_{w,k}+S_{r,k}}$.

To resolve this, we estimate separate margin rates for wholesale and retail trade using a RAS method, which is an iterative scaling method. Under this method, the row and column totals are given and the individual items in the matrix are found by iteratively normalising to the row totals and the column totals until the items in the matrix no longer change.[9]

For most OECD countries, we have valuation tables, which allocate wholesale and retail trade margins to use categories. Equating retail margins with the margins on household consumption and wholesale margins with the residual, we can compute wholesale and retail margins. For the overall wholesale and retail industry, we find that wholesale and retail margins each make up approximately 50 percent of the total margins. So, as a shortcut, we assume:

$$\begin{aligned} \sum_w M_w &\equiv WM = \frac{1}{2} \times M \\ \sum_r M_r &\equiv RM = \frac{1}{2} \times M \end{aligned} \tag{3}$$

Where M is the sum of margins across all 9 good-producing industries and we define WM as total wholesale margins and RM as total retail margins. To initialise the RAS method, we set the initial margins M_w and M_r assuming the total margin rate applies to both, $\widetilde{M}_w =$

[8] In the industrial classification, the distinction within wholesale and retail trade is not by the products that are sold but the type of store, see, e.g., Timmer and Ypma (2007).

[9] See e.g., Temurshoev and Timmer (2011).

$\frac{M_w+M_r}{S_w+S_r} \times S_w$ and $\widetilde{M}_r = \frac{M_w+M_r}{S_w+S_r} \times S_r$. Since all elements of the margin data are positive, the RAS method quickly converges to a unique solution.[10]

We verify this RAS method for 20 OECD countries, for which we have both the actual margin rates by use from the valuation matrices and the outcomes of the RAS method. Table 1 shows the results of this comparison. The average retail margin rate based on the RAS method is somewhat higher than the observed rate in the data, 0.36 versus 0.33, while the wholesale rate is a bit lower at 0.13 versus 0.14. The standard deviation across countries and products is also similar. The correlation between the two series is higher for the wholesale margin rate, at 0.84, than for the retail margin rate, at 0.57, but even a correlation of 0.57 is not low.

Table A6. Wholesale and retail margin rates: observed vs. RAS method

	Average		Standard deviation		Correlation
	Observed	RAS	Observed	RAS	Observed-RAS
Retail (household consumption)	0.33	0.36	0.12	0.14	0.57
Wholesale (other)	0.14	0.13	0.07	0.06	0.84

Notes: The table shows the margin rates from the OECD SUT and valuation tables for 20 OECD countries for goods-producing industries for 2017 and the estimated margin rates based on the RAS method described in the main text. The retail margin rate is defined as the margins on household consumption expenditure divided by household consumption expenditure at purchasers' prices. The wholesale margin rate is defined as all other margins divided by all other uses.

Table A7. Average wholesale and retail margins by product: observed vs. RAS method

	Retail		Wholesale	
	Observed	RAS	Observed	RAS
Agriculture	0.33	0.34	0.11	0.12
Food, beverages & tobacco	0.29	0.30	0.13	0.11
Textiles, wearing apparel & leather	0.43	0.44	0.18	0.17
Wood, paper and printing	0.31	0.36	0.13	0.13
Petroleum, chemicals, rubber & plastics	0.28	0.33	0.13	0.12
Non-metallic mineral and metal products	0.36	0.35	0.12	0.12
Electrical and electronic equipment	0.32	0.37	0.14	0.14
Machinery	0.35	0.42	0.15	0.15
Transport equipment	0.22	0.27	0.10	0.09

[10] Applying an unconstrained RAS can lead to retail margin rates in excess of 100 percent. At the detailed industry level, the maximum observed margin rate in OECD data is 70 percent, so we constrain the RAS procedure to not exceed a retail margin rate of 70 percent. In 7 out of 200 cases, the RAS retail margin rate is at this constrained level.

Other manufacturing	0.39	0.44	0.19	0.16

Notes: The table shows the average margin rates by product for goods-producing industries in 20 OECD countries, see notes to Table 1.

Table 2 shows the average wholesale and retail margin rates by product and this table highlights the importance of the procedure we followed. The averages from the RAS method are close to the observed averages and the variation across products is very similar with correlations of 0.90 (retail) and 0.95 (wholesale). If we had used a single margin rate, the scope for compositional bias would have been severe. And if we had used the same margin rate across products, we would have missed some of the notable variation between products, with much higher margin rates in, for example, textiles than in transport equipment. Of course, applying this method that we validated for OECD countries to a much broader and more diverse set of countries is a big step. However, we expect that broad patterns, such as that the retail margin rate is larger than the wholesale margin rate, will hold in that broader set of countries, too.

