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Tradability and sectoral productivity differences across countries

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Abstract

Sectoral differences are generally argued to be important for understanding cross-country productivity differences. In this paper we argue that traded versus non-traded is a key distinction as we find that productivity in the non-traded sector does not systematically vary with a country's income level, compared to other two-way splits that are less distinctive. We base our analysis on newly developed measures of sectoral relative prices and productivity for 84 countries across 3 years. These data incorporate several recent measurement advances to provide more reliable estimates than previous studies, notably allowing us to relax the common assumption of a constant marginal product of labor across sectors. Relaxing that assumption and recognizing the tradability of some services industries are important to our main finding. These results emphasize the importance of reducing trade costs for enhancing productivity.

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

JEL classification: C43, D24, E01, O14, O41, O47

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1. Introduction

A key result in development accounting is that differences in GDP per worker are largely accounted for by differences in (total factor) productivity (Caselli, 2005; Hsieh & Klenow, 2010; Inklaar et al., 2019). To understand what drives these aggregate productivity differences, many studies analyze two-sector models of the economy, distinguishing agriculture versus non-agriculture (e.g., Restuccia et al., 2008; Gollin et al., 2014), traded versus non-traded (Balassa, 1964, Samuelson, 1964, Hassan, 2016), manufacturing versus non-manufacturing (Rodrik, 2013), consumption versus investment (Hsieh and Klenow, 2007) and traditional versus non-traditional services (Duarte and Restuccia, 2020). As argued in Herrendorf and Valentinyi (2012, H&V henceforth), these distinctions imply a range of non-comparable two-sector decompositions of the economy and argue for an encompassing set of sectoral productivity comparisons.

In this paper we bring a fresh perspective to this approach, analyzing productivity across 12 sectors that map into the two-sector distinctions from the previous paragraph. Our main contribution is through improved productivity measurement. We develop new estimates of cross-country relative prices, i.e., purchasing power parities (PPPs). In contrast to H&V, we measure relative prices for sectoral value added rather than final expenditure, accounting for differences in the terms of trade[1] and using direct measurement of output prices for several key sectors.[2] We also distinguish between relative prices of sectoral (gross) output and intermediate inputs.[3] Finally, we allow for variation in the marginal product of labor, in contrast to H&V, who assume that the marginal value products for all production factors are equalized across sectors.

These conceptual improvements to measurement are partly enabled by advances in data availability. Many of the development accounting exercises and the work of H&V are based on the data of Penn World Table (PWT) 6.x, comparing global prices for 1996. We draw on the three most recent rounds of global price comparisons, for 2005, 2011 and 2017, benefiting from the measurement improvements in this more recent period.[4] We also have data on sectoral

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[1] Following Cavallo et al. (2023).

[2] We extend the framework of Freeman, Inklaar and Diewert (2021) to measure output prices in agriculture and mining.

[3] Following Inklaar and Diewert (2016).

[4] The basic data are from the International Comparison Program, ICP, for 2005 (World Bank, 2008), 2011 (World Bank, 2014) and 2017 (World Bank 2020). ICP 2005 are adjusted for biases based on Inklaar and Rao (2017).

employment (as well as value added) from the Economic Transformation Database (Kruse et al., 2023) which, combined with OECD STAN and Eurostat, provide comprehensive coverage. Combined with data on country-wide produced and human capital and factor shares of PWT version 10.01 (Feenstra et al., 2015), we develop greatly improved estimates of sectoral productivity. Our sample covers 84 countries across the global income distribution for the years 2005, 2011 and 2017. We follow H&V and analyze the correlation between sectoral productivity differences and GDP per worker.

Our main novel result is that the distinction between the traded and non-traded sector is most important for understanding aggregate productivity differences across countries. We find that productivity in the traded sector varies with GDP per worker, while productivity in the non-traded sector does not. To define the non-traded sector, we use export and import shares for the countries in our data as well as estimates of tradability by Jensen and Kletzer (2005). Their indicator is based on the mismatch (across the United States) of local demand and local supply, with a larger mismatch indicating greater tradability. Based on these three indicators, we argue that only few sectors are non-traded, notably the public sector, construction and real estate, and we find that productivity in this non-traded sector does not systematically vary with GDP per worker. Productivity in the traded sector does vary systematically, regardless of whether we use a narrow definition of the traded sector, that primarily covers goods-producing industries, or a broader one that also includes tradable services.

Results for other two-way splits are less conclusive, a result different than reached by H&V. In a comparison where we sequentially change our methods to match those of H&V, we find that relaxing the assumption of a common marginal product of labor is the main reason why we reach different results. This is in line with Gollin et al. (2014), who find that labor productivity in agriculture is systematically lower than in the non-agricultural economy, in particular in lower-income countries. The result on traded versus non-traded aligns with Duarte and Restuccia (2020), who distinguish traditional and non-traditional services by whether the income elasticity is positive or negative. Though this is a different conceptual approach, their group of traditional services largely overlaps with our definition of the non-traded sector.

Comparing productivity across countries in services is challenging since relative prices are harder to measure. However, long-run time series evidence for the United States also shows that productivity growth of traded services is positive, while productivity growth of non-traded services has been stagnant. We also examine the sensitivity of our cross-country results to the assumption of a common marginal product of capital across countries for a subset of 42 countries with sectoral capital data and find further confirmation for our finding on the traded versus non-traded sector and mixed or inconclusive evidence on other two-way splits.

Studies comparing sectoral productivity across countries have long faced a difficult trade-off. One could implement a very data-intensive measurement approach requiring relatively few structural assumptions, but this would limit the set of countries considered to a few, generally higher-income countries, see e.g., Jorgenson, Kuroda and Nishimizu (1987) and Inklaar and Timmer (2009) or the more recent work by Fadinger, Ghiglino and Teteryatnikova (2022), who cover a broader range of countries. Alternatively, one could specify a model with more structure and assumptions to cover a broad range of countries, see e.g., Hsieh and Klenow (2007) for an approach based on a growth model or Fadinger and Fleiss (2011) for one based on a trade model. The approach of H&V proved an important step forward, requiring fewer assumptions but still allowing broad country coverage. Subsequent work by (e.g.) Hassan (2016) and Duarte and Restuccia (2020) has also followed H&V's approach. Our work takes this line of research one step further, leveraging greater data availability on sectoral prices and employment to relax crucial assumptions, in particular on the constancy of the marginal product of labor across sector. Similarly, we do not have to make assumptions on the production structure where expenditure prices equal valued added prices (H&V) or rely on data for a limited set of countries and calibration (Duarte and Restuccia, 2020), but instead we have the data on the input-output structure of our 84 countries to estimate value added prices. The result is an analysis that covers a broad enough range of countries to speak to the development accounting literature with minimal theoretical structure.

Our work also relates to recent studies on productivity convergence. Development accounting shows the growth path that high-income countries have taken, thereby suggesting scope for future development of lower-income countries. Productivity convergence aims to establish how far along a development path different groups of countries are. Work by Rodrik (2013) highlights how formal manufacturing industries show strong evidence of convergence in contrast to the (combined) informal manufacturing and non-manufacturing sector. Herrendorf, Rogerson and Valentinyi (2022) recently showed that convergence is absent for the total manufacturing sector (i.e., formal and informal together). Viewing our results in this light, provides further evidence that manufacturing activities are not uniquely relevant for development and that traded services industries may provide a fruitful path for development as well.

Finally, this work shows the continued relevance of the Balassa-Samuelson hypothesis for understanding differences in international prices and productivity. With greater scope for scale and competition, the traded sector can realize substantial productivity growth and the prices in the traded sector have less scope for variation due to (international) competitive pressure. By extension, this also confirms the insight of Baumol (1967) that economies can be characterized by progressive and stagnant sectors. And as Baumol et al. (1985) conclude: "The service sector happens to contain some of the economy's most progressive activities as well as its most stagnant." In that, we also relate to the literature on trade costs and productivity growth. For example, Bernard, Jensen and Schott (2006) find that manufacturing industries experiencing large declines in trade costs show relatively strong productivity growth. Miroudot, Sauvage and Shepherd (2012) find the same effect for services industries, showing that the impact of trade costs on productivity growth is of similar magnitude for services as for goods-producing industries. Seen through this lens, the high level of productivity in goods and traded services in high-income countries can be explained by reductions in trade costs for both goods and services. This would be in line with the findings of Lee (2023) who documents that trade costs are lower for trade between high-income countries in goods and (producer) services than for lower-income countries.[5]

2. Productivity measurement

For the analysis of this paper, we compute sectoral total factor productivity (TFP) estimates for a broad set of developed and developing countries (see the Appendix for the list of countries covered) for the years 2005, 2011, and 2017. For a consistent analysis of cross-country productivity levels, we require input, output, and productivity estimates which are comparable across countries. 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). We follow this method, hereinafter referred to as the Inklaar/Diewert method, which 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 follows.

[5] Lee (2023) defines as producer services what we label 'traded services'; the composition in their paper is very similar to ours.

