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ARTICLE

Development and sectoral labor income shares

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Abstract

The macroeconomic literature assumes that sectoral labor income shares and output per person are uncorrelated across countries. This paper shows that the data reject this assumption for a large set of countries. The labor shares of the manufacturing and market services sectors systematically increase with output per person relative to those of other sectors, leading to a shift of labor income across sectors with economic development. The empirical evidence suggests that capital deepening and cross-sector differences in the degree of capital-labor substitutability may be important for understanding these patterns. Researchers can directly use the provided dataset of labor shares to calibrate macroeconomic models.

Keywords: Labor share; income distribution; capital-labor substitution; development accounting

JEL classifications: E01; E25; O11

1. Introduction

Since Bernanke and Gürkaynak (2001) and Gollin (2002) documented that the labor share of national income is uncorrelated with output per person across a large number of countries, this fact has become a standard feature of macroeconomic models, with broad implications for the shape of the production function, inequality, and cross-country comparisons.[1] What's more, even studies seeking to understand outcomes at the *sectoral* level, such as which sectors are responsible for developing countries' low productivity, generally assume that the steadiness of the national labor share carries over to sectoral labor income shares.[2] However, this aggregate steadiness might mask underlying, offsetting movements of sectoral labor shares. If such movements were systematically related to output per person, they would bias the results of studies that assume common sectoral labor shares across countries. Yet, despite their central role in economic analyses, there is a surprising lack of data on sectoral labor shares in general and whether they correlate with output per person in particular.

This paper addresses the question of whether the shares of value-added paid to labor at the sectoral level correlate with national output per person.[3] Therefore, I first create a comprehensive panel dataset of sectoral labor shares, covering several years and a wide range of development levels: The maximum value of real output per person, adjusted for purchasing power, is over 17 times larger than the minimum value (United States \$51, 119 versus India \$2, 909). Then, I use panel regression techniques to analyze whether sectoral labor income shares change systematically with national output per person across and within countries and to what extent other variables, such as capital intensity and trade openness, matter for the evolution of sectoral labor shares.

This paper makes three main contributions. In its first contribution, it presents a novel panel dataset of sectoral labor shares that accounts for intermediate-input linkages across sectors and the labor income of the self-employed. This extends the seminal studies of cross-country national labor shares by Bernanke and Gürkaynak (2001) and Gollin (2002) to a more detailed,

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sub-national level. Additionally, the dataset substantially increases the number of data points on sectoral labor shares by expanding the point-in-time results for the United States in 1997 by Valentinyi and Herrendorf (2008) to several countries and years. Previous studies that analyzed labor shares across countries at the sub-national level have two important limitations that this paper addresses.[4] First, the studies did not adjust for the labor income of the self-employed. Exceptions are Askenazy et al. (2018), Decreuse and Maarek (2017), and Bentolila and Saint-Paul (2003), which analyzed imputed labor earnings, assuming that the self-employed earn the same wages as employees. Section 3 discusses the drawbacks of this approach. This matters because Gollin (2002) showed that significantly higher self-employment rates in developing countries can lead to a systematic understatement of the national labor share, potentially biasing cross-country comparisons. The second limitation is that these previous studies focused on industry-level labor shares, whereas this paper studies sectoral (or final expenditure) labor shares (e.g., the labor income share in the car manufacturing industry *versus* the labor income share embodied in cars). In the context of economic development, focusing on sectoral labor shares instead of industry labor shares offers at least three important advantages: first, changes in industry labor shares may reflect a relabeling of activity due to outsourcing, as opposed to shifts in economic fundamentals (e.g., van Neuss, 2019). However, outsourcing does not affect sectoral labor shares because sectors incorporate intermediate-input linkages that effectively capture any outsourcing. For example, if car manufacturers shift from having in-house cleaning staff at their factories to purchasing cleaning services from an outside firm, and cleaning services have, on average, lower labor shares than car manufacturers, the data will show this as an increase in the industry labor share of car manufacturers. This problem does not plague final expenditure: holding the labor share of cleaning services fixed, it does not matter whether the cleaning services were supplied in-house or outsourced, because they are implicitly reflected (via intermediate inputs) in the final expenditure labor share of cars (Herrendorf et al., 2013). Indeed, Berlingieri (2014) presented evidence that outsourcing can account for a sizable share of the reallocation from the manufacturing to the services sector in the United States economy between 1947 and 2002. The second advantage of the sectoral perspective is that final expenditure categories are typically more comparable across rich and poor countries than industries: for instance, 'spending on food' is easier to define and compare than output in the agricultural industry. This means that data on final expenditure are readily available in cross-country studies, whereas data on industry output are not necessarily available (Herrendorf and Valentinyi, 2012). The third advantage of considering labor shares in final expenditure categories is the close link to consumer preferences in demand-driven theories of structural transformation, where changes in consumer expenditure with development lead to the reallocation of resources across sectors (e.g., Kongsamut et al., 2001). As clarification, consider the example of a book. From an industry-output perspective, a book represents consumption of wood from forestry, processing from manufacturing, and retail services from the retail industry. In the case of final expenditure, the book represents consumption of manufactured goods. In demand-driven theories of structural transformation, consumers care about the final expenditures perspective; thus, internal consistency dictates sectoral production functions that require information on sectoral labor income shares to discipline functional forms and parameters (Herrendorf et al., 2013).

The second contribution of this paper is to analyze the relationship between sectoral labor shares and output per person. In contrast to the standard assumption in the macroeconomic literature, I find that sectoral labor shares significantly correlate with output per person both across and within countries; the steadiness of the national labor share does not carry over to the sectoral level.[5] This finding suggests that macroeconomic studies that rely on the assumption of common sectoral labor shares across countries may yield biased results. The labor shares of the manufacturing and the services sectors evolve significantly differently with economic development compared to the labor share of the other sectors (agriculture, mining, construction, and utilities), leading to a shift in labor income between sectors as countries grow more prosperous. Additionally, while

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the labor share dynamics in the manufacturing sector are relatively homogeneous, the services sectoral labor shares display a significant degree of heterogeneity: Labor shares of the market services sector (e.g., communication and transport services) rise compared to non-market services (e.g., health and social services) as output per person increases. These results are informative for macroeconomic models that analyze the determinants of structural change and that examine which sectors are responsible for the low productivity in developing countries. Moreover, these findings identify sectors that, all else equal, tend to reduce inequality in society over the course of economic development: the manufacturing and market services sectors.[6] This matters because inequality can fuel social conflict, and recent research suggests it can also harm economic growth (Halter et al., 2014).

In the third contribution, this paper provides evidence on the channel through which development and sectoral labor shares are linked. In line with evidence on the *within-country* evolution of national labor shares (Karabarbounis and Neiman, 2014) and industry-level labor shares (Bentolila and Saint-Paul, 2003), I find that the capital-to-labor ratio significantly correlates with sectoral labor shares not only within but also *across* countries. Intuitively, in a competitive world where sectoral production functions are not Cobb-Douglas, changes in sectoral labor shares are exclusively related to capital deepening and hence reflect changes in the relative prices of capital and labor. The link between capital deepening and sectoral labor shares is significantly more positive in the manufacturing and market services sectors than in the other sectors. These facts are consistent with the findings of Alvarez-Cuadrado et al. (2018), who argued that multisector models should incorporate production functions with non-unitary elasticities of substitution that differ across industries. All the findings are robust to controlling for other relevant factors that the literature frequently uses to explain the movement of national labor shares, including trade openness (Elsby et al., 2013; Harrison, 2022; Jayadev, 2007; Stockhammer, 2017), union density or worker-bargaining power (Askenazy et al., 2018; Fichtenbaum, 2011), and product market price-setting power (Blanchard and Giavazzi, 2003; De Loecker and Eeckhout, 2018; Diez et al., 2018).

The finding that meaningful heterogeneity exists between market and non-market services is not new, though it has not previously been documented for labor shares. For example, Baumol et al. (1985) found that labor productivity growth in the United States varies greatly across service-sector sub-industries. Duarte and Restuccia (2020) emphasized the importance of accounting for heterogeneity in the services sector when analyzing sectoral productivity differences. In their study, Duarte and Restuccia (2020) focused on intermediate input shares and relative price differences within the services sector, so they had nothing to say about non-service activities and sectoral labor shares.

Another literature to which this paper relates has shown that labor shares evolve differently within industries over time in the United States (Elsby et al., 2013; Jones, 2003; Young, 2010). Specifically, Elsby et al. (2013) found that the labor share in manufacturing industries declined substantially more than in the services industries in the United States during 1987–2011, and Young (2010) documented the same pattern for the period 1958–1996, whereas Jones (2003) found the opposite during 1960–1996. Rodríguez and Jayadev (2013) used United Nations National Accounts Data and found that most industry labor shares show statistically significant negative time trends. All these studies focused on within-country industry-level outcomes, so they are silent about sectoral labor shares and their evolution across countries.

Finally, two relevant papers have studied the correlation between income shares and output per person across countries in the manufacturing industry. Ortega and Rodríguez (2006) analyzed United Nations data on manufacturing sub-industries and found that the *capital* income shares in the manufacturing industry are decreasing with income across countries. Recently, Maarek and Orgiazzi (2020), analyzing the same United Nations data, found a clear U-shaped pattern with development: manufacturing labor shares first decline with output per person, then rise again. An advantage of these studies is their data coverage, which includes some of the least-developed

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economies. I extend these studies by accounting for intermediate input linkages and labor income of the self-employed, and by documenting the evolution of other sectors, such as services, which typically account for larger shares of economic activity and employment across countries than manufacturing.

This paper is organized as follows. Section 2 outlines the methodology for mapping labor shares by industry into final expenditure using input–output tables. Section 3 describes the data sources used and discusses the different adjustments for the labor income of the self-employed. Section 4 analyzes the relationship between sectoral labor shares and output per person. Section 5 discusses to what extent capital deepening and other possible factors can account for the findings, and Section 6 concludes.