Implementation: PPPs

Given the procedure described above, we have information on M_i and S_i for all 9 wholesale industries and all 9 retail industries in every country, so for equation (3) we can compute $\frac{m_{i,j}}{m_{i,k}}$ for every i, j and k. To compute the margin PPPs, we still need $PPP_{j,k}^{S_i}$, though. For that, we rely on ICP PPPs at the basic heading level, aggregated to the level of the 9 goods-producing industries distinguished here, using expenditure shares as weights. For many products, we cannot separately distinguish wholesale and retail PPPs, so we assume $PPP_{j,k}^{S_w} = PPP_{j,k}^{S_r}$. For products used as investment (i.e., part of gross fixed capital formation) we can separately distinguish a wholesale trade and a retail trade PPP. For example, for electrical and electronic equipment we include the PPP for Audio-visual, photographic and information processing equipment (basic heading category 110911), which includes products for household consumption, in the retail trade PPP while we use the PPP for Electrical and optical equipment (1501112) for the wholesale trade PPP.

This allows us to compute margin PPPs $PPP_{j,k}^{Y_i}$ for all 9 retail and wholesale industries. Finally, we aggregate the margin PPPs using shares of M_i in total output of wholesale and retail trade to arrive at the PPP for the broader retail and wholesale industry. The overall trade PPP is then computed as the unweighted average of the retail and wholesale trade PPP.

Data construction

As discussed above, we rely on the RAS method to estimate separate margin rates for wholesale and retail trade, which are then used to compute margin PPPs. Moreover, we assume that the wholesale and retail margins each make up 50 percent of the total margins. Thus, to utilize the RAS method we only require total margins and sales data for the different industries. This data is collected primarily from the OECD Supply and Use Tables database, as well as Eurostat. Moreover, we rely on work by the Groningen Growth Development Centre (GGDC) for margins data for several SSA countries, the Asian Development Bank (ADB) for Asian countries, and several country-specific sources for LAC countries (based on data availability). Table A8 below provides the set of countries for which we have margins data:

Table A8. Countries for which we have margins data, and their source.

ARG	CZE	IRL	NOR
AUS	DEU	ITA	PER
AUT	DNK	JPN	POL
BEL	ECU	KEN	PRT
BGD	ESP	KOR	SEN
BOL	ETH	LKA	SVK
BRA	FIN	LUX	SWE
CAN	FRA	MAR	THA
CHE	GBR	MEX	TUR
CHL	GHA	MMR	TZA
CHN	GRC	MUS	USA
CMR	HUN	MYS	VNM
COL	IDN	NGA	ZAF
CRI	IND	NLD	

Source	List of countries **(55)**
OECD, Eurostat SUTs database	AUS, AUT, BEL, BRA, CAN, CHE, CHL, CMR, COL, CRI, CZE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, HUN, IDN, IRL, ITA, JPN, KOR, LUX, MAR, MEX, NLD, NOR, POL, PRT, SEN, SVK, SWE, TUR, USA, ZAF
ADB Supply and Use Tables	BGD, CHN, IND, LKA, MYS, MMR, VNM
GGDC	ETH, GHA, KEN, MUS, NGA, TZA
Individual country sources	ARG, BOL, ECU, PER

Importantly, for several countries, we only have margins data for a single year. In these cases, we assume equal retail and wholesale margin rates for the other years. We rely on the latest ICP benchmark release to compute PPPs for the year 2017, where we make a distinction between consumption and investment goods. For the remaining countries for which we could not make a margins adjustment due to a lack of SUTs data, we rely on the unadjusted overall goods relative price.

Business

In line with Inklaar and Timmer (2014), for the computation of the Business PPP, an overall consumption price is used, following the practice in ICP for estimating the PPP for financial intermediation services indirectly measured (FISIM). Thus, the Business PPP is imputed based on an aggregate price, which in turn is constructed using a set of basic heading (unadjusted) expenditure PPPs for consumption.

Finance

For the computation of Finance PPPs, we make a margin adjustment to one of the basic headings involved in computing the Finance PPP, namely FISIM. We collect data on bank margin rates (measured as the difference between lending and deposit rates) from International Monetary Fund (IMF) International Financial Statistics (IFS) and the ECB MIR database. We compute margin rates relative to the US (US=1), and these rates are then multiplied with the basic heading for FISIM. By doing this, we essentially treat FISIM as a margin industry, similar to wholesale and retail trade. This adjusted basic heading PPP is then used for the computation of the Finance PPP.

Other sectors

For the construction of the PPPs for the other sectors (Public Utilities, Construction, Transport, Real estate, Public services, and Other services), we do not make any adjustments, so these sectoral PPPs reflect unadjusted expenditure PPPs.