Suppose that a production unit i in country j 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), we assume 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 $x \gg 0_N$:

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

We define the *value* of net output m in country j as v_{jm} for $m = 1, \dots, M$. Thus, there are M net outputs considered, and $v_{jm} > 0$ implies that net output m reflects a commodity that is produced, while $v_{jm} < 0$ 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 j is $p_{jm} > 0$, 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_{km} of net output m for country j as $y_{jm} \equiv v_{jm}/p_{jm}$ for $m = 1, \dots, M$; $j = 1, \dots, J$.

Having defined our net outputs, we next sum over the net outputs to estimate *total value added* v_j for each country j:

$$v_j \equiv \sum_{m=1}^{M} v_{jm} \,; j = 1, \dots, J \tag{2}$$

Furthermore, the *implicit quantity* of primary input n used in production in country j is defined as $x_{jm} \equiv V_{jn}/w_{jn}$, where V_{jn} reflects the *value* and w_{jn} the *price or PPP* of primary input n. The total value of primary inputs in country j is then computed as the sum of inputs:

$$V_j \equiv \sum_{n=1}^{N} V_{jn} \,; j = 1, \dots, J \tag{3}$$

Moreover, define the *value added output share* as $s_{jm} = v_{jm}/v_j$. Under the assumption that the value added function has a translog functional form and features constant returns to scale, Diewert and Morrison (1986) show that a Törnqvist–Theil output price index can be used to compute the aggregate PPP of value added between country j and country k:

$$P_{j/k} \equiv \exp\left[\sum_{m}^{M} \frac{1}{2}\left(s_{jm} + s_{km}\right) \ln\left(\frac{p_{jm}}{p_{km}}\right)\right] \tag{4}$$

Equation (4) reflects a bilateral index, where the estimated PPPs will depend on the base country chosen, which is not desirable. To overcome this issue, we turn it into a multilateral index by using the method by Caves et al. (1982) and averaging over all possible choices of the base country to compute base invariant PPPs P_j. Afterwards, we normalize the PPPs such that USA=1. In our current setting of sectors and countries, we then arrive at our estimates of *real* value added estimates Y_{ij} by dividing nominal value added by the *value added* PPP deflator in sector i in country j:

$$Y_{ij} \equiv \left[v_{ij}/P_{ij}\right]; \quad i = 1, \dots I; \; j = 1, \dots, J. \tag{5}$$

In a similar fashion, we can compute the aggregate quantity of our primary input X_j in country j relative to country k using a Törnqvist-Theil input quantity index with primary input cost shares $S_{jn} = V_{jn}/V_j$:

$$X_{j/k} \equiv \exp\left[\sum_{n}^{N} \frac{1}{2}\left(S_{jn} + S_{kn}\right) \ln\left(\frac{x_{jn}}{x_{kn}}\right)\right] \tag{6}$$

Here again, we use the method by Caves et al. (1982) to compute a multilateral quantity index X_{ij} which is base country independent, and we normalize these estimates such that USA=1. Finally, we compute TFP in country j in sector i by dividing real value added by the aggregate quantity of the primary inputs: $A_{ij} = Y_{ij}/X_{ij}$. This provides us with a set of input, output, and productivity estimates which are comparable across countries and over time.

3. Implementation and data

Implementing the approach detailed in the previous section requires sectoral data on nominal values and prices (PPPs) of value added and factor inputs. This section provides a general description of the data required to estimate the PPPs which are used to measure real value added. Afterwards, we describe the data involved for calculating the factor inputs. For a more detailed description, please see the Appendix.

3.1 Estimating value added PPPs

For the estimation of real value added, PPPs are used to deflate nominal value added, where data on sectoral nominal value added is retrieved from the Economic Transformation Database (ETD) (Kruse et al., 2023), OECD STAN, and Eurostat. For the computation of the sectoral PPPs, we rely primarily on the PPP benchmark data from the ICP for the years 2005, 2011, and 2017 (the latest available benchmark). The ICP provides detailed product-level data on expenditures and expenditure-based PPPs which reflect purchaser prices of final goods and services. We map the product PPPs to the relevant sectors and aggregate the PPPs using the expenditure data to compute sector-level product PPPs, based on the method by Inklaar and Diewert (2016) described above. Importantly, we apply a double deflation procedure to measure real value added, where we compute separate PPPs for gross output and intermediate inputs, in line with the literature (Jorgenson et al. 1987; Inklaar and Timmer, 2014). That is, we compute sector gross output (PPP_j^{GO}) and intermediate input (PPP_j^{II}) PPPs, which are then used to estimate value added PPPs as follows:

$$\ln PPP_{j,\cdot}^{VA} = \frac{1}{1-\alpha_{j,\cdot}}\left[(\ln PPP_j^{GO} - \ln \overline{PPP^{GO}}) - \zeta_{j,\cdot}(\ln PPP_j^{II} - \ln \overline{PPP^{II}})\right] \tag{7}$$

Where $\ln \overline{PPP} = \frac{1}{J}\sum_J ln\, PPP$; cross-country average of ln *PPP*, and $\zeta_{j,\cdot} = \frac{1}{2}(\zeta_j + \frac{1}{J}\sum_J \zeta_j)$; average of the intermediate input share ζ in country *j* and of the cross-country average intermediate input share. To compute industry gross output PPPs, we require information on how much of each product the industry produces. Similarly, for the intermediate input PPP calculation, we need data on the intermediate inputs used within each industry. For this data, we rely on Supply and Use Tables (SUTs), which we retrieve from the OECD, Eurostat, the Asian Development Bank (ADB), Mensah and de Vries (2023), and additional country-level sources. With respect to the intermediate input PPPs, an important remark here is that we do not directly observe intermediate input prices. Instead, we assume that the basic price of a good is independent of its use and rely on product PPPs to estimate intermediate input PPPs.

Importantly, with respect to the estimation of PPPs, several sectors require special attention. Agriculture and mining are industries that mostly produce intermediates. As mentioned above, the PPPs produced by the ICP reflect purchaser prices of *final* goods and services, thus, these expenditure-based PPPs are not adequate for measuring output in agriculture and mining. Instead, for these sectors we draw on gross output values and quantities data, which allows us to obtain a direct measurement of output prices for these sectors, reflecting a notable improvement over using expenditure prices. For agriculture, we obtain this data from FAOSTAT, and for mining we rely on subsoil assets data from the World Bank (Lange et al., 2018).

Moreover, another important point to note is that ICP PPPs reflects *purchaser prices,* and thus these prices include domestic trade costs (trade and transport margins, taxes less subsidies) and *import* prices, and exclude *export* prices. However, the appropriate price for deflating industry output is a *domestic basic* price since industry output covers *produced* goods and services. Therefore, for manufacturing we estimated *adjusted expenditure* PPPs, by "stripping away" domestic trade costs, netting out the import price, and adding the export price. We do this adjustment based on Cavallo et al. (2023):

$$\frac{P_{ij}^{Y}}{P_{ik}^{Y}} = \left(\frac{P_{ij}^{C}/\tau_{ij}}{P_{ik}^{C}/\tau_{ik}}\right)^{\frac{1-\omega_{ij}^{X}}{1-\omega_{ij}^{M}}} \left(\frac{\tilde{P}_{ij}^{M}}{\tilde{P}_{ik}^{M}}\right)^{\frac{\left(-\omega_{ij}^{M}*\left(1-\omega_{ij}^{X}\right)\right)}{1-\omega_{ij}^{M}}} \left(\frac{\tilde{P}_{ij}^{X}}{\tilde{P}_{ik}^{X}}\right)^{\omega_{ij}^{X}} \tag{8}$$

where P_{ij}^{Y} reflects domestic output prices, P_{ij}^{C} reflect consumption prices, τ_{ij} reflects domestic trade costs (margins and net taxes), and $\tilde{P}_{ij}^{M}$ and $\tilde{P}_{ij}^{X}$ reflects quality-adjusted import prices and export prices. The subscript *k* reflects the base country (in this case the U.S.). Törnqvist weights ω_{ij}^{M} and ω_{ij}^{X} are computed as $\omega_{ij}^{M} = \frac{1}{2}(\eta_{ij}^{M} + \frac{1}{J}\sum_{J}\eta_{ij}^{M})$; $\omega_{ij}^{X} = \frac{1}{2}(\eta_{ij}^{X} + \frac{1}{J}\sum_{J}\eta_{ij}^{X})$, where η_{ij}^{M} and η_{ij}^{X} reflect import and export shares (relative to total use), respectively. Taking these variables to the data, P_{ij}^{C} reflects the expenditure PPP from the ICP, data on domestic trade costs and import and export shares stem from the SUTs, and the export and import prices reflect quality-adjusted export and import price data from Feenstra and Romalis (2014).

With respect to trade, wholesale and retail trade are margin industries, i.e., firms earn their income by charging a margin on the products they sell to their customers. The challenge in comparing output prices for margin industries is that we do not observe the margin price. To overcome this data constraint, we follow the conceptual approach of Timmer and Ypma (2006) and estimate margin PPPs for the trade sector (see the Appendix for a more elaborate discussion on this). Finally, in line with Inklaar and Timmer (2014), for the computation of the Business sector PPP, an overall consumption price is used, in line with the approach by the ICP for estimating the PPP for financial intermediation services indirectly measured (FISIM). Table 1 below provides a brief overview of the method and data used for the PPP calculation for different sectors.