2. Method—Linking industries and sectors

In the real world and the data, industries use capital, labor, and intermediate inputs to produce both output for final expenditure and intermediate inputs for other industries. Moreover, industries may produce multiple outputs, and different industries may produce the same output. In other words, the use of intermediate inputs leads to a whole chain of intersectoral linkages that one must consider to compute the sector of final expenditure labor shares. Establishing a mapping between industries in the data and final expenditure, therefore, requires additional information about industry output and labor income as well as intersectoral linkages through intermediate inputs. Given the necessary information, one can first compute the industry labor shares and then subsequently collect all the industry labor shares that belong to a particular final expenditure sector, both directly because the industry delivers final output to that sector and indirectly through the provision of intermediate inputs to other industries whose output belongs to that particular sector. The remainder of this section describes the method in detail, closely following Valentinyi and Herrendorf (2008).

Suppose the economy consists of I industries and C commodities (goods and services), where industries combine intermediate inputs with capital and labor to produce output. Let $\mathbf{W}$ denote the $(C \times I)$ Make Matrix.[7] Rows are associated with commodities and columns with industries: element (c, i) gives the share of one dollar of commodity c that industry i produces. The $(C \times 1)$ commodity output vector $\mathbf{q}$ shows for each commodity the total dollar value of the output of that commodity that is delivered to final expenditures and other industries as intermediate inputs. Let $\mathbf{B}$ denote the $(C \times I)$ Use Matrix. Entry (c, i) shows the dollar value of commodity c that industry i uses as intermediate input per dollar of gross output that it produces. The $(I \times 1)$ industry output vector $\mathbf{g}$ shows for each industry the total dollar value of the gross output of that industry. Finally, let the $(C \times 1)$ vector $\mathbf{e}$ denote the vector of dollar expenditure for final uses. Entry c gives the final uses of commodity c.

The vectors and matrices are linked by accounting identities as follows:

$$\mathbf{q} = \mathbf{B}\mathbf{g} + \mathbf{e}\,, \tag{1}$$

$$\mathbf{g} = \mathbf{W}'\mathbf{q}\,. \tag{2}$$

The first identity (1) states that the value of the total output of a commodity equals the value of this commodity used as an intermediate input in the production of gross output by the different industries plus the value of final expenditure on this commodity. The second identity (2) links the value of an industry's gross output to the value of this industry's commodity output that is used as intermediate inputs and for final uses.

Denote the $(I \times I)$ identity matrix by $\mathbf{1}$. Combining the above identities to eliminate the vector of commodity outputs gives

$$\mathbf{g} = \mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}\mathbf{e}\,, \tag{3}$$

whereby the $(I \times C)$ matrix $\mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}$ is the Industry-by-Commodity Total Requirements Matrix. Rows are associated with industries and columns with commodities: entry (i, c) shows

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the dollar value of industry *i*'s gross output required, directly and indirectly through intermediate input linkages, to deliver one dollar of commodity *c* to final uses.

For each commodity *c*, denote by $\mathbf{e}_c$ the $(C \times 1)$ vector that records the final dollar expenditures on commodity *c*, such that all other entries except *c* equal zero. Let α_{li} and α_{vi} denote the labor income and value-added, respectively, generated per unit of industry *i*'s gross output. Collect all the values in the $(I \times 1)$ vectors $\alpha_{\mathbf{l}}$ and $\alpha_{\mathbf{v}}$. With this notation, the share of value-added paid to labor embodied in commodity *c* is

$$\lambda_c = \frac{\alpha_{\mathbf{l}}'\mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}\mathbf{e}_c}{\alpha_{\mathbf{v}}'\mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}\mathbf{e}_c}\,. \tag{4}$$

Here, the vector $\alpha_{\mathbf{l}}'\mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}$ computes labor income in each commodity and the vector $\alpha_{\mathbf{v}}'\mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}$ computes value-added in each commodity. The expenditure vector $\mathbf{e}_c$ selects a particular commodity for which to compute the labor share. Note that using a $(C \times 1)$ vector of ones computes a measure of the national labor share as a simple average over all final expenditure labor shares.

The described approach accounts for the relabeling of economic activities due to outsourcing at the industry level. However, using industry-level labor income shares to compute commodity labor income shares may introduce bias, since firms within an industry are likely heterogeneous in both their labor income shares and commodity mix.

The computed commodity labor income shares remain unbiased only if firms' labor income shares are uncorrelated with their output supply patterns. To see this, consider an industry with two firms: Firm H (80% labor income share) and Firm L (20% labor income share), each contributing equally to industry output (50% average labor share). Both supply Chemicals and Textiles commodities.

Scenario 1 (Unbiased): If both firms produce 70% Textiles and 30% Chemicals, the commodity labor shares equal the industry average (50% each), correctly reflecting true values. This is because the Industry-by-Commodity Total Requirements Matrix uses average supply coefficients, which correctly reflect the composition of supply to final-use categories.

Scenario 2 (Biased): If Firm H produces 100% Textiles while Firm L produces 10% Textiles and 90% Chemicals, the true labor shares become 74.5% for Textiles and 20% for Chemicals. Using the industry average (50%) would underestimate the labor share in Textiles and overestimate that in Chemicals.

Therefore, the analysis below assumes that firms' output supply patterns do not correlate with their labor income shares in value added. However, it is important to consider this limitation when interpreting the results.

For future reference, note that the method allows mapping labor and capital inputs from industries to commodities. Let $\tilde{h}_i$ and $\tilde{k}_i$ denote the labor and capital inputs per unit of industry *i*'s gross output and collect all the values in the $(I \times 1)$ vectors $\mathbf{H}$ and $\mathbf{K}$, respectively. With this notation, the capital and labor inputs embodied in commodity *c* are

$$h_c = \mathbf{H}'\mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}\mathbf{1}_c\,, \tag{5}$$

$$k_c = \mathbf{K}'\mathbf{W}'(\mathbf{1} - \mathbf{B}\mathbf{W}')^{-1}\mathbf{1}_c\,, \tag{6}$$

whereby $\mathbf{1}_c$ is a $(C \times 1)$ selection vector with entry *c* equal to one for commodity *c* and zero otherwise.

3. Data

To assess the correlation between sectoral labor shares and output per person, I combine several sources to construct a panel dataset of such shares for a large cross-section of countries spanning the years 1995–2009.[8] This requires three datasets: first, labor income, value-added, and output

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at the industry level, the latter two being measured net of taxes and subsidies. These variables are available in the World Input-Output Database (WIOD), described in Timmer et al. (2015). This version of the WIOD adheres to the System of National Accounts (SNA) 1993. Second, data on industry-level "Net Operating Surplus and Mixed Income" from Eurostat, national statistics offices, and the OECD (see Online Appendix OA.A for details on the additional datasets). This variable is the sum of corporate-sector profits and the operating surplus of private unincorporated enterprises (OSPUE) net of depreciation. Third, I compute the Industry-by-Commodity Total Requirements Matrix from the Supply and Use Matrices in the WIOD to link industries to sectors.

3.1 Labor income

Labor income is the sum of two components: (1) the compensation of employees and (2) the labor income of the self-employed. Data on the first component is readily available in the WIOD, which uses national account statistics and labor force surveys to compute employees' total compensation. However, as Krueger (1999) emphasized, national account statistics do *not* account for the second component, labor income of the self-employed. Some share of the reported earnings of the self-employed should be attributed to labor income, with the remainder comprising returns on invested capital, land rents, or monopoly profits. Gollin (2002) showed that the significantly higher self-employment rates in developing countries can lead to a systematic understatement of the national labor share in developing countries if the labor income of the self-employed is not properly taken into account. I consider three measures of the labor income share, each dealing with the labor income of the self-employed differently.

Payroll share. For the first measure, I consider only the labor income of employees in the corporate sector. Specifically, this *payroll share* measure of labor income can be written

$$\text{Labor share} = \frac{\text{corporate employee compensation}}{\text{value added} - \text{net taxes}}. \tag{7}$$

This measure has the advantage of being transparent and yielding unambiguous payments to labor, as advocated by Karabarbounis and Neiman (2014). However, if the structure of employment changes with development, especially in the importance of self-employment as Gollin (2002) documented, then the payroll share might be a poor approximation of the labor share. Studies of industry labor shares typically rely on this measure; see, for example, Azmat et al. (2012), Daudey and García-Peñalosa (2007), Maarek and Orgiazzi (2013, 2020), Oishi and Paul (2018), and Ortega and Rodríguez (2006).

Equal wages. Second, the WIOD contains information about the average working hours of employees and self-employed by industry, which I use to impute the same hourly wage for the self-employed as for corporate employees. Specifically, the *equal wages* labor income share is

$$\text{Labor share} = \frac{\text{corporate employee compensation}}{\text{employee hours worked}} \times \frac{\text{total hours worked}}{\text{value added} - \text{net taxes}}. \tag{8}$$

I perform this analysis separately for each year and industry to improve the imputation accuracy. This method is the same as that used by the United States Bureau of Labor Statistics to compute its headline measure of labor income. This *equal wages* measure will provide a good approximation of the labor share to the extent that the self-employed command wages essentially the same as those of employees in the corporate sector. It will be a poor approximation if there are systematic differences in earnings ability between employees and the self-employed. A version of this measure, using the ratio of the number of self-employed to employees instead of their worked hours, was analyzed by Bentolila and Saint-Paul (2003) and Gollin (2002).