Table 1. Summary sources and methods for sectoral PPP calculation

Sector	Method	Data
Agriculture	Output PPPs	Crops and livestock farm-gate price data from FAOSTAT
Mining	Output PPPs	Natural resources data from World Bank
Manufacturing	Adjusted expenditure PPPs: "stripping away" domestic trade costs and adjusting for Terms-of-trade (SUTs)	Expenditure PPPs from International Comparison Program (ICP), margins, tax, and trade data from Supply and Use Tables (SUTs)
Trade	Margin PPPs	Expenditure PPPs from ICP, margins data from SUTs
Business	Expenditure PPPs, based on overall consumption PPP	Expenditure PPPs from ICP
Other sectors	Expenditure PPPs	Expenditure PPPs from ICP

3.2 Estimating factor inputs

For the calculation of TFP, we rely on the following production function with constant returns to scale:

$$y_{ij} = A_{ij}\left(k_{ij}\right)^{\theta_{ij}}\left(l_{ij}\right)^{\varphi_{ij}}\left(h_{ij}\right)^{\alpha_{ij}} \tag{9}$$

Where y_{ij} reflects sectoral output, A_{ij} reflects sectoral TFP and θ_{ij}, φ_{ij}, and α_{ij} ($\alpha_{ij} = 1 - \theta_{ij} - \varphi_{ij}$) reflect the sectoral factor shares of physical capital, land, and labor, respectively, for sector i in country j. The variables y_{ij}, k_{ij}, l_{ij}, and h_{ij} reflect sectoral output of physical capital, land, and labor, and are included in per-worker terms. Moreover, labor reflects total hours worked multiplied by a human capital index which is based on average years of schooling and an (assumed) rate of return to schooling. Unfortunately, sector-level data on production factors is notoriously scarce for developing countries. H&V circumvent this lack of data by making three assumptions: competitive markets, mobile production factors, and Cobb-Douglas production functions where factor shares are uniform across countries. From these assumptions, it follows that marginal products are equalized across sectors, and that implies that a sector's share of factor *input* equals that sector's share of factor *income*.

But in contrast to H&V, we do have information on sectoral employment data from the ETD (Kruse et al., 2023), supplemented with sectoral employment data from OECD STAN and Eurostat. This allows us to relax the assumption that the marginal product of labor is equalized across sectors. Given the evidence by Gollin et al. (2014) on the large productivity gap between agriculture and non-agriculture, it is important to account for this friction in labor instead of assuming that labor is mobile across sectors, see also the discussion below.

In another relaxation of H&V assumptions, we estimate country/sector specific factor cost shares rather than follow their approach of assuming factor cost shares in all countries to be equal to those in the US. We sketch the procedure here, providing further details in the Appendix. While we do not directly observe factor payments at the country/sector level, PWT (Feenstra et al., 2015) provides country-level data on the labor share in GDP. The remainder of GDP is assumed to flow to owners of capital and land. There is no comprehensive cross-country data on this capital/land division, but this is available for the US and for 20 of the Asian countries in our sample from the Asia Productivity Organization. For this set of countries, we find that the capital/land division can be predicted from each country's capital and land intensity. We can thus compute the total income flowing to labor, capital and land and for each sector, (nominal) value added is income flowing to that sector. To estimate country/sector-specific income flows, we first take US factor shares as a starting point but then iteratively adjust sector income to sum to factor-level totals and to sector-level totals, a procedure also known as the RAS method. This RAS method quickly converges to a set of sectoral income flows that are consistent with both sets of totals. Since we initialize this method using US factor shares, we implicitly assume that a sector that is (e.g.) relatively capital-intensive in the US, will also be relatively capital-intensive in other countries. But as we show in our results, this still leads to notable variation in sectoral cost shares and, for some sectors, markedly different productivity results.

Bringing these pieces together, we estimate factor input per worker according to the following three equations:

$$k_{ij} = \frac{\left(\frac{\theta_{ij} v_{ij}}{\sum_i \theta_{ij} v_{ij}}\right) CK_j}{EMP_{ij}} \tag{10}$$

$$h_{ij} = h_j = HC_j * avh_j \tag{11}$$

$$l_{ij} = \begin{cases} i = \text{Agriculture} & \dfrac{AL_j}{EMP_{ij}} \\ i = \text{Other} & \dfrac{\left(\frac{\varphi_{ij} v_{ij}}{\sum_{i \neq agr} \varphi_{ij} v_{ij}}\right) OL_j}{EMP_{ij}} \end{cases} \tag{12}$$

Equation (10) divides across sectors the economy-wide capital stock, measured as variable CK_j from PWT,[6] using each sector's share in capital income. That share is derived from v_{ij}, (nominal) sectoral value added and θ_{ij} the capital income shares in sector i of country j. Equation (11) makes a simpler assumption, namely that labor input per worker is equal across sectors. We measure labor input per worker using variables from PWT, namely HC_j, which is the average years of schooling adjusted with the average rate of return to schooling for each level of education,[7] and avh_j, average hours worked per person. For land, finally, we make a distinction between arable land (AL) and other land (OL), both available from FAOSTAT. Arable land, as in H&V, is assumed to be only used in agriculture. Other land, which is the total land area minus land for agricultural purposes, forests and inland and coastal areas, is allocated to the other sectors based on each sector's share in land income. Here φ_{ij} is the land income share in sector i of country j.

4. Results

We compile all necessary data for a sample of 84 countries and the years 2005, 2011 and 2017.[8] To be included in the sample, we require data on at least sectoral employment and a recent input-output or supply-use table. The other data requirements, notably on relative output prices and factor inputs, are less restrictive. Taking the 183 countries in PWT as the global numbers, our data covers 88 percent of the world population. The median GDP per worker level in our sample is higher than that for the world ($44 000 versus $33 000) and the 90/10 ratio for the 84 countries is 15 versus a global ratio of 19. Though our sample is richer and less unequal than the full set of countries, the role of (aggregate) productivity differences in accounting for variation in GDP per worker is very similar, suggesting our country coverage is representative.[9]

In discussing our results, we first illustrate the relevance of the measurement improvements we make, regarding relative prices, estimating sectoral factor cost shares and relaxing assumptions on the marginal product of labor. We then present our main results on the systematic variation in productivity across sectors and sector groupings. Finally, we discuss the sensitivity of our

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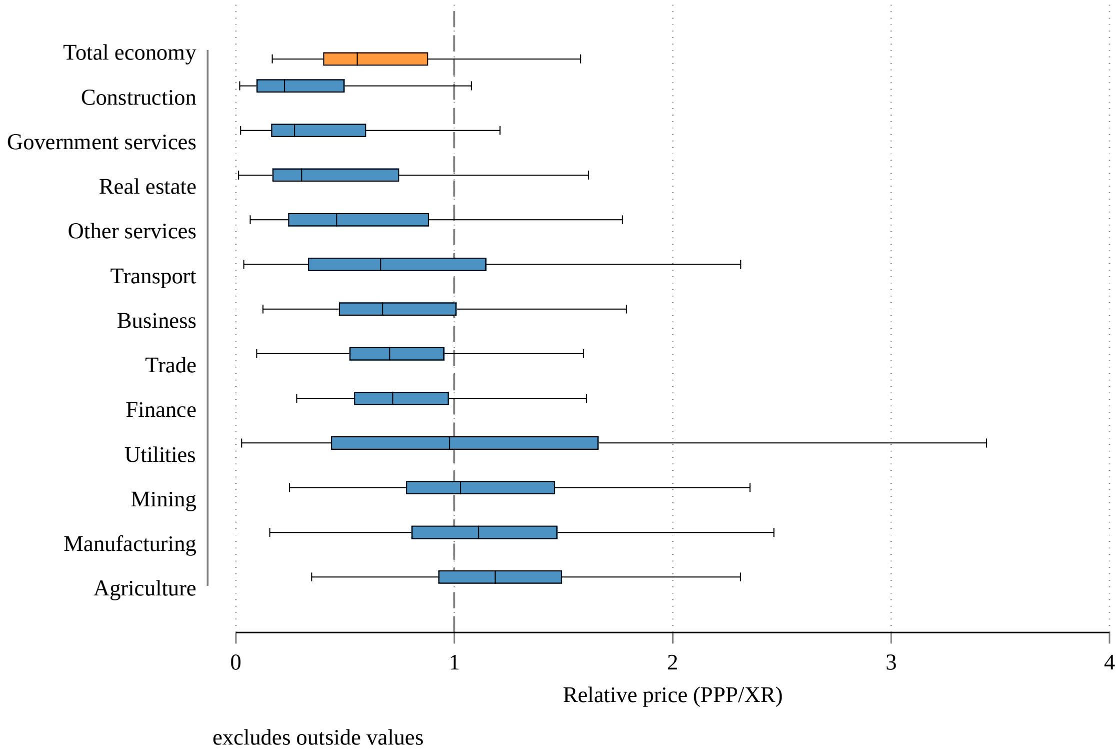
[6] For some countries, PWT has no data on CK (relative capital services), so instead we use CN (relative capital stock) for the comparison.
[7] As in Caselli (2005) and H&V, we assume the first four years of schooling have a return of 13.4 percent, the next four of 10.1 percent and any subsequent years of 6.8 percent.
[8] The list of countries covered is in Appendix Table A.1
[9] Using PWT and regressing log TFP on log GDP per worker for our sample of 84 countries and 3 years gives a coefficient of 0.349, which is not significantly different from the 0.359 for the full set of countries in PWT.

results to concerns about international price comparisons in services and to sectoral variation in the marginal product of capital.

Measurement improvements

The measurement methods we apply represent some clear advances compared to earlier approaches. First, we make no assumptions on the law of price holding, as in, for example, Rodrik (2013) and we impose notably less structure than the approach of H&V or Duarte and Restuccia (2020). While H&V impose a common marginal product of labor across sectors, we use sectoral employment data. And rather than assuming equal factor cost shares to those in the United States, we use variation in country-level labor cost shares, endowments of capital and land and sectoral composition to estimate country/sector specific cost shares.

Figure 1. Value added prices across sectors



Notes: Figure shows boxplots for each sector's value added price level across the 84 countries, with the solid box indicating the range from 25th to 75th percentile and the solid line indicating the median value.

We illustrate the importance of relaxing these assumptions in the following figures and table. Figure 1 shows a boxplot of the estimated sector relative prices (value added PPP divided by the market exchange rate) for the 12 sectors of our analysis and the total economy, averaged across the three years. As the figure shows, relative prices differ noticeably across sectors, with the median for agriculture, manufacturing and mining closest to the law of one price but showing notable variation around that median. There is also notable variation across the other sectors. For example, the median price level in the transport sector is at 0.66, close to the median for the total economy of 0.71, but for construction the median is only 0.22. This illustrates how careful price measurement at the sectoral level is crucial for the type of productivity comparison of this paper.

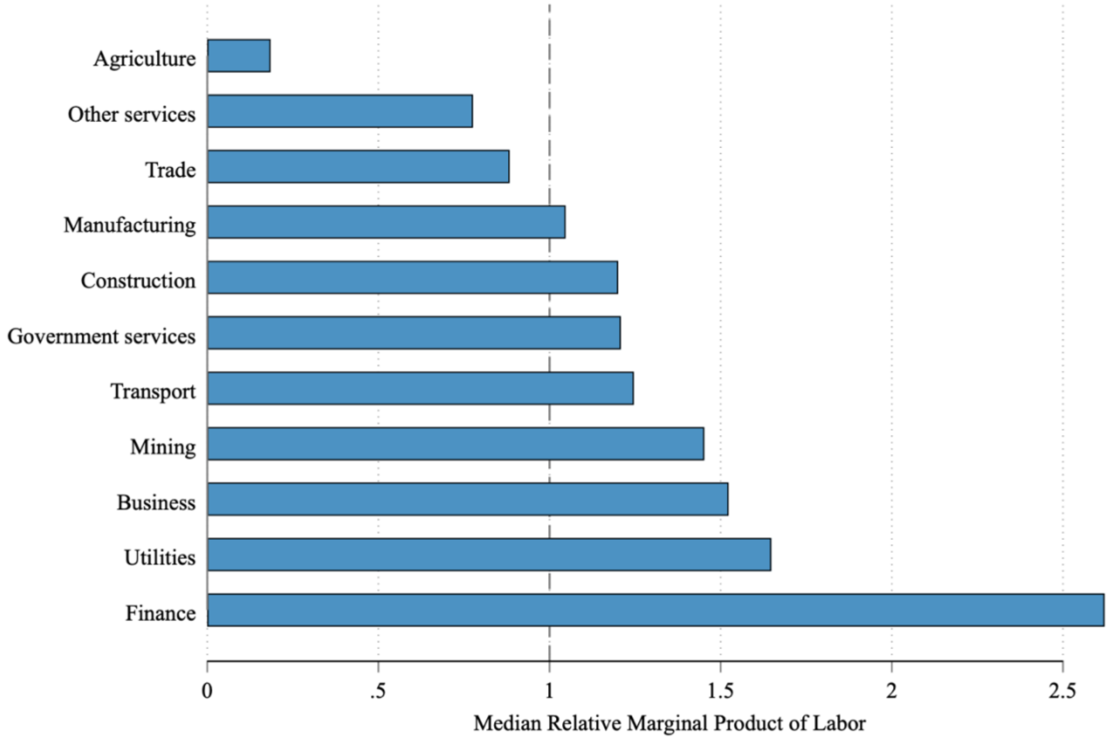
In Table 2 we show summary statistics for the sectoral factor shares that we estimate using the RAS method described above. For some sectors, the cross-country variation in factor shares is only limited; for example, in business services, the country at the 25th percentile for labor share is at 0.615 and the 75th percentile is at 0.705. These, in turn, do not differ strongly from the US labor share for business services of 0.718. But, as a counter example, the land share in agriculture varies substantially across countries, with an interquartile range from 0.247 to 0.638 (the US share is 0.370). As we show below, the impact of using our estimated country/sector factor share varies between settings but can be substantial where the cross-country variation in sector shares is large.

Table 2. Sectoral factor shares summary statistics.

	Labor			Capital			Land		
Sector	Median	25th	75th	Median	25th	75th	Median	25th	75th
Agriculture	0.214	0.152	0.300	0.293	0.176	0.433	0.466	0.291	0.670
Mining	0.204	0.175	0.239	0.736	0.651	0.796	0.045	0.022	0.106
Manufacturing	0.439	0.393	0.490	0.506	0.422	0.575	0.038	0.018	0.085
Utilities	0.292	0.247	0.336	0.681	0.606	0.740	0.020	0.010	0.048
Construction	0.775	0.725	0.813	0.134	0.099	0.170	0.075	0.033	0.140
Trade	0.616	0.561	0.655	0.292	0.226	0.355	0.070	0.034	0.144
Transport	0.635	0.591	0.678	0.321	0.259	0.383	0.031	0.015	0.067
Business	0.664	0.617	0.709	0.314	0.258	0.371	0.016	0.008	0.036
Finance	0.534	0.487	0.583	0.414	0.340	0.484	0.036	0.018	0.078
Real estate	0.162	0.136	0.186	0.695	0.575	0.779	0.118	0.061	0.254
Government	0.724	0.684	0.757	0.236	0.188	0.287	0.030	0.014	0.062
Other services	0.751	0.711	0.782	0.196	0.153	0.243	0.039	0.017	0.077

Notes: Table shows the factor shares for the median country, and at the 25th and 75th percentile. Factor shares are estimated using a RAS-method on country-level factor income and sector-level value added, see main text for details.

Figure 2. Relative marginal product of labor across sectors



Notes: The marginal product of labor (MPL) in each country and sector is computed as the labor share times labor productivity. The relative MPL is the sector's MPL divided by the economywide MPL. The figure shows the median relative MPL across countries for each sector. Real estate is omitted because a substantial part of this industry consists of income from owner-occupied housing.

To estimate sectoral factor inputs, H&V assume for all factors that a sector's share of economy-wide factor inputs equals that sector's share of economy-wide factor costs, i.e., that the factor price is equal across sectors. Thanks to the growing availability of sectoral employment data, notably from the Economic Transformation Database (Kruse et al., 2023), we can relax this assumption for labor, as detailed above. That also allows us to illustrate to what extent the H&V assumption is violated in practice. To do so, we compute each sector's marginal product of labor (MPL) as $MPL_{ij} = \alpha_{ij} \times y_{ij}$ and compare this with the country-level MPL, $RMPL_{ij} = MPL_{ij}/MPL_j$. Figure 2 plots the median RMPL for each sector with larger deviations from one indicating larger deviations from the H&V assumption. Such deviations are particularly marked for agriculture with a median RMPL of 0.20. This RMPL below one is in line with the findings of Gollin et al. (2014) and more generally with a development literature arguing that there is surplus labor in agriculture. But the variation around one is notable for most sectors, with finance an outlier in the other direction. These estimates of RMPL are imperfect, for instance because cross-sector variation in effective labor input per worker will vary across sectors and because of possible error in estimating sectoral labor shares. However, Gollin et al. (2014) find that adjusting for differences in human capital of agricultural workers does not eliminate MPL differences, so these remaining measurement issues are unlikely to bring us back to the H&V assumption of a common MPL.

Systematic price and productivity variation

With this illustration of the importance of the key measurement advances in our analysis, we turn to the analysis of price and productivity differences. To succinctly summarize the patterns in our data, we follow H&V and use regressions of relative prices and relative productivity on income levels. For relative prices, this leads to the following equation:

$$\log(p_{ijt}) = \alpha_i + \beta_i \log(y_{jt}) + \delta_t + \varepsilon_{ijt} \tag{13}$$

where p_{ijt} is the value added price level in sector i in country j, y_{jt} is GDP per worker in country j in the three years of our sample ($t = 2005, 2011, 2017$) and δ_t are year fixed effects. A parallel equation is used for analyzing productivity differences:

$$\log(A_{ijt}) = \alpha_i + \gamma_i \log(y_{jt}) + \delta_t + \varepsilon_{ij} \tag{14}$$

where A_{ijt} is TFP in sector i in country j at time t. The coefficients β_i and γ_i can be interpreted as the degree to which prices and productivity vary with income. If, for example, γ_i is equal to zero, then there are no systematic TFP differences across countries. If this coefficient equals one, this means that systematic TFP differences are equal to per capita GDP differences.