Imputed OSPUE. In national accounts statistics, the income of the self-employed is a part of OSPUE. As Gollin (2002) argued, reallocating OSPUE between capital and labor of the self-employed may provide an improved measure of the labor share. One problem is that OSPUE is

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usually unavailable at the industry level; countries report only the sum of corporate-sector profits and the OSPUE net of the consumption of fixed capital (NOPS). Therefore, I follow Bernanke and Gürkaynak (2001) and construct an alternative measure of the labor share that combines information about the corporate share of the labor force from the WIOD with manually collected data on NOPS by industry. I derive *imputed OSPUE* for each industry by the following procedure: First, I compute total income as the sum of NOPS and corporate-employee compensation. Second, I multiply total income by the share of non-corporate employees in the labor force. Assuming that the non-corporate share of total income equals that of the non-corporate labor force, this last step yields the measure of imputed OSPUE. Finally, I split imputed OSPUE into labor and non-labor income, assuming the labor-income share in imputed OSPUE is the same as in the corporate sector. Specifically,

$$\begin{aligned}\text{Imputed OSPUE} = (&\text{corporate employee compensation} + \text{NOPS}) \\ &\times \left(1 - \frac{\text{employee hours worked}}{\text{total hours worked}}\right). \end{aligned} \tag{9}$$

Then,

$$\text{Labor share} = \frac{\text{corporate employee compensation}}{\text{value added} - \text{net taxes} - \text{imputed OSPUE}}. \tag{10}$$

The advantage of this approach is that it is transparent and straightforward, and it makes sense to assume that imputed OSPUE includes both capital and labor income. The disadvantage of this approach is that it implicitly assumes that income shares are the same for establishments that differ significantly in size and structure. To implement this approach, I collect data on NOPS from Eurostat, national statistics offices, and the OECD.[9]

3.2 The roles of housing and depreciation

A large share of the real estate industry's output is recorded as *imputed* rent paid by homeowners to themselves. Therefore, Rognlie (2015) argued that imputed rents from owner-occupied housing should be treated as a form of labor income akin to self-employed income: in part, they reflect labor by the homeowners themselves. The consequences of not accounting for this form of labor income can potentially be sizeable. For example, Rognlie (2015) showed that the rise in housing value added can explain a large portion of the decline in the aggregate labor share of the United States over the last few decades. A possible solution is to only analyze labor income in the corporate sector, as advocated by Karabarbounis and Neiman (2014b) and Rognlie (2015). However, Gutiérrez and Piton (2020) showed that this will not fully resolve the measurement issues, because even in the corporate sector imputed rents can be a substantial share of value added. Instead, they propose to exclude *all* real estate activities from wages and value added. This method fully controls for housing, but it has the drawback of "over-controlling" by excluding residential real estate in addition to commercial real estate. None of this paper's main results are notably affected by whether the wages and value-added of the real estate industry are included or excluded.[10]

As is standard in the analysis of labor income shares (e.g., Elsby et al., 2013; Karabarbounis and Neiman, 2014), this paper here is silent about what the residual, non-labor income part of value added net of taxes and subsidies consists of; some part will be capital income, while some other part may reflect super-natural profits. Additionally, depreciation accrues to neither labor nor capital but is included in value added (Bridgeman, 2018). While the share of value added paid to labor is unaffected by the split of residual value added, it is important to remember that a decrease (increase) in the labor share may not imply that capital owners are gaining (losing).

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3.3 Supply and use matrices

The WIOD provides Supply and Use Matrices for each year from 1995 to 2011 for 40 countries.[11] This set of countries includes all major economies, accounting for more than 85% of the world's GDP. A disadvantage of the WIOD is the lack of observations for the least developed countries, particularly Sub-Saharan Africa. However, the dataset is ideally suited for the analysis of sectoral labor shares for three main reasons: First, the WIOD is based on official and publicly available data from statistical offices to ensure high data quality and harmonization. Second, the dataset has been specifically designed to trace developments over time through benchmarking to time series of output, trade, and consumption from national accounts statistics. Dietzenbacher et al. (2013) described the construction and concepts of the WIOD in detail. Finally, the WIOD provides data on the quantities and prices of input factors by industry, including labor income and gross value added net of taxes and subsidies. These data are provided in the so-called Socio-Economic Accounts and can be combined with the Supply and Use Matrices as they follow the same industry classifications. I use the International Supply and Use Matrices to compute sectoral labor shares because these matrices allow me to distinguish between domestic and foreign buyers of goods and services, and between domestic and foreign suppliers of intermediate inputs. The matrices are in basic prices, and margin values are included in the trade and transport industries. This approach means that margins are treated as intermediate inputs, with the margin industries as the supplying industries. The International Use Matrix also contains information on final domestic expenditure by expenditure category. Finally, the Supply and Use Matrices provide harmonized information about intermediate input linkages between 35 industries and 59 final expenditure categories (Appendix Tables A1–A3 list the expenditure categories and industries).

3.4 The treatment of intangible capital

The WIOD, Release 2013, adheres to the SNA 1993. A key feature of the SNA 1993 is that spending on research and development (R&D) is not accounted for as formation of (intangible) capital. Instead, this spending represents an intermediate input in the production process, thereby reducing an industry's value added by the same amount. By decreasing the denominator, higher R&D expenditure tends to increase the labor income share in value added, all else equal. Since R&D spending is primarily concentrated in some rich countries, this might be of first-order importance for the empirical relationship between economic development, labor income shares, and capital-labor ratios.[12]

I have computed the shares of R&D investment in value added for the period 1995-2009 in NACE 2-digit industries using KLEMS data.[13] Online Appendix Tables OA.B3 and OA.B4 replicate the below main analysis, entirely excluding R&D-intensive industries from the Total Requirements Matrix and hence from the computation of sectoral labor shares and capital-labor ratios. Reassuringly, none of this paper's main results are notably affected by whether these industries are included or excluded.

4. Empirical results

This section first examines the correlation between national labor share measures and economic development. It benchmarks the results using three different labor share measures (payroll share, equal wages, and imputed OSPUE) against those often found in the literature. Subsequently, this section presents evidence that sectoral labor income shares increase with output per person and discusses heterogeneity across sectors.

4.1 The national labor share

To assess how the different adjustment methods affect the association between the national labor share and the level of economic development, I use least squares to estimate

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Table 1. Income elasticity estimates of the national labor share

	Payroll share	Equal wages	Imputed OSPUE
	(1)	(2)	(3)
Log(GDP) ($\hat{\beta}$)	0.193***	0.116***	0.123***
	(0.034)	(0.027)	(0.031)
Mean	0.491	0.577	0.571
Standard deviation	0.093	0.085	0.089
Observations (country × year)	570	570	570

Notes: Estimates of the income elasticity of the national labor share, $\hat{\beta}$, from Regression (11). Log(GDP) is the log of real output per person, measured in PPP (2017 US $). Standard errors in parentheses, allowing for clustering at the country level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

$$\log\left(\lambda_{jt}^{\text{GDP}}\right) = \delta + \beta \log\left(\text{GDP}_{jt}\right) + \varepsilon_{jt}\,, \tag{11}$$

where $\lambda_{jt}^{\text{GDP}}$ is the national labor share in country j in year t, and GDP_{jt} denotes real output per person using prices that are constant across countries and over time, hereafter PPP, from the Penn World Table 10.01 (PWT), see Feenstra et al. (2015). The parameter β is the *income elasticity of the labor share*, measuring the percentage change in the labor share associated with a 1% increase in output per person. Table 1 presents the regression results for each measure of labor income (Online Appendix Figures OA.C1A-C display the underlying data).[14]

Column (1) shows that the average payroll share is only 49.1%, and this measure exhibits the relatively highest variation across time and countries. The income elasticity is positive and statistically significant: the payroll share increases by 0.193% when output per person increases by 1%, on average. If a country with a labor share equal to the sample average experienced output per person growth of 20%, the payroll labor share is predicted to increase from 49.1% to 51.0%. Consistent with the literature, adjusting for the labor income of the self-employed weakens the positive association between the labor share and the level of development. The income elasticity of the equal-wage labor share is only 0.116, but the average equal-wage labor share is almost nine percentage points higher than the average payroll share. The estimated income elasticity and the average value of the imputed OSPUE labor share fall between the other two measures. The finding that the national payroll share is increasing with development is consistent with previous studies (e.g., Gollin, 2002; Jayadev, 2007). However, the estimated slope coefficients of the equal-wage and imputed-OSPUE labor shares are significantly positive, which contrasts with Bernanke and Gürkaynak (2001) and Gollin (2002), who did not find a significant relationship between this labor share measure and economic development. By contrast, Izyumov and Vahaly (2015) also found that national labor income shares positively correlate with output per person. They updated Gollin's results to the period 1990-2008 and included additional countries, using the same database as Gollin but instead analyzed imputed OSPUE.

To better understand why the results here differ from those of the majority of the literature, Figure 1A shows a comparison of the imputed-OSPUE labor share to the OSPUE labor share as documented in Gollin (2002) (Table 2, p. 470). Because the sample period of Gollin's data and the WIOD do not overlap - Gollin's latest observation is from 1992, while the WIOD begins in 1995 - the horizontal axis uses a normalization; it expresses a country's output per person in PPP relative to the United States in 1992 for Gollin's sample and 1995 for the WIOD sample. The countries in the WIOD more than proportionally represent countries with low labor shares as compared to Gollin, and some of the relatively least-developed countries with high labor shares are absent from the WIOD (e.g., Burundi, Réunion, Ukraine, Vietnam). This selection tends to increase the correlation between labor shares and development in the WIOD data. As an additional check, Figure 1B compares the imputed-OSPUE labor share and the labor share in the

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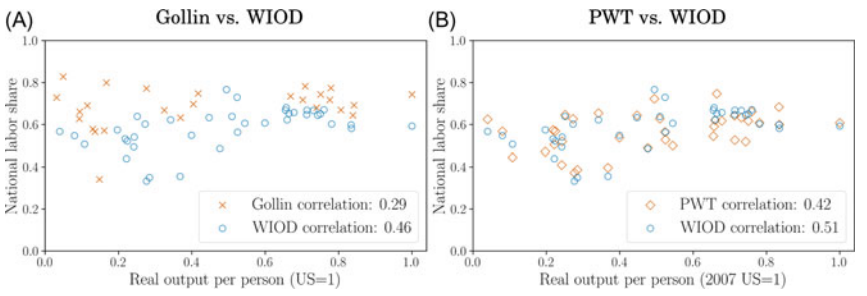


Figure 1. Benchmarking national labor income shares.
Notes: Panel A shows the national labor shares computed using OSPUE in Gollin (2002) (Table 2, p. 470, "Adjustment 2") and using imputed OSPUE here. The horizontal axis in Panel A shows a country's real output per person relative to the United States in 1992 for Gollin's data and 1995 for the WIOD data. Panel B compares the 1995 national labor shares in the PWT to those of the same countries in the WIOD.

PWT, both for 1995. The national labor shares generally match closely, and the relatively low labor shares among developing countries are visible in both datasets. These findings suggest that it is unlikely that systematic measurement differences between this paper and the earlier studies and benchmark data account for the positive relationship between national labor share and development. Instead, the differences seem driven by the selection of countries in the WIOD.[15]

Despite focusing on a selected set of countries, my analysis provides a unique view of sectoral labor shares across a large set of countries spanning various stages of development and all major economies, accounting for over 85% of world GDP. Importantly, the selection of countries should not affect results about *relative* sectoral labor shares - differences within countries between sectors - and within-country results over time. Accordingly, I confirm below that the findings for the income elasticity of sectoral labor shares hold when using only within-country variation for the estimation.