We estimate β_i and γ_i, first, for individual sectors but subsequently also common for groups of sectors β_is and γ_is for groups of sectors, such as the non-agricultural sector or the traded sector. In those case, we estimate equations (13) and (14) using as weights the share of each sector in total value added. This ensures that the level of sectoral disaggregation of our data does not affect these more aggregate results.

Table 3 shows that there is substantial variation across sectors in the price-income relationship. As noted above, for the total economy coefficients we use price and productivity data for each sector and use value added weights in the regression. Price levels, on average, increase with income, with construction and non-market services prices rising relatively faster, and agriculture and industry prices relatively slower. Productivity tends to vary less systematically with income than prices, indicating that part of the reason why prices in rich countries are higher is that factor costs are higher.

We now turn to the question how to most parsimoniously account for the variation in β_i and γ_i across sectors. Like H&V, we use different two-way splits: traded versus non-traded, agriculture versus non-agriculture, manufacturing vs. non-manufacturing and investment versus consumption. Traded versus non-traded warrants particular discussion. H&V follow a typical approach by classifying manufactured products as traded and services and construction as non-traded. Yet in their distinction between traditional and non-traditional services, Duarte and Restuccia (2020) also discuss that there is increasing scope for trade in what they label 'non-traditional services'.

Table 3. Variation in prices and productivity with GDP/worker by sector.

Sector	Price Level β_i	Productivity level γ_i
Total economy	0.277	0.326
	(0.022)	(0.019)
Agriculture	0.057	0.632
	(0.028)	(0.033)
Mining	-0.104	0.498
	(0.019)	(0.033)
Manufacturing	0.328	0.300
	(0.025)	(0.031)
Utilities	0.490	-0.110
	(0.053)	(0.052)
Construction	0.649	0.187
	(0.057)	(0.052)
Trade	0.298	0.515
	(0.032)	(0.031)
Transport	0.574	0.111
	(0.041)	(0.045)
Business	0.360	0.147
	(0.018)	(0.029)
Finance	0.179	0.326
	(0.020)	(0.037)
Real estate	0.649	-0.183
	(0.039)	(0.041)
Government	0.591	0.126
	(0.041)	(0.031)
Other services	0.644	0.347
	(0.025)	(0.044)

Note: Column 2 shows estimates of β_i based on equation (13), column 3 shows estimates of γ_i based on equation (14). The coefficient for Total economy in both columns reflects the coefficient from the regression for all sectors jointly, with value added shares used as weights. Robust standard errors are reported in parentheses.

To examine this more closely, we turn to three indicators of tradability, a sector's export share and import share and an estimate of the fraction traded based on locational Ginis, based on the work of Jensen and Kletzer (2005) and Jensen and Gervais (2019). Table 4 shows export and import shares, computed based on the Supply-Use tables we have available and averaged across countries.[10] The export share is defined as a sector's exports as a share of its gross output, the import share is defined as imports over total use of the product.[11] The third indicator is not based on observed trade flows but on the geographical concentration of production and consumption. The disparity between local supply and local demand is an indicator of the extent of trade in an industry. We use the resulting estimates of the traded share of each sector's employment from Jensen and Kletzer (2005, Table 4) based on data for the United States.

Table 4. Sector tradability according to export and import shares and geographical concentration.

Sector	Export share	Import share	Share traded from geographical Ginis	Classification
Agriculture	0.28	0.16	1.00	Broad/Narrow
Mining	0.78	0.48	1.00	Broad/Narrow
Manufacturing	0.62	0.28	0.86	Broad/Narrow
Utilities	0.08	0.06	0.19	Non
Construction	0.02	0.01	0.00	Non
Trade	0.13	0.07	0.23	Broad
Transport	0.22	0.15	0.70	Broad/Narrow
Business	0.17	0.12	0.69	Broad
Real estate	0.00	0.00	0.91	Non
Finance	0.11	0.08	0.68	Broad
Government services	0.01	0.01	0.08	Non
Other services	0.04	0.05	0.23	Non

Notes: The export share is the ratio of sectoral exports over gross output, the import share is the ratio of sectoral imports over total use. Both are calculated from the Supply-Use tables for each country, and we report here the cross-country average shares. The 'shared traded from geographical Ginis' is computed from Jensen and Kletzer (2005, Table 4).

[10] All countries are pooled in computing this average, but the ranking is not sensitive to whether the average is computed only for high-income or low-income countries.
[11] This definition is in line with the international trade literature, e.g., Arkolakis, Costinot and Rodriguez-Claire (2012).

Table 4 shows that there is considerable variation in tradability across sectors and differences across the three indicators. The three goods-producing sectors, agriculture, mining and manufacturing, have the highest export and import shares but the transport sector is quite close to the export and import shares in agriculture. Especially when also considering the third indicator based on geographical concentration of production and consumption, some of the services industries appear as more tradable. Especially finance and business services score high on this third indicator, at comparable levels to the transport sector. The tradability of the (wholesale and retail) trade sector is lower, but going by the export and import shares, it is comparable to finance. One outlier is real estate, which has zero export and import shares but is geographically concentrated. This is, in part, because real estate firms (i.e., those that rent residential and/or commercial property) represent only a modest portion of the overall industry, which also includes imputed rents from owner-occupied housing.

The final column of Table 4 gives our classification into traded and non-traded. To recognize the fact that this is less of a binary classification than, say, agriculture vs. non-agriculture, we use a narrow definition, which only includes agriculture, mining, manufacturing and transport, and a broad definition that also includes trade, finance and business services. Utilities, construction, real estate, government and other services are classified as non-traded.

Table 5 shows the results of estimating equations (13) and (14) for the different classifications, again using value added weights. Based on these results, manufacturing is not distinct from non-manufacturing, for both prices and productivity the β_i and γ_i coefficients do not differ significantly. Output prices in the investment sector actually vary more than in the consumption sector and for productivity the variation is significantly less, in contrast to H&V and Hsieh and Klenow (2007). Productivity varies more in agriculture than in non-agriculture and this difference is large and significant. This is consistent with the evidence from Gollin et al. (2014) on productivity differences, mirrored in Figure 2's results on the marginal product of labor.

The top part of Table 5 provides our main novel result, namely that the systematic variation in prices is significantly lower and the variation in productivity is significantly higher in traded sectors than non-traded sectors. Indeed, productivity in the non-traded sector does not systematically vary with income level. This result is not affected by whether we use the narrow or the broad definition of tradability. This is not to argue that only tradability matters for understanding sectoral variability in prices and productivity. For example, productivity variability in agriculture is significantly larger (and price variability significantly smaller) than in other traded sectors, suggesting that the specific features of that sector—such as resource misallocation—are additionally important. More generally, and as shown in Table 3, there is variation within the traded and non-traded sector.

Table 5. Sector relative prices, productivity, and income levels; from sectors to alternative two-sector splits.

Group	Price Level β_i	Productivity level γ_i
Broad traded	0.174	0.399
	[0.137 – 0.210]	[0.366 – 0.431]
Narrow traded	0.135	0.369
	[0.090 – 0.181]	[0.324 – 0.414]
Non-traded	0.658	0.024
	[0.616 – 0.701]	[-0.024 – 0.071]
Agriculture	0.010	0.567
	[-0.044 – 0.064]	[0.501 – 0.634]
Non-agriculture	0.418	0.247
	[0.385 – 0.451]	[0.209 – 0.284]
Manufacturing	0.297	0.356
	[0.250 – 0.343]	[0.293 – 0.419]
Non-manufacturing	0.266	0.332
	[0.216 – 0.316]	[0.291 – 0.374]
Consumption	0.232	0.353
	[0.184 – 0.280]	[0.312 – 0.394]
Investment	0.459	0.232
	[0.381 – 0.537]	[0.149 – 0.315]

Notes: Column 2 shows estimates of β_i based on equation (13), column 3 shows estimates of γ_i based on equation (14). Sectoral value added shares are used as weights. We show the coefficient from these equations and the 95-percent confidence interval in square brackets, based on robust standard errors. See Table 4 for the broad/narrow/non-traded classification. Investment sectors are defined here as manufacturing and construction.

Still, the result for traded versus non-traded sectors is powerful for a few reasons. First, it allows us to trace all systematic variation in productivity to a specific group of sectors. Second, it sheds a different light on the results of Duarte and Restuccia (2020). Their grouping of services into 'traditional' and 'non-traditional' was based on the income elasticity of demand while our grouping into traded and non-traded services is based on the tradability indicators of Table 4. Yet the grouping is very similar and they, too, find much greater systematic variation of productivity in non-traditional (i.e., traded) services than in traditional (i.e., non-traded) services.