4.2 The sectoral labor shares

This section investigates the relationship between sectoral labor shares and development. Following Bernanke and Gürkaynak (2001), all analyses use the imputed-OSPUE labor shares. Initially, I allocate final expenditure to three sectors: manufacturing outputs, services, and other goods (agriculture, mining, utilities, and construction), see Appendix Tables A1–A2. Note that the national labor share is the weighted average of the underlying sectoral labor shares, with weights equal to the amount of final expenditure. Therefore, the national labor share may change as the expenditure vector shifts with development, even when sectoral labor shares are fixed. To prevent potential shifts in expenditure vectors from affecting results, I compute the national and sectoral labor shares in the following analyses using simple averages of all the underlying final expenditure labor shares. Using uniform weights marginally increases the correlation between the national labor share and development from 0.58 to 0.61 (Online Appendix Figures OA.C3A-B), suggesting that expenditure weights of final expenditure categories with relatively small income elasticities tend to increase with development.

Overview. I begin with some graphs indicating correlations before applying regression techniques. Figure 2 displays the national and sectoral labor shares. The labor shares of the manufacturing (Figure 2B) and services sectors (Figure 2C) increase at a similar rate with development; the correlation coefficients are 0.62 and 0.65, respectively, slightly exceeding the correlation of the national labor share with output per person. That is, the relative labor shares of manufacturing and services are higher in rich countries compared to developing countries. The labor share of the other goods sector also increases with development, but at a much lower rate than manufacturing and services (Figure 2D). As argued in the previous section, the positive correlations may be due to

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Table 2. Regression estimates of relative labor shares in the manufacturing and other goods sectors

Final expenditure category	$\hat{\beta}_c$	S.e.	Mean
Panel A. Manufacturing goods			
Food products and beverages	−0.022***	(0.008)	0.550
Tobacco products	−0.031***	(0.007)	0.543
Textiles	0.013**	(0.006)	0.634
Wearing apparel; furs	0.016**	(0.006)	0.637
Leather and leather products	−0.026***	(0.008)	0.649
Wood and products of wood and cork (except furniture)	0.031***	(0.007)	0.610
Pulp, paper and paper products	0.040***	(0.006)	0.575
Printed matter and recorded media	0.041***	(0.006)	0.577
Coke, refined petroleum products and nuclear fuels	−0.052***	(0.019)	0.428
Chemicals, chemical products and man-made fibers	0.003	(0.008)	0.500
Rubber and plastic products	0.027***	(0.006)	0.576
Other non-metallic mineral products	0.019***	(0.006)	0.551
Basic metals	0.058***	(0.007)	0.586
Fabricated metal products, except machinery and equipment	0.061***	(0.007)	0.588
Machinery and equipment n.e.c.	−0.001	(0.007)	0.627
Office machinery and computers	0.058***	(0.007)	0.595
Electrical machinery and apparatus n.e.c.	0.055***	(0.007)	0.586
Radio, television and communication equipment	0.055***	(0.007)	0.585
Medical, precision and optical instruments, watches	0.052***	(0.007)	0.585
Motor vehicles, trailers and semi-trailers	0.056***	(0.008)	0.607
Other transport equipment	0.054***	(0.008)	0.611
Furniture; other manufactured goods n.e.c.	0.065***	(0.006)	0.625
Secondary raw materials	0.110***	(0.008)	0.628
Panel B. Other goods			
Products of agriculture, hunting and related services	−0.106***	(0.020)	0.583
Products of forestry, logging and related services	−0.098***	(0.019)	0.594
Fish and fishing products; services incidental of fishing	−0.091***	(0.022)	0.588
Coal and lignite; peat	−0.065***	(0.021)	0.501
Crude petroleum and natural gas	−0.054***	(0.020)	0.482
Metal ores	−0.021	(0.023)	0.483
Other mining and quarrying products	−0.091***	(0.020)	0.488
Electrical energy, gas, steam and hot water	−0.161***	(0.013)	0.393
Collected and purified water, distribution of water	−0.139***	(0.015)	0.413
Construction work	0.036***	(0.008)	0.617

Notes: Coefficient estimates $\hat{\beta}_j$ from Regression (12). Standard errors are in parentheses, allowing for clustering at the country level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

the selection of countries in the WIOD rather than a stylized fact that holds in a representative cross-section of countries. However, there is no reason to expect this country selection to affect the *relative* correlations between the national and sectoral labor shares.

As argued earlier, substantial heterogeneity within the service sector has long been recognized in the literature; see, for example, Baumol et al. (1985); Duarte and Restuccia (2020); Elsby et al. (2013). To investigate whether differential patterns exist among labor shares within the services sector, I split services into market and non-market services. Non-market services

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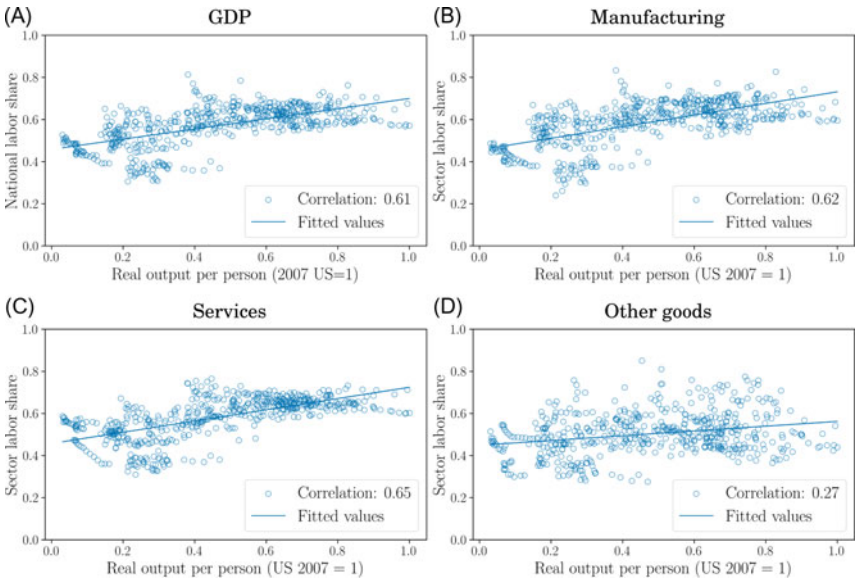


Figure 2. National and sectoral labor shares.
Notes: National and sectoral labor shares for each year and country. Fitted values from regressing the respective labor share on real output per person (PPP) relative to the United States in 2007. Appendix Tables A1–A2 provide the allocation of final expenditure categories to sectors.

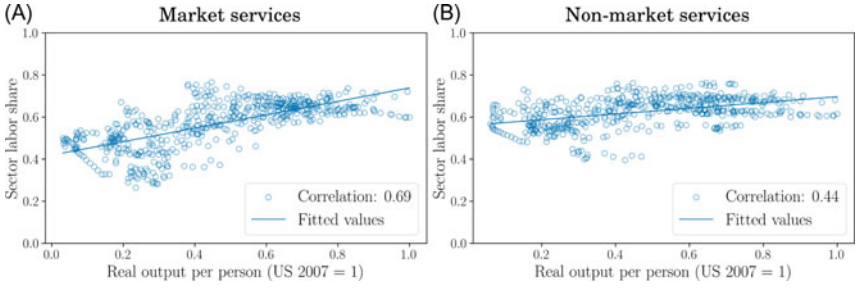


Figure 3. Market and non-market services labor shares.
Notes: Sectoral labor shares for each year and country. See notes in Figure 2.

include real estate, government and defense, health and social work, education, and sanitation services. Appendix A describes each non-market service in detail and explains that although the public sector typically carries out these services, private-sector companies also frequently provide these services. Market services include all other services, such as wholesale and retail trade, communication and transport services, financial intermediation, and research and development. Figure 3A displays the average labor shares of the market services sector, and Figure 3B of the non-market services sector. There is substantial heterogeneity in market and non-market services: Labor shares in the former increase more with development than those in non-market services; the correlation coefficients are 0.69 and 0.44, respectively.

Figure 2 suggests that the variance of the aggregate labor income shares is higher in the poorest countries. The variance of labor shares in the richest 10% of observations is only 35% of the variance in the poorest 10%, and these findings hold qualitatively across various rich vs. poor categorizations. This fact was already documented by Gollin (2002), who suggested that perhaps data quality may be a problem in poor countries. To examine to what extent measurement error can explain the higher labor share variance in poor countries, I investigate whether labor shares in sectors typically affected by more severe measurement issues (e.g., agriculture) exhibit a higher

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Table 3. Regression estimates of relative labor shares in the services sector

Final expenditure category	$\hat{\beta}_c$	S.e.	Mean
Panel A. Market services			
Trade, maintenance of motor vehicles	0.006	(0.011)	0.468
Wholesale trade	0.083***	(0.011)	0.557
Retail trade; repair	−0.003	(0.011)	0.609
Hotels and restaurants	0.043***	(0.011)	0.609
Land transport	0.052***	(0.010)	0.596
Water transport	0.032***	(0.011)	0.578
Air transport	0.058***	(0.010)	0.580
Supporting transport	0.062***	(0.013)	0.542
Post and telecommunication	0.112***	(0.013)	0.563
Financial intermediation	0.058***	(0.013)	0.498
Insurance and pension funding	0.030**	(0.013)	0.508
Services auxiliary to financial intermediation	0.032*	(0.019)	0.523
Renting of machinery and equipment	0.024*	(0.014)	0.582
Computer and related services	0.181***	(0.022)	0.589
Research and development	0.105***	(0.021)	0.601
Other business services	0.121***	(0.019)	0.592
Membership organization	0.031**	(0.014)	0.627
Recreation	0.023*	(0.013)	0.629
Other services	0.029**	(0.013)	0.629
Panel B. Non-market services			
Real estate	−0.104***	(0.029)	0.195
Public administration and defense services	−0.130***	(0.010)	0.749
Education	−0.090***	(0.008)	0.833
Health and social work	−0.112***	(0.007)	0.752
Sewage and sanitation	−0.085***	(0.010)	0.637

Notes: Coefficient estimates $\hat{\beta}_j$ from Regression (12). Standard errors are in parentheses, allowing for clustering at the country level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

variance than those in sectors with presumably less severe measurement issues (e.g., manufacturing), see, e.g., Angrist et al. (2021).[16] The variance of agriculture labor shares in the richest 10% of observations is 82% of the variance in the poorest 10%. In contrast, the variance ratio between the richest and poorest 10% is around 90% in the presumably more accurately measured manufacturing sector. Therefore, even though the variance in agriculture is higher in poor countries than in rich countries, the relative variance difference of eight percentage points between more and less reliably measured sectors can only explain part of the story.

Regression analyses. To examine the relationship of the sectoral labor shares relative to the national labor share, I begin by computing the ratio of each final expenditure category labor share to the unweighted national labor share. Then, I estimate the following regression separately for each category

$$\log\left(\lambda_{cjt}/\lambda_{jt}^{\mathrm{GDP}}\right) = \delta + \beta_c \log\left(\mathrm{GDP}_{jt}\right) + \varepsilon_{cjt}\,, \tag{12}$$

whereby λ_{cjt} is the labor share in final expenditure category c in country j in year t. The coefficient estimates $\hat{\beta}_c$, as well as the sample average of each labor share, are displayed in Table 2 for the manufacturing and other goods sectors, and in Table 3 for the services sector.

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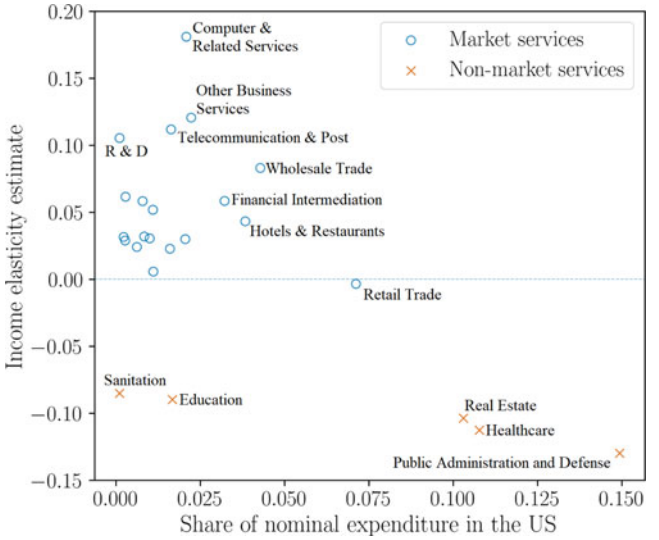


Figure 4. Income elasticity of relative labor shares: Pooled estimates.
Notes: Coefficient estimates $\hat{\beta}_c$ from Regression (12). See Table 3 for underlying coefficient and standard error estimates. The horizontal axis shows the nominal expenditure share of the relevant commodity in GDP in the United States.

Most of the manufacturing sector's labor shares increase relative to the national labor share with economic development. By contrast, labor shares of the other goods sector exhibit a relative decline, which is strongest in the utilities categories (Electrical energy, gas, steam and hot water; Collected and purified water, distribution of water) and among agriculture, forestry, and fishing. The exception is construction work, which has a significantly positive coefficient estimate.

The estimates for the services sector lie in a wide range from –0.13 to 0.18. There are individual services for which the labor share systematically rises faster than the aggregate labor share with development, e.g., Computer and related services, Research and development, and Business services. In contrast, for non-market services, the labor shares generally decline relative to the aggregate labor share, e.g., Real estate, Education, Government, and Health and social work.

Figure 4 visualizes the relationship between estimates for the services sector and nominal expenditure shares. The non-market services categories account for the largest shares in nominal expenditure. This explains the above finding that the expenditure-weighted aggregate labor share displays a somewhat weaker correlation with development than the unweighted labor share.

The wide range of relative income elasticities in services, ranging from significantly positive to very negative, is an essential component of the heterogeneity in services highlighted in this paper. For comparison, relative labor shares in the manufacturing sector exhibit much less variation. The large majority shows a positive relationship with output per person, with a maximum estimate of 0.11, and the negative coefficient estimates do not fall below –0.05. The standard deviation of the coefficient estimates is over twice as large in the services sector as in manufacturing: 0.077 and 0.037, respectively.

To further analyze the relationship between development and sectoral labor shares, I estimate the following regression:

$$\log(\lambda_{cjt}) = \delta + \beta \log(\mathrm{GDP}_{jt}) + \sum_s \omega_s [\log(\mathrm{GDP}_{jt}) \times D_s] + \sum_s \gamma_s D_s + \mathrm{Category}_c + \mathrm{Country}_j + \mathrm{Year}_t + \varepsilon_{cjt}, \quad (13)$$

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Table 4. Relative income elasticity of sectoral labor shares

	(1)	(2)	(3)	(4)	(5)
Log(GDP) ($\hat{\beta}$)	0.162***	0.071	0.071	0.070	−0.131
	(0.034)	(0.043)	(0.043)	(0.042)	(0.079)
Manufacturing ($\hat{\gamma}_M$)		−0.968**	−0.968**	−1.123***	−1.051***
		(0.370)	(0.370)	(0.366)	(0.363)
Manufacturing × log(GDP) ($\hat{\omega}_M$)		0.113***	0.113***	0.114***	0.107***
		(0.037)	(0.037)	(0.036)	(0.036)
Services ($\hat{\gamma}_S$)		−0.978			
		(0.618)			
Services × log(GDP) ($\hat{\omega}_S$)		0.110*			
		(0.061)			
Market serv. ($\hat{\gamma}_{MS}$)			−1.393**	−1.507**	−1.344**
			(0.612)	(0.595)	(0.577)
Market serv. × log(GDP) ($\hat{\omega}_{MS}$)			0.151**	0.150**	0.135**
			(0.060)	(0.059)	(0.058)
Non-market serv. ($\hat{\gamma}_{NM}$)			0.341	0.268	0.275
			(0.605)	(0.587)	(0.589)
Non-market serv. × log(GDP) ($\hat{\omega}_{NM}$)			−0.022	−0.022	−0.025
			(0.060)	(0.058)	(0.058)
Constant ($\hat{\delta}$)	−2.240***	−1.445***	−1.445***	−1.227***	0.917
	(0.361)	(0.435)	(0.435)	(0.433)	(0.841)
Year-fixed effects	✓	✓	✓	✓	✓
Category-fixed effects				✓	✓
Country-fixed effects					✓
Observations	31,157	31,157	31,157	31,157	31,157
Adjusted R^2	0.097	0.130	0.138	0.470	0.638

Notes: Coefficient estimates from Regression (13). The dependent variable is the log labor share, pooled across final expenditure categories, years, and countries. Log(GDP) is the log of real output per person, measured in PPP (2017 US $). The excluded category is other goods. Appendix Tables A1–A2 list the allocation of expenditure categories to the manufacturing, services, other goods, market services, and non-market services sectors. Standard errors are in parentheses, allowing for clustering at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

whereby D_s is an indicator variable that equals one if the expenditure category c is associated with commodity sector s. I include these sector-fixed effects in two ways: first, levels of D_s to capture potential persistent differences in sectoral labor shares ($\hat{\gamma}_s$), and second, interaction terms of D_s and $\log(\text{GDP}_{jt})$ measure the *relative* income elasticity of the labor shares in sector s compared to the omitted sector ($\hat{\omega}_s$). Since the WIOD is a non-representative sample of countries, focusing on relative (within-country) income elasticities is necessary to obtain reliable estimates. To examine the potential heterogeneous effects of development on sectoral labor shares, I estimate Regression (13) with varying sector definitions. All regressions include year-fixed effects, Year_t, to capture business cycle effects. Some regressions additionally include category- and country-fixed effects, Category_c and Country_j, respectively. The former accounts for a small number of expenditure categories for which data are unavailable for a subset of years (mainly mining), whereas the country-fixed effects change the regression to a within-country analysis that only exploits differences over time.

Table 4 displays the main results, whereby the omitted category in columns (2)–(5) is the other goods sector. Column (1) shows that, on average, labor shares increase with development: the estimated income elasticity is 0.162. This estimate is higher than the one presented in Table 1 because

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I include year-fixed effects and use simple averages to compute national labor shares, thereby preventing expenditure weights from affecting the results. The estimates of the interaction terms in column (2) show the manufacturing ($\hat{\omega}_M$) and services sector's ($\hat{\omega}_S$) excess income elasticities compared to the other goods sector ($\hat{\beta}$). Both coefficients are positive and statistically significant, whereas there is no evidence that the labor shares of the other goods sector ($\hat{\beta}$) correlate with economic development.

In column (3), I again split the services sector into market and non-market services. The results confirm the heterogeneity apparent from Figures 3 and 4. The labor shares in the market services sector rise significantly faster with economic development than in the other goods sector. The interaction term of non-market services with income per capita is not significant. Because some countries have not reported expenditures on some commodities in some years, the panel is unbalanced. If richer countries systematically stopped spending money on low-income elasticity expenditure categories, such as mining, this would bias the estimates. Column (4) shows that this is not a concern because controlling for possible changes in expenditure composition across countries does not notably change the estimates.

Finally, column (5) adds country-fixed effects, so the coefficients only measure the relative income elasticity within countries. The point estimate for the other goods sector decreases from 0.07 to –0.13, but remains not significantly different from zero. Importantly, the *relative* income elasticity estimates do not notably change: The labor shares of the manufacturing and market services sector have significantly higher income elasticities than those of the other goods and non-market services sector. However, even in the selected WIOD sample of countries, the labor income shares of the manufacturing and market services sectors are no longer increasing with development. At the usual confidence levels, I cannot reject the hypotheses that the sums of ($\hat{\beta} + \hat{\omega}_M$) and ($\hat{\beta} + \hat{\omega}_{MS}$) each equal zero. This result aligns with the recent literature documenting a decline in labor shares in the United States and other countries over time.[17] The novel contribution here is to identify the other goods and non-market services sectors as the main drivers of this decline.