The impact of measurement improvements

Compared to H&V we have introduced a series of measurement improvements which may be important in understanding why our results differ from those of H&V. In our results the traded/non-traded distinction is considerably more salient, and we find larger productivity variation in the consumption sector than in the investment sector instead of smaller variation. To understand the relevance of different measurement changes, we calculate several alternative sets of sectoral TFP, to move closer to the data and methods of H&V. The first set approximates H&V the most and then we cumulatively improve measurement until the fourth set is based on our preferred method:

1. Using ICP expenditure PPPs for all sectors, assuming the same MPL for all sectors, assuming factor shares equal those in the US.
2. Using value added PPPs for all sectors, assuming the same MPL for all sectors, assuming factor shares equal those in the US.
3. Using value added PPPs for all sectors, using sectoral employment data, assuming factor shares equal those in the US.
4. Using value added PPPs for all sectors, using sectoral employment data, estimating country-sector specific factor shares.

The first set of TFP estimates is conceptually closest to H&V, but still differs from their estimates along several dimensions: (i) the 86 countries that H&V cover are not the same as the 84 covered here, (ii) their analysis is on data for 1996, ours is for 2005, 2011 and 2017, (iii) in their approach, sectors are distinguished by type of expenditure, not by type of production activity and as consequence, sectors that predominantly produce intermediate products, such as agriculture or mining, are not identified separately in H&V and (iv) our measurement approach does not allow us to reliably distinguish TFP of detailed manufacturing industries. This means that H&V's "Food" sector does include the food processing industry, while ours only covers agriculture and H&V's "Investment" sector separately distinguishes investment sectors within manufacturing while ours includes manufacturing as a whole.[12]

[12] There are some further, smaller differences. We rely on PWT for estimates of produced and human capital by country while H&V compile their own measures. Our aggregation of sectoral output across products and industries uses a Törnqvist-Theil-type index, see equation (4), while H&V sum implied quantities. These differences do not have a material impact on the results.

Table 6 compares estimates of γ_i by H&V and based on our data. Panel A approximates the five sectors of H&V based on our 12 sectors; panel B approximates their two-way splits. The first line in panel A is for the total across sectors, with the first column showing the H&V's γ_i at 0.46 and the final column showing the 0.32 from Table 3. Reading across the columns, we see that the first two sets of TFP estimates show a very similar figure of 0.48 but when allowing for variation in the MPL across sectors in TFP set 3—enabled by the availability of sectoral employment data—the coefficient decreases considerably. A similar pattern of changes can be observed across the individual sectors as well, with notable decreases in the γ_i between set 2 and 3.

The comparison for the construction industry clarifies why H&V—and Hsieh and Klenow (2007) before them—find a larger γ_i in investment industries compared to consumption industries while we find the reverse. Based on their methods, we reach a very similar conclusion as H&V but allowing for sectoral differences in MPL considerably reduces the systematic variation in TFP in the construction industry.

Table 6. Comparison to Herrendorf and Valentinyi (2012) with alternative TFP estimates

	H&V	This paper: 1. Exp PPPs	2. Same MPL	3. Same shares	4. Final
A. H&V sectors					
Total	0.46	0.49	0.49	0.32	0.33
Food	0.68	0.37	0.54	0.52	0.57
Mfd. consumption	0.48	0.55	0.51	0.41	0.39
Equipment	0.84	0.60	0.47	0.38	0.36
Services	0.22	0.56	0.48	0.19	0.21
Construction	0.77	0.70	0.43	0.06	0.10
B. H&V two-way splits					
Traded	0.65	0.32	0.43	0.41	0.40
Non-Traded	0.30	0.57	0.46	0.17	0.19
Food	0.68	0.37	0.54	0.52	0.57
Non-Food	0.40	0.57	0.48	0.23	0.25
Consumption	0.46	0.46	0.50	0.34	0.35
Investment	0.81	0.62	0.42	0.23	0.23

Notes: The table shows estimates of γ_i based on equation (14). Column H&V is based on Table 3 of Herrendorf and Valentinyi (2012). Subsequent columns use progressively more sophisticated estimates of sectoral TFP, see main text for details. The sectors and two-way splits approximate H&V classification with our 12 sectors, Food refers to Agriculture, Manufactured consumption is total Manufacturing and Mining, Services include Utilities, Trade, Transport, Finance, Real estate, Business, Government and Other services. Equipment is also total Manufacturing. Traded refers to Agriculture, Mining, and Manufacturing, and Non-Traded the rest of the sectors. Investment refers to Manufacturing and Construction, and Consumption refers to the rest of the sectors. The table reports 2 decimal places to be consistent with Herrendorf & Valentinyi (2012).

For Food and Services, the comparison is less clear, the γ_i of H&V is most similar to our preferred TFP measure rather than the measure that is methodologically most similar. This is most likely because of differences between the PPPs for 1996 used by H&V and ours for 2005, 2011 and 2017.

The comparison for manufactured consumption and equipment is complicated by the fact that our sectoral employment data do not allow us to distinguish these two parts of manufacturing. However, the γ_i in TFP set 1 for total manufacturing of 0.60 is close to the average of manufactured consumption and equipment of 0.66. For manufacturing, the use of double-deflated value added PPPs has a substantial impact as does allowing for differences in sectoral MPL.

Price measurement in services

Measuring relative prices across countries is not straightforward (Deaton and Heston, 2010) and doing so in the context of sectors is even more challenging since the price surveys of the ICP capture prices of final expenditure rather than sectoral output. Given the importance of prices of services sectors for our results—i.e., the distinction between tradable and non-tradable services—it is helpful to discuss their reliability.

As emphasized by Deaton and Heston (2010), several categories of products/sectors are particularly challenging to conceptualize—what they term as 'comparison resistant'— and these are primarily in the non-traded sector: government, health, education, construction and real estate. In those sectors it is challenging to conceptualize output and/or adequately account for differences in their quality. At the same time, substantial effort has been made to improve on this situation, see, e.g., World Bank (2014, 2020).

Yet we can also find confirmatory evidence in time series data. Our finding that high-income countries have (systematically) higher productivity levels in traded sectors but not in non-traded sectors has as a corollary that in high-income countries, productivity growth in traded sectors will be faster over the long run than in non-traded sectors. This is Baumol's cost disease as the counterpart to the Balassa-Samuelson effect. And while productivity measurement over time is also not straightforward, there is a more substantial body of data to draw upon.

To provide a long-run perspective for a high-income country, we use the BEA-BLS production account data, which, combined with historical data, provide a time series from 1963 to 2020. We use the categorization of traded versus non-traded sectors from Table 4 and distinguish goods-producing traded sectors from traded services.

Table 7 shows that TFP growth has been fastest in goods-producing traded industries, at 1.6 percent on average per year. But traded services have also shown consistently positive growth at 0.6 percent per year. The difference in productivity growth between traded goods-producing and traded services is substantial, but the very rapid TFP growth in computers and electronic products (at 10.5 percent on average per year) magnifies this difference. Average annual TFP growth in goods-producing industries excluding computers and electronic products was 0.7 percent. In contrast, productivity in the non-traded sector of the US has stagnated over this 57-year period. And that is not just traceable to government, see (e.g.) Goolsbee and Syverson (2023) on the decades-long decline of productivity in the construction sector. This is not to argue that there is no productivity growth in the non-traded sector at all, but rather that traded services show a notably different productivity growth pattern than the non-traded sector.[13]

Table 7. Average annual TFP growth in the United States

	1963-2020 (%)
Traded goods-producing	1.6
Of which:	
Computers and electronic products	10.5
Other goods-producing	0.7
Traded services	0.6
Non-traded	–0.1

Notes: Sectoral TFP growth and value added from the BEA-BLS Production Account, combined with the Historical Data. We compute a Törnqvist aggregate across sectors using the classification of (broad) traded and non-traded from Table 4 and distinguishing between traded goods-producing and traded services.

Sectoral variation in MPK

One substantial improvement over earlier work is that we no longer have to assume constant MPL across sectors thanks to better data on sectoral employment. But the lack of data on sectoral capital input (and land use) means we still have to assume constant marginal product of capital (MPK) and of land. To assess the importance of this assumption, we use data from

[13] These results are for the US only, but Lee (2023) shows very similar results for a broader group of countries.

the Socio-Economic Accounts (SEA) of the World Input-Output Database (WIOD, Timmer et al., 2015). The SEA has data on sectoral capital stocks for 42 countries in our 84-country sample. Note that those 42 countries are primarily the higher-income countries of our sample, the average GDP per worker level (for 2005) was approximately $30 000 for the SEA sample and $10 000 for the 42 countries not in the SEA sample.