The results are robust when using an alternative output-per-person measure and weighted least squares with expenditure weights.[18] The relative income elasticity estimates resulting from expenditure weights are only around half as large as the equally weighted elasticities computed. The interaction term between output per person and manufacturing remains significant, but the one between market services becomes insignificant. This finding suggests that commodities with relatively high elasticities receive a systematically lower share of aggregate expenditure than the other goods sector with development. Moreover, including sector-year interaction effects to purge the data of more unobserved heterogeneity does not notably affect any of the coefficient estimates.[19]

The striking fact that emerges from Figures 3 and 4, and Table 4 is that many individual market services labor shares increase systematically faster with development than the labor shares in non-market services, which show a relative decline with development. These results hold across and within countries. Additionally, the recent decline of national labor shares over time appears driven mainly by the other goods and non-market services sectors, while manufacturing and market services labor shares are roughly constant within countries.

5. Possible explanations for the empirical findings

What may explain the observed patterns in sectoral labor shares? One possible explanation is that countries do not operate the same sectoral technology, and these differences in production technologies somehow correlate with output per person. As Gollin (2002) argued, this answer is not very appealing because why should the relationship between inputs and outputs suddenly shift at national borders? And if geography is so essential for sectoral production technologies, then how

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Table 5. Correlation matrix and summary statistics

	National labor share	Output per person	Capital-labor ratio
National labor share	1		
Output per person	0.650***	1	
Capital-labor ratio	0.621***	0.855***	1
Mean	0.560	25,799	2,415
Standard deviation	0.085	13,002	1,366

Notes: Output per person gives real output per person, measured in PPP (2017 US $); Capital-labor ratio gives the capital stock, adjusted for the flow of services, measured in capital PPPs (2017 US $) per hour worked by employees and self-employed.

come sectoral labor shares differ more between the United States and Mexico than between the United States and Japan? Therefore, this section focuses on two other possible explanations: differences in sector-specific factor inputs, combined with production functions with a non-unitary elasticity of substitution, and differences across countries in the competitiveness of factor markets that create a gap between the wage and the marginal value product of labor.

5.1 The capital-labor ratio

In a competitive world where the production function is not Cobb-Douglas, changes in the labor share are exclusively related to capital accumulation and hence reflect changes in the competitive price of capital (e.g., Karabarbounis and Neiman, 2014). To examine the extent to which differences in sectoral capital accumulation matter for the relationship between income and sectoral labor shares, I add a proxy for sectoral capital accumulation to the regression model from the previous section. This proxy is the ratio of capital services to total hours worked by employees and self-employed within each sector, the *capital-labor ratio*.[20] I propose a method to compute this variable in four steps: First, I link data on total hours worked by employees and self-employed by industry to sectors using the Industry-by-Commodity Total Requirements Matrix, see Equation (5). Data on total hours by industry is directly available in the WIOD. Second, using the same linking process, I compute the capital stock for each sector using Equation (6). The WIOD provides data on the real fixed capital stocks at constant national prices by industry. Third, because the capital stock data are recorded in national currency units, I compute each sector's share of the aggregate capital stock in the WIOD and use these capital input shares to allocate a country's aggregate capital services in PPP from the PWT to commodities.

This method has the advantage of producing comparable capital input series even when relative capital prices differ across sectors. It will produce biased estimates if the relative capital prices across sectors systematically vary with income levels. I have analyzed capital PPPs at the industry level for a subsample of 20 countries for which capital PPPs are available in the Groningen Growth and Development Centre database (Inklaar and Timmer, 2009). I can reject the hypothesis at the usual confidence level that the industry capital PPPs relative to the aggregate capital PPP correlate with output per person, with absolute values of t-statistics typically less than one. This analysis suggests that disaggregated capital PPPs do not systematically vary with income levels for the subset of studied countries beyond the variation already captured by the aggregate capital PPPs.

Table 5 shows that the capital-labor ratio positively correlates with output per person and the national labor share. The sample size is around 2% smaller due to missing data on gross fixed capital or hours worked in the WIOD, mainly for the categories "metal ores" and "secondary raw materials".

To examine whether differences in the capital-labor ratio can account for the behavior of the relative sectoral labor shares, I estimate the following regression model:

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$$\begin{aligned}\log(\lambda_{cjt}) &= \delta + \beta\ \log(\mathrm{GDP}_{jt}) + \sum_s \omega_s\,[\log(\mathrm{GDP}_{jt}) \times D_s] + \\ &+ \beta^k\ \log(k_{cjt}) + \sum_s \omega_s^k\,[\log(k_{cjt}) \times D_s] + \sum_s \gamma_s^k\, D_s \\ &+ \mathrm{Category}_c + \mathrm{Country}_j + \mathrm{Year}_t + \varepsilon_{cjt}\,,\end{aligned} \tag{14}$$

whereby the new terms relative to Regression (13) is k_{cjt}, the capital-labor ratio in expenditure category c in country j in year t. The coefficient ω_s^k gives, for sector s, the relative elasticity of the labor shares with respect to the capital-labor ratio, hereafter *capital-labor elasticity*.

Table 6 displays the results. For comparability, columns (1) and (3) repeat the estimates from the baseline Regression (13) using only labor share observations for which the capital-labor ratios are available, with and without country-fixed effects, respectively. Reassuringly, the previous findings continue to hold in this sample; the coefficient estimates in columns (1) and (3) are virtually unchanged compared to the results using the full sample.

Column (2) displays the effects of controlling for the log capital-labor ratios and their interactions with the sector-indicator variables. The striking result that emerges is that the relative income elasticities of the sectoral labor shares no longer differ from one another. Additionally, the estimated capital-labor elasticity in the other goods sector is significantly negative with $\hat{\beta}^k = -0.178$. However, this may reflect sample selection bias, as the WIOD countries are not representative. The relative capital-labor elasticity of the manufacturing sectoral labor share ($\hat{\omega}_M^k$) is statistically significant and positive: a 1% increase in the capital-labor ratio is associated with a 0.134% increase in the manufacturing sectoral labor share relative to the other goods sector. A similar observation holds for the market services sector: labor shares associated with market services show significantly larger increases than other goods when the capital-labor ratio increases. Column (4) focuses on within-country variation. Controlling for the capital-labor ratio renders all relative income-elasticity estimates insignificant. In contrast, the relative capital-labor elasticity of the other goods sector is significantly negative, and those of the manufacturing and market services sectors are now significantly positive.[21]

Finally, column (5) of Table 6 displays results when the regression controls for country-by-sector interaction effects instead of just for country fixed effects. This purges potentially unobserved, stable cross-country differences in labor income shares at the sector level, such as persistent labor market institutions or policies specific to a sector within a country (like manufacturing sectoral labor market policies in Germany versus Mexico). The coefficient estimates for the capital-labor ratio become somewhat larger in absolute magnitude, whereas the previous result—relative income elasticity estimates of the sectoral labor shares do not differ from one another once the regression controls for the capital-labor ratio—remains unchanged.

The results presented here provide important context for the findings in the previous section. Specifically, the excess elasticity of the manufacturing and market services sectoral labor shares is the result of two factors: first, capital-labor ratios across all sectors are increasing with economic development; and second, capital deepening has a *relatively* positive effect on the manufacturing and market services sectoral labor shares compared to those of the other goods sector. Taken together, these factors can account for both the within-country and cross-country estimates presented in the previous section.

5.2 Union density, markups, and trade openness

Online Appendix OA.D discusses to what extent union bargaining power, product market power, and trade openness might be able to explain the differences in the relative capital-labor and income elasticities of sectoral labor shares. While there is no conclusive evidence that union bargaining power, as proxied by union density, affects the correlation between the capital-output

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Table 6. Relative income elasticity of sectoral labor shares, controlling for the sectoral capital-labor ratios

	(1)	(2)	(3)	(4)	(5)
Log(GDP) ($\hat{\beta}$)	0.070	0.291***	-0.131	0.096	0.140**
	(0.042)	(0.072)	(0.079)	(0.069)	(0.061)
Manufacturing	−1.123***	0.235	−1.051***	−0.094	0.523
	(0.366)	(0.417)	(0.362)	(0.412)	(0.444)
Manufacturing × log(GDP) ($\hat{\omega}_M$)	0.114***	−0.055	0.107***	−0.003	−0.065
	(0.036)	(0.047)	(0.036)	(0.046)	(0.045)
Market serv.	−1.513**	−0.262	−1.352**	−0.278	0.762
	(0.593)	(0.674)	(0.571)	(0.670)	(0.581)
Market serv. × log(GDP) ($\hat{\omega}_{MS}$)	0.150**	−0.003	0.135**	0.012	−0.082
	(0.059)	(0.075)	(0.057)	(0.075)	(0.062)
Non-market serv.	0.268	0.962	0.276	0.936	0.107
	(0.587)	(0.908)	(0.589)	(0.800)	(0.565)
Non-market serv. × log(GDP) ($\hat{\omega}_{NMS}$)	−0.022	−0.096	−0.026	−0.090	−0.020
	(0.058)	(0.111)	(0.058)	(0.095)	(0.069)
Log(k) ($\hat{\beta}^k$)		−0.178***		−0.221***	−0.229***
		(0.043)		(0.036)	(0.037)
Manufacturing × log(k) ($\hat{\omega}^k_M$)		0.134***		0.079**	0.096***
		(0.031)		(0.030)	(0.032)
Market serv. × log(k) ($\hat{\omega}^k_{MS}$)		0.119***		0.085**	0.091**
		(0.043)		(0.041)	(0.040)
Non-market serv. × log(k) ($\hat{\omega}^k_{NMS}$)		0.049		0.038	0.074
		(0.081)		(0.062)	(0.069)
Constant	−1.227***	−2.962***	0.914	−0.769	−1.237*
	(0.434)	(0.638)	(0.835)	(0.694)	(0.627)
Year-fixed effects	✓	✓	✓	✓	✓
Category-fixed effects	✓	✓	✓	✓	✓
Country-fixed effects			✓	✓	
Country × sector effects					✓
Observations	31,127	31,127	31,127	31,127	31,127
Adjusted R^2	0.470	0.491	0.638	0.676	0.722

Notes: Coefficient estimates from Regression (14). The dependent variable is the log labor share, pooled across final expenditure categories, years, and countries. Log(GDP) is the log of real output per person, measured in PPP (2017 US $). Log($k$) is the log of the capital-labor ratio. The excluded category is other goods. Appendix Tables A1–A2 list the allocation of expenditure categories to the manufacturing, services, other goods, market services, and non-market services sectors. Standard errors are in parentheses, allowing for clustering at the country level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

ratios and the sectoral labor shares, higher aggregate markups significantly decrease the relative labor shares of the other goods and the non-market services sector, but have a considerably smaller effect on the labor shares in the manufacturing and market-services sectors. That markups correlate with labor shares in the non-market services sector might seem surprising, given that they are called "non-market". However, this sector also includes private companies that provide healthcare and education services, as well as property developers related to real estate services, which operate in market environments. Overall, the tendency for rising markups to accompany falling labor shares documented here dovetails with the findings in De Loecker and Eeckhout (2018) and Diez et al. (2018), who argued that rising markups have played an essential role in the decline of labor shares around the world over the last three decades. More trade openness, measured

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as higher shares of exports and imports in GDP, significantly correlates with labor shares in the market services sector but does not affect the relative income elasticity or the capital-labor elasticity of sectoral labor shares. These findings offer a more nuanced understanding of the effects of trade compared to the results for national labor shares in the existing literature (Harrison, 2022; Jayadev, 2007; Stockhammer, 2017). Two related studies that present evidence on how trade openness affects labor shares at the industry level are Decreuse and Maarek (2015, 2017). Decreuse and Maarek (2015) found that openness is partly responsible for the decline in labor shares of the manufacturing industry within developing countries over time. For developed countries, Decreuse and Maarek (2017) found that trade does not affect labor shares within industries over time but does lead to a reallocation of production factors to industries with relatively low labor shares. Both studies focus on within-country industry-level outcomes, which complement the results presented here for sectoral labor shares and their evolution across countries.

5.3 Implications for sectoral elasticities of substitution

Despite being unable to determine causality, the evidence presented in this section suggests that the capital-labor ratio plays an important role in understanding the documented relationship between relative labor shares and output per person within and across countries. This is consistent with the view that the evolution of labor shares mainly reflects changes in competitive prices due to capital accumulation (e.g., Bentolila and Saint-Paul, 2003; Dao et al., 2017; Karabarbounis and Neiman, 2014). Specifically, the empirical results suggest that sectors produce output according to a production function with non-unitary constant elasticity of substitution (CES), such that factor accumulation leads to changes in labor shares. See Alvarez-Cuadrado et al. (2018) and Herrendorf et al. (2015), who incorporated this mechanism into multi-sector growth models.

With CES production functions, capital and labor inputs can be either gross complements or gross substitutes. If the elasticity of the capital-labor ratio to the ratio of factor prices is greater than one, input factors are gross substitutes, and if it is less than one, they are gross complements. Intuitively, under gross complementarity, the share of income going to the inputs that are becoming relatively scarcer rises because these factors become increasingly important in the production process. Unfortunately, obtaining reliable estimates of the elasticity of substitution requires substantially longer time series than are available from the WIOD (e.g., Klump et al., 2007; León-Ledesma et al., 2010).

The literature has not yet reached a definitive conclusion on whether capital and labor more closely resemble gross complements or substitutes. On the one hand, Karabarbounis and Neiman (2014) argued prominently that the decline in labor shares worldwide can be attributed to an increase in the capital-labor ratio combined with an elasticity of substitution above one. On the other hand, calibration exercises by Alvarez-Cuadrado et al. (2018) and Herrendorf et al. (2015) suggested that capital and labor are gross complements. In addition, a recent survey by Raval (2017) found that the large majority of estimates of the elasticity of substitution are below one, with a median of 0.54.

How can a CES production framework explain the finding that the labor shares of the manufacturing and market services sectors increase significantly faster with the capital-labor ratio than those of the other goods sector? As Appendix B formally shows, if capital and labor inputs are gross complements, a sufficient condition for the relative coefficient estimates would be that, for instance, capital-augmenting technological change was relatively faster in the manufacturing and market services sectors than in the other goods sector, all else equal. In this case, effective capital inputs grow relatively faster than effective labor inputs. This causes a *more than proportional* increase in the ratio of the marginal product of labor to the marginal product of capital. The increase leads to a rising labor share since production factors are paid their marginal products in competitive markets. Intuitively, the relative price of labor increases faster than the relative quantity of labor inputs demanded falls. Under gross substitutability, labor-augmenting technological

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change would need to be sufficiently faster in the manufacturing and market services sectors than in the other goods sector, for example, all else equal. Alternatively, if one were to assume that technological change at the sector level was neutral, both over time and across countries, the coefficient estimates would imply a lower elasticity of substitution in the manufacturing and market services sectors compared to the other goods sector. This aligns well with evidence on industry-level elasticity of substitution estimates from Herrendorf et al. (2015), who found that the elasticity of substitution in the US agriculture industry is larger than one, whereas it is below one in the manufacturing and services sectors.

6. Conclusion

In this paper, I measure sectoral labor income shares for a large set of 38 countries over the period 1995-2009, taking into account intermediate input linkages and the labor income of the self-employed. I present evidence that sectoral labor shares systematically correlate with output per person and that the labor shares of the manufacturing and market services sectors increase significantly more with economic development than those of the non-market and other goods sectors. These findings hold across and within economies and are robust to the recently identified empirical challenge of accounting for imputed rents in the housing sector. My findings suggest that it may be reasonable to use models that give rise to constant factor shares in analyses focusing solely on rich countries; however, these models do not appear to be appropriate for studies involving the poorest countries. Instead, the sectoral labor share computed here can be used directly in development accounting exercises and to calibrate multisector models.

There are also cases in which assuming that labor shares are not systematically related to output per person may yield incorrect answers. For instance, when Caselli (2005) conducted a development accounting exercise using a CES production function, assuming that labor shares do not correlate with output per person, the data indicate that poor countries utilize physical capital more efficiently than rich countries. This counterintuitive result arises in his setting because a high output-capital ratio implies that capital is used efficiently, and the output-capital ratio decreases as income per person rises. In contrast, the correlation between the efficiency with which capital is utilized and income per person becomes positive when allowing for a positive correlation between labor shares and output per person. This requires that labor and capital are sufficiently strong complements in the CES production function, which seems not unreasonable based on the available evidence (Caselli, 2005).

The capital-labor ratio exhibits a significant correlation with sectoral labor shares both across and within countries. Moreover, once the regression models control for the sectoral capital-labor ratios, the excess sensitivity of the manufacturing and market services sectoral labor shares with respect to output per person vanishes. This is because the link between capital deepening and sectoral labor shares is significantly more positive in the manufacturing and market services sectors than in the other sectors. By contrast, accounting for union density, product market markups, and trade openness does not notably affect the correlations between sectoral labor shares and economic development or capital-labor ratios. Taken together, these findings suggest that the capital-labor ratio is important for understanding the relationship between relative labor shares and output per person within and between countries. This is consistent with the view that the evolution of labor shares mainly reflects changes in competitive prices due to capital accumulation rather than deviations from the competitive benchmark. Several forces may be driving up aggregate savings relative to labor in more developed countries, leading to higher capital-to-labor ratios. Alternatively, Karabarbounis and Neiman (2014) stressed the role of falling prices for investment goods; in their account, lower prices lead to more aggregate capital investment and, ultimately, capital deepening. However, investigating the sources of the differences in capital intensity is beyond the scope of this paper.

While the studied sample of countries covers a wide range of development levels, the analysis does not include some important regions that have typically been the focus of the development

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literature, such as Sub-Saharan Africa. Expanding the set of sectoral labor shares to include more countries, particularly the least-developed ones, is a promising avenue for future research.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1365100526101011.

Competing interests. The author declares none.

Notes

1 The development accounting literature typically assumes an aggregate production function of the Cobb-Douglas type with labor shares that are identical across countries (e.g., Hall and Jones, 1999; Caselli, 2005; Hsieh and Klenow, 2010; Jones, 2016). The consequences of changes in the national labor share for inequality and for the wealth-income ratio are discussed by, e.g., Acemoglu and Robinson (2015) and Jones (2015).
2 The assumptions that sectoral labor shares are either common to all countries or do not vary systematically with economic development are standard in the macroeconomic literature (e.g., Gollin et al., 2014; Herrendorf and Valentinyi, 2012; Hsieh and Klenow, 2007).
3 Following the seminal papers of Valentinyi and Herrendorf (2008) and Herrendorf and Valentinyi (2012), I refer to final expenditure categories as sectors.
4 Example of such studies include Askenazy et al. (2018); Azmat et al. (2012); Bentolila and Saint-Paul (2003); Daudey and García-Peñalosa (2007); Decreuse and Maarek (2015, 2017); Maarek and Orgiazzi (2013, 2020); Oishi and Paul (2018), and Ortega and Rodríguez (2006).
5 There is some evidence of a positive relationship between national labor shares and growth (Charpe et al., 2020) and economic development (Izyumov and Vahaly, 2015). By contrast, a recent study by van Treeck (2020) found the opposite.
6 Checchi and García-Peñalosa (2010) showed that labor shares are an important determinant of income inequality in developed economies.
7 Boldface letters denote vectors and matrices throughout the paper.
8 These countries are Austria, Australia, Belgium, Brazil, Bulgaria, Canada, China, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, India, Indonesia, Japan, Korea, Latvia, Lithuania, Malta, Mexico, Netherlands, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Taiwan, Turkey, the United Kingdom, and the United States.
9 The WIOD already adjusts for the labor income of the self-employed using the equal wages measure in advanced economies. For less advanced economies, additional data sources, such as household surveys and census data, are used. These countries include Brazil, China, India, Indonesia, Mexico, Taiwan, and Turkey. For these seven countries, I do not make any additional adjustments for the labor income of the self-employed.
10 See results in Online Appendix OA.B, Tables OA.B1 and OA.B2, which replicate the below main analysis, following the method of Gutiérrez and Piton (2020).
11 I only compute labor shares up to 2009 because of missing data on employment and labor income in the later years.
12 A small number of rich countries in Eastern Asia, North America, and Western Europe exhibit the highest ratios of R&D spending to GDP, see UNESCO Institute for Statistics (UIS), https://databrowser.uis.unesco.org/browser/SCIENCE_TECHNOLOGY_INNOVATION/UIS-SDG9Monitoring, date of extraction: 11 June, 2025.
13 Five industries account for over 60% of all R&D spending, whereby the numbers in parentheses indicate the respective shares of R&D investment in value added: Manufacture of basic pharmaceutical products (13.5%) – ISIC Rev. 3 code: 24; Manufacture of computer, electronic and optical products (13.3%) – ISIC Rev. 3 code: 30t33; Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment (8.2%) – ISIC Rev. 3 code: 34t35; Manufacture of chemicals and chemical products (6.0%) – ISIC Rev. 3 code: 24; Manufacture of electrical equipment (5.6%) – ISIC Rev. 3 code: 30t33.
14 I exclude Ireland and Luxembourg from the analysis because these countries have high numbers of observations where the sectoral labor shares persistently exceed one or are negative.
15 Online Appendix Figure OA.C2 presents further evidence supporting this conclusion: unlike in the WIOD subsample, there is no significant correlation between the national labor share and output per person when all countries in the PWT are considered.
16 I thank an anonymous reviewer for suggesting this line of analysis.
17 For example, Elsby et al. (2013) and Karabarbounis and Neiman (2014).
18 See Online Appendix Table OA.B5 for the estimates.
19 Online Appendix Table OA.B6 displays the estimates.
20 I use data on capital services rather than capital stocks because countries differ systematically in their investment patterns: high-income countries tend to invest more in short-lived assets, such as computers and software, and less in long-lived assets, like office buildings or roads. The data on capital services account for differences in the marginal products of the various capital assets; see the discussion in Inklaar et al. (2019).