To ensure comparability with the baseline productivity estimates, we use the SEA data to estimate the share of each sector in the total capital stock and apply that share to the total capital input from PWT that we use in the baseline. So, the difference between the two is that in our baseline we use the sectoral share of capital income to divide capital input across sectors and we compare that to using the sectoral share of capital stocks.[14]

Table 8. TFP, constant versus varying marginal product of capital (MPK)

Group	All countries	SEA sample	SEA sample, varying MPK
Broad traded	0.40	0.64	0.65
Narrow traded	0.37	0.60	0.59
Non-traded	0.02	0.03	0.00
Agriculture	0.57	0.61	0.37
Non-agriculture	0.25	0.45	0.48
Manufacturing	0.36	0.67	0.82
Non-manufacturing	0.33	0.40	0.36
Consumption	0.35	0.45	0.40
Investment	0.23	0.49	0.60

Notes: The table shows estimates of γ_i based on equation (14). The column 'All countries' replicates the final column from Table 5 with estimates based on data for all 84 countries. The estimates in the 'SEA sample' column are based on a sample for the 42 countries that are also in the WIOD Socio-Economic Accounts. The column 'SEA sample, varying MPK' uses capital stock shares based on the SEA to estimate sectoral capital input.

Table 8 shows the result of this analysis. We first contrast the results on γ_i from Table 5 for all 84 countries to the same productivity measure but then for the 42 countries in the SEA sample. The final column of Table 8 then shows the estimates of γ_i based on the SEA's capital stock shares instead of the capital income shares in our baseline. We first note that the SEA sample shows differences in patterns, with the distinction between agriculture and non-agriculture shrinking and the difference between manufacturing and non-manufacturing increasing.[15]

[14] The SEA data cover the period 2000–2014. To get estimates for 2017, we calculate 2014 capital/value added ratios from the SEA data and apply that to the 2017 value added data from our dataset.

[15] Regarding manufacturing, this implies a non-linearity with productivity only starting to rise with GDP per worker only above a certain level of GDP per worker. Given the result of Herrendorf, Rogerson and Valentinyi

There is also some indication that the investment sectors have larger variability than the consumption sectors, though that difference in the 'SEA sample' column is small. The result for traded versus non-traded is qualitatively similar and quantitatively even stronger.

Comparing the last two columns shows that relaxing the common-MPK assumption has the biggest impact on agriculture. Instead of greater systematic variability than in non-agriculture, the variability is actually smaller when using SEA capital stock shares. This implies that capital stock shares in agriculture are lower than capital income shares in low-income countries compared to high-income countries. This could imply misallocation of resources, though it could also point to limitations of our method for estimating sectoral income shares. Either way, if our method overestimates agricultural capital intensity in low-income countries then we underestimate agricultural (total factor) productivity. For the other comparisons, relaxing the constant-MPK assumption makes little difference, though the systematic variability in investment now is notably larger than in consumption sectors. This reinforces the main novel result from our paper, that productivity in traded sector systematically varies with the level of GDP per worker while productivity in the non-traded sector does not.

5. Conclusions

An important contribution of this paper is in the construction of new relative price estimates for 12 sectors across a set of 84 countries spanning most of the world income distribution. These relative prices, which we provide in a new version of the GGDC Productivity Level Database, are based on data from the three recent rounds of the International Comparison Program, for 2005, 2011 and 2017, as well as a range of additional sources. Most important amongst those additional sources is the sectoral employment data from the Economic Transformation Database (Kruse, et al., 2023), which allows us to provide more reliable estimates of sectoral productivity and relaxing a crucial and misleading assumption of constant marginal products of labor across sectors. In comparison to existing studies, we find that relaxing this assumption matters substantially for the results. Furthermore, we use newly developed Input-Output Tables for these 84 countries, combined with export and import relative prices to estimate sectoral value added prices.

(2022), this could point to informal manufacturing holding down productivity across much of the GDP/worker distribution until the point where the more dynamic nature of formal manufacturing (Rodrik, 2013) takes over.

We find new evidence on the importance of tradability for a sector's contribution to economic development, emphasizing the relevance of tradable services alongside goods-producing industries. Using indicators of actual trade (export and import shares) and tradability based on the location of supply versus demand in the US, we argue that sectors such as transport, trade, finance and business services are also tradable to a notable degree. We find that the traded sector's productivity systematically varies with income while the non-traded sector's productivity does not.

The importance of tradability for understanding cross-country productivity differences confirms the enduring relevance of Baumol and Balassa-Samuelson for understanding how countries grow rich, namely through productivity improvements in the traded sector, broadly viewed. This does not yet answer *how* tradability matters. Rodrik (2016) argued that manufacturing is particularly instrumental in the process of growth as a technologically dynamic sector, able to absorb unskilled labor and not constrained by the size of the home market. That still takes tradability as given and does not give insight into what factors make tradability so important. Is it greater exposure of firms to competition? Is it the possibility to achieve greater scale? And is the relationship between the level of traded costs and productivity growth or is productivity growth dependent on continued decreases in trade costs? The importance of such questions for understanding the scope for economic development suggests these are fruitful avenues for future research.

Further research is also warranted to understand whether the reasons for why high-income countries have grown more productive in the past, are relevant for lower-income countries today. As discussed, development accounting is important for charting the development path that has already been taken, while the options for future development may be different. The emergence of global value chains may have changed the relevance of trade costs, continued automation may limit the importance of foreign sourcing and lower-income countries may face other constraints that are not apparent when comparing to those countries that have already grown rich.

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Appendix

Appendix Table A 1. List of the 84 countries covered in the analysis.

Argentina	Egypt	Republic of Korea	Philippines
Australia	Spain	Lao People's DR	Poland
Austria	Estonia	Sri Lanka	Portugal
Belgium	Ethiopia	Lithuania	Romania
Bangladesh	Finland	Luxembourg	Russian Federation
Bulgaria	France	Latvia	Rwanda
Bolivia	United Kingdom	Morocco	Senegal
Brazil	Ghana	Mexico	Singapore
Botswana	Greece	North Macedonia	Slovakia
Canada	Hong Kong	Myanmar	Slovenia
Switzerland	Croatia	Mauritius	Sweden
Chile	Hungary	Malawi	Thailand
China	Indonesia	Malaysia	Tunisia
Cameroon	India	Namibia	Turkey
Colombia	Ireland	Nigeria	Taiwan
Costa Rica	Iceland	Netherlands	Tanzania
Cyprus	Israel	Norway	Uganda
Czech Republic	Italy	Nepal	United States
Germany	Japan	New Zealand	Viet Nam
Denmark	Kenya	Pakistan	South Africa
Ecuador	Cambodia	Peru	Zambia

Appendix Table A 2. List of the sectors covered in the analysis.

Sector	ISIC Rev. 4 code
Agriculture	A
Mining	B
Manufacturing	C
Public Utilities	D+E
Construction	F
Trade	G+I
Transport	H
Business	J+M+N
Finance	K
Real estate	L
Government services	O+P+Q
Other services	R+S+T+U

Construction of the PPPs

In this section, we describe in more detail the construction of sectoral PPPs, which are used to compute real value added estimates which are comparable across countries. 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. We first describe the computation of the PPPs for agriculture and mining, the two sectors from our sample for which we do not use the expenditure PPPs from ICP, but instead calculate output PPPs by utilizing data on output prices and values. Afterwards, we describe the calculation of the PPPs for the other sectors, where we rely on the expenditure PPPs from ICP. This provides us with a set of product PPPs. In turn, as described above, these product PPPs are used (together with information from SUTs on how much of each product an industry produces and consumes), to estimate industry gross output, intermediate input, and value added PPPs.

Agriculture

For the computation of agricultural PPPs, we collected crops and livestock farm-gate price and production data for the period 1991-2018 from the FAOSTAT database from the Food and Agriculture Organization (FAO) of the United Nations (FAO, 2019). The PPP for 1990 was estimated by extrapolating prices based on the change in the industry deflator in country j relative to the U.S. 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:

$$\omega_m^k = \begin{cases} p_m^k & if\ W_m > C_m^k \\ W_m & if\ W_m \leq C_m^k \end{cases} \tag{A1}$$

As production costs are not observed when a commodity is not produced, Equation (A1) 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[16]. 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.

Mining

The computation of the mining PPPs follows a similar approach to that of agriculture. Here, we rely on data on prices and production of 15 subsoil assets from the World Bank (Lange et al., 2018). These subsoil assets cover both mineral assets (e.g. gold, iron, silver) and energy assets (e.g. coal, gas, oil). Also here, we relied on *Hicksian reservation prices* for assets which

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

are not produced. As the period coverage of this data only goes until 2014, we estimated PPPs for the years 2015-2018 using the same extrapolation method used for the agriculture PPPs.

Manufacturing

For the estimation of manufacturing PPPs, we first calculate expenditure PPPs for nine manufacturing industries, where Table A3 serves as an illustration to indicate the number of basic headings from the ICP 2017 round mapped to each industry. As described 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 retrieve data on domestic margins and net taxes from Supply and Use Tables for the countries where this is available (discussed below). Moreover, we use quality-adjusted export and import prices for goods, which have been constructed by Feenstra and Romalis (2014). Afterwards, we compute the aggregate manufacturing PPP by aggregating the PPPs of the manufacturing industries using the Inklaar/Diewert method.

Appendix Table A3. Number of basic headings covered per manufacturing 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:

$$M_i = S_i - C_i = m_i S_i, \text{for } i \in w, r;\ w = 1, \ldots, W; r = 1 \ldots R \qquad \text{(A2)}$$

Let M_i be the gross margin (i.e., the gross output) of an industry i 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 (2006) and define the margin PPP for industry i as:

$$PPP_{j,k}^{Y_i} = \frac{m_{i,j}}{m_{i,k}} PPP_{j,k}^{S_i} \tag{A3}$$

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.

Trade, 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 $W = R = 9$.[17] 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 normalizing to the row totals and the column totals until the items in the matrix no longer change.[18]

[17] 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 (2006).
[18] See e.g., Temurshoev and Timmer (2011).

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:

$$\sum_w M_w \equiv WM = \frac{1}{2} \times M$$
$$\sum_r M_r \equiv RM = \frac{1}{2} \times M \qquad (A4)$$

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, $\widetilde{M}_w = \frac{M_w+M_r}{S_w+S_r} \times S_w$ 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.[19]

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 A4 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.

Appendix Table A 4. 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.

[19] 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.

Appendix Table A 5. 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
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 A4.

Table A5 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.

Trade, 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 also rely on the Asian Development Bank (ADB) for margins data on Asian countries, Mensah and de Vries (2023) for data on Sub-Saharan African countries, and country-specific sources for several LAC countries (based on data availability). Table A6 below provides the set of countries for which we have margins data:

Appendix Table A 6. The 72 countries with margins data and their source.

Source	List of countries
OECD, Eurostat SUTs database (42)	AUS, AUT, BEL, BGR, BRA, CAN, CHE, CHL, COL, CRI, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IDN, ITA, JPN, KOR, LUX, LVA, MAR, MEX, MKD, NLD, NOR, NZL, POL, PRT, ROU, SGP, SVK, SVN, SWE, TUR, USA
ADB SUTs (14)	BGD, CHN, HKG, IND, KHM, LAO, LKA, MYS, MMR, NPL, PAK, THA, TWN, VNM
Mensah and de Vries (2023) (11)	CMR, ETH, GHA, KEN, MUS, NGA, RWA, SEN, TZA, ZAF, ZMB
Individual country sources (5)	ARG, BOL, ECU, PER, RUS

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. 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 services 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 PPPs for the finance sector, we make a margin adjustment to one of the basic headings involved in computing the Finance PPP, namely the PPP for 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 PPPs reflect unadjusted expenditure PPPs. 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.

Estimating sectoral factor inputs

For the estimation of TFP, we require estimates of value added, as well as the factor inputs capital, land and labor. We use data on sector nominal value added and employment from the ETD (Kruse et al., 2023), OECD STAN, and Eurostat. Nominal value added is deflated by our estimated PPPs to obtain real value added estimates. As described in the main text, for the estimation of the sectoral factor inputs, we require data on sectoral factor incomes. We rely initially on U.S. factor shares, where we retrieve this data from the U.S. Bureau of Labor Statistics (BLS). In addition, we also estimate country-specific sectoral factor incomes and we do this as follows. While we do not directly observe factor payments at the country/sector level, we do have data at the country-level on labor income, which is retrieved from PWT (Feenstra et al., 2015). The residual income (GDP minus labor income) that remains is assumed to be allocated to the factor inputs capital and land. While there is no comprehensive cross-country data on the income split between capital and land, for 20 of the Asian countries in our sample there is data available on the capital stock of *produced assets* and *land*, separately, from the Asia Productivity Organization. We take this data, and using the real rate of return (irr) and the average depreciation rate of the capital stock ($delta$) from PWT (Feenstra et al., 2015), we compute capital income by multiplying the produced capital stock with the sum of the real rate of return and the depreciation rate: $(irr + delta) * produced\ capital\ stock$. For land income, we multiply the real rate of return with the capital stock of land: $irr * land$.

Next, we calculate the capital income ratio as capital income divided by the sum of capital and land income. We regress the capital income ratio on the log of capital per capita and the log of total land per capita, where capital per capita reflects capital services divided by total population, and this data is retrieved from PWT (Feenstra et al., 2015). Additionally, total land (area land) comes from FAOSTAT. For this set of countries, we find that the capital/land division can be predicted from each country's capital and land intensity. We use these predicted values to impute values for land and capital income for the countries in our dataset. Since we have data on labor income, data on capital and land income can also be retrieved. Hence, we can thus compute the total income flowing to labor, capital and land (factor-level totals), and for each sector, we have data on (nominal) value added, which is the income flowing to that sector (sector-level totals). Next, we iteratively adjust sector income (using U.S. data as initial values) to sum to factor-level totals and to sector-level totals, a procedure also known as the RAS method (note that RAS is used as well in the trade PPP calculation). This RAS method quickly converges to a set of sectoral income flows that are consistent with both sets of totals.

Estimating TFP when employment equals zero

A sector that requires careful attention with regards to productivity measurement is real estate. This sector produces value added but does not have an employment equivalent. Therefore, we estimate TFP for this sector by only considering capital and land as primary factor inputs involved in producing output. Freeman et al. (2021) devised an approach to measure productivity in a setting where a production unit does not utilize all primary factor inputs, and we follow their approach. That is, we first adjust sectoral value added by subtracting labor compensation:

$$\tilde{v}_{ij} = \left(1 - \alpha_{ij}\right) * v_{ij} \tag{A5}$$

Similarly, the PPP used to deflate value added also needs to be adjusted to be the appropriate deflator for the modified value added estimate. We do this as follows. First, we compute the share of value added and labor compensation in modified value added:

$$\kappa_{ij} = \frac{v_{ij}}{\tilde{v}_{ij}} \tag{A6}$$

$$\sigma_{ij} = \frac{\alpha_{ij} v_{ij}}{\tilde{v}_{ij}} \tag{A7}$$

Next, we estimate a modified value added PPP (USA=1) by subtracting the price of labor (PPP^h) from the value added PPP:

$$\ln \widetilde{PPP}_{ij} = \kappa_{ij,\cdot}(\ln PPP_{ij}^{VA} - \ln \overline{PPP_{\iota}^{VA}}) - \sigma_{ij,\cdot}(\ln PPP_{ij}^{h} - \ln \overline{PPP_{\iota}^{h}}) \tag{A8}$$

Where $\ln \overline{PPP} = \frac{1}{J}\sum_J ln\, PPP$; the cross-country average of $\ln PPP$, $\kappa_{ij,\cdot} = \frac{1}{2}(\kappa_{ij} + \frac{1}{J}\sum_J \kappa_{ij})$; the average of the share κ in sector *i* in country *j* and of the cross-country average share, and $\sigma_{ij,\cdot} = \frac{1}{2}(\sigma_{ij} + \frac{1}{J}\sum_J \sigma_{ij})$; average of the share σ in sector *i* in country *j* and of the cross-country average share.

The PPP for labor PPP^h is estimated based on country-level relative wages, where we divide the wage *w* in country *j* by the wage in the U.S., the base country:

$$PPP^h = \frac{w_j}{w_{usa}} \tag{A9}$$

In turn, wages are estimated by dividing labor compensation by employment (adjusted for human capital):

$$w_j = \frac{\alpha_j * v_j}{EMP_j * HC_j} \tag{A10}$$

With the adjusted VA PPP, we are able to deflate the modified value added where labor compensation has been subtracted from:

$$\tilde{y}_{ij} = \frac{\tilde{v}_{ij}}{\widetilde{PPP}_{ij}} \tag{A11}$$

Finally, we estimate TFP as before, but now with only capital *K* and land *L* as factor inputs (we use capital letters here to point out that capital and land are not denoted in per-worker terms), where the factor shares $\tilde{\theta}$ and $\tilde{\varphi}$ add up to one:

$$\tilde{A}_{ij} = \frac{\tilde{y}_{ij}}{(K_{ij})^{\tilde{\theta}_{ij}}(L_{ij})^{\tilde{\varphi}_{ij}}} \tag{A12}$$

Effect of different assumptions on TFP

To provide an example of the impact of the different measurement methods and assumptions on TFP, Table A7 below shows estimates for the agricultural sector in India relative to the US in 2017. This comparison of relative levels may help build intuition for the type of changes seen in Table 6 of the main text. As the Table shows, the use of expenditure versus value added PPPs has a notable impact on the TFP estimates. The PPP for agricultural value added, at 70 rupees to the dollar, is much closer to the exchange rate of 65, while the PPP based on retail prices for food is much lower at 32. Relaxing the assumption of the same MPL has a smaller impact as does using our estimates for the sectoral factor shares. Restricting the sample to the set of SEA countries leads to a higher productivity level. The difference is relatively large, in most cases the difference between the samples is less than 2 percent. The reason the difference in sample matters is that the multilateral productivity index compares each country to an average country and in the case of agriculture, the difference in estimated factor shares makes a notable difference in the parameters for this average. Recall that in Table 2, the average interquartile range of factor shares was notably larger in agriculture than in other sectors, 14 percentage points versus 5 percentage points (on average) for the other sectors. Finally, allowing for variation in the MPK leads to higher productivity levels still. This indicates that using the capital income share overestimates agricultural capital input compared to using the capital stock share.

Appendix Table A7. TFP in agriculture in India, 2017, USA=1.

Measurement variant	TFP level
Expenditure PPPs	0.78
Same MPL	0.36
Same factor shares	0.32
Baseline	0.38
Baseline (SEA sample)	0.45
Varying MPK	0.57