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21 Online Appendix Table OA.B6, columns (3)–(4), shows that controlling for potentially more unobserved heterogeneity by including sector-by-year interaction effects does not notably affect any of the coefficient estimates.

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Appendix A. Further details of the data

A.1 Final expenditure classification

According to the 2002 version of the statistical classification of products by activity (CPA) in the European Economic Community, the expenditure categories included in non-market services are described as:

Table A1. Classification of expenditure categories - Manufacturing and Other Goods

CPA	Description	Sector
1	Products of agriculture, hunting, and related services	Other Goods
2	Products of forestry, logging, and related services	Other Goods
5	Fish and other fishing products; services incidental to fishing	Other Goods
10	Coal and lignite; peat	Other Goods
11	Crude petroleum and natural gas; services incidental to oil and gas extraction excluding surveying	Other Goods
12	Uranium and thorium ores	(omitted)
13	Metal ores	Other Goods
14	Other mining and quarrying products	Other Goods
15	Food products and beverages	Manufacturing
16	Tobacco products	Manufacturing
17	Textiles	Manufacturing
18	Wearing apparel; furs	Manufacturing
19	Leather and leather products	Manufacturing
20	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials	Manufacturing
21	Pulp, paper and paper products	Manufacturing
22	Printed matter and recorded media	Manufacturing
23	Coke, refined petroleum products and nuclear fuels	Manufacturing
24	Chemicals, chemical products and man-made fibers	Manufacturing
25	Rubber and plastic products	Manufacturing
26	Other non-metallic mineral products	Manufacturing
27	Basic metals	Manufacturing
28	Fabricated metal products, except machinery and equipment	Manufacturing
29	Machinery and equipment n.e.c.	Manufacturing
30	Office machinery and computers	Manufacturing
31	Electrical machinery and apparatus n.e.c.	Manufacturing
32	Radio, television and communication equipment and apparatus	Manufacturing
33	Medical, precision and optical instruments, watches and clocks	Manufacturing
34	Motor vehicles, trailers and semi-trailers	Manufacturing
35	Other transport equipment	Manufacturing
36	Furniture; other manufactured goods n.e.c.	Manufacturing
37	Secondary raw materials	Manufacturing
40	Electrical energy, gas, steam and hot water	Other Goods
41	Collected and purified water, distribution services of water	Other Goods
45	Construction work	Other Goods

Notes: Classification according to the 2002 version of the *statistical classification of products by activity* (CPA) in the European Economic Community. See: https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-44-02-610-1f.

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Table A2. Classification of expenditure categories - Market and Non-Market Services

CPA	Description	Sector
50	Trade, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	Market Services
51	Wholesale trade and commission trade,except of motor vehicles and motorcycles	Market Services
52	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	Market Services
55	Hotel and restaurant services	Market Services
60	Land transport; transport via pipeline services	Market Services
61	Water transport services	Market Services
62	Air transport services	Market Services
63	Supporting and auxiliary transport services travel agency services	Market Services;
64	Post and telecommunication services	Market Services
65	Financial intermediation services, except insurance and pension funding services	Market Services
66	Insurance and pension funding services, except compulsory social security services	Market Services
67	Services auxiliary to financial intermediation	Market Services
70	Real estate services	Non-Market Services
71	Renting services of machinery and equipment without operator and of personal and household goods	Market Services
72	Computer and related services	Market Services
73	Research and development services	Market Services
74	Other business services	Market Services
75	Public administration and defense services; compulsory social security services	Non-Market Services
80	Education services	Non-Market Services
85	Health and social work services	Non-Market Services
90	Sewage and refuse disposal services, sanitation and similar services	Non-Market Services
91	Membership organization services n.e.c.	Market Services
92	Recreational, cultural and sporting services	Market Services
93	Other services	Market Services
95	Private households with employed persons	(omitted)

Notes: Classification according to the 2002 version of the *statistical classification of products by activity* (CPA) in the European Economic Community. See: https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-44-02-610-1f.

CPA 70: The activities of real estate services are very diverse: real estate agents rent or sell on a commission basis; traders buy and sell property; valuers, facilities, and estate managers provide professional services; owners let property; and finally, it includes imputed rents of owner-occupied dwellings. Most of these activities relate to the secondary market, which concerns existing property. However, some, such as property developers, are active in the primary market and are more closely related to construction.

CPA 75: This section includes activities of a governmental nature, typically carried out by the public administration. This consists of the enactment and judicial interpretation of laws and their pursuant regulation, as well as the administration of programs based on them, legislative activities, taxation, national defense, public order and safety, immigration services, foreign affairs, and

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Table A3. Classification of industries

ISIC rev.3 code	Industry name
AtB	Agriculture, Hunting, Forestry and Fishing
C	Mining and Quarrying
15t16	Food, Beverages and Tobacco
17t18	Textiles and Textile Products
19	Leather, Leather and Footwear
20	Wood and Products of Wood and Cork
21t22	Pulp, Paper, Paper, Printing and Publishing
23	Coke, Refined Petroleum and Nuclear Fuel
24	Chemicals and Chemical Products
25	Rubber and Plastics
26	Other Non-Metallic Mineral
27t28	Basic Metals and Fabricated Metal
29	Machinery, n.e.c.
30t33	Electrical and Optical Equipment
34t35	Transport Equipment
36t37	Manufacturing, n.e.c.; Recycling
E	Electricity, Gas and Water Supply
F	Construction
50	Sale and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
51	Wholesale Trade, except of Motor Vehicles and Motorcycles
52	Retail Trade and repair, except of Motor Vehicles and Motorcycles
H	Hotels and Restaurants
60	Inland Transport
61	Water Transport
62	Air Transport
63	Other Supporting Transport Activities; Activities of Travel Agencies
64	Post and Telecommunications
J	Financial Intermediation
70	Real Estate Activities
71t74	Renting of Machinery and Equipment; Other Business Activities
L	Public Admin and Defence; Compulsory Social Security
M	Education
N	Health and Social Work
O	Other Community, Social and Personal Services
P	Private Households with Employed Persons

Notes: Codes follow the International Standard Industrial Classification of All Economic Activities (ISIC) Rev. 3.

the administration of government programs. The legal or institutional status is not, in itself, the determining factor for an activity to belong in this section rather than the activity being of a nature specified in the previous paragraph. This means that activities classified elsewhere in NACE do not fall under this section, even if carried out by public entities. For example, administration of the school system (i.e., regulations, checks, curricula) falls under this section, but teaching itself does not (CPA 80), and a prison or military hospital is classified as health (CPA 85). Similarly, non-government units may carry out some activities described in this section.

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CPA 80: This section includes education at any level or for any profession. The instructions may be oral or written and may be provided by, for example, the internet. It includes education by driving schools and the different institutions in the regular school system at different levels, as well as adult education, literacy programs, etc. Also included are military schools and academies, prison schools, etc., at their respective levels. The section includes public as well as private education.
CPA 85: This section includes the provision of health and social work activities. Activities include a wide range of activities, from health care provided by trained medical professionals in hospitals and other facilities to residential care activities that still involve a degree of health care activities to social work activities without any involvement of health care professionals. Dental and veterinary practice services are also included.
CPA 90: This section includes activities related to the management (including collection, treatment, and disposal) of various forms of waste, such as solid or non-solid industrial or household waste, as well as contaminated sites. The output of the waste or sewage treatment process can either be disposed of or become an input into other production processes. Water supply activities are also grouped in this section since they are often carried out in connection with, or by units also engaged in, sewage treatment.

Appendix B. Further details on the capital-labor ratio

To clarify how factor accumulation can account for the empirical findings, suppose that there are four sectors: manufacturing, market services, non-market services, and other goods, $s = \{M, MS, NMS, OG\}$, respectively. Each sector produces output according to a possibly sector-specific constant-elasticity-of-substitution (CES) function:

$$Y_s = \left[\phi_s \left(A_s L_s\right)^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - \phi_s) \left(B_s K_s\right)^{\frac{\sigma_s - 1}{\sigma_s}}\right]^{\frac{\sigma_s}{\sigma_s - 1}}, \tag{B.1}$$

whereby L_s and K_s are labor and capital used in sectors s, ϕ_s governs the relative importance of the factor inputs, and $\sigma_s \in (0, \infty)$ is the elasticity of substitution between capital and labor, defined by

$$\sigma_s \equiv \frac{\partial k_s}{\partial \omega} \frac{\omega}{k_s}, \tag{B.2}$$

where the ratio of real wages to the rental rate of capital, ω, is the same across sectors. When $\sigma_s > 1$, the factors are *gross substitutes*, and when $\sigma_s < 1$, they are *gross complements*. A_s denotes the level of labor-augmenting technology, and B_s denotes capital-augmenting technology. Therefore, the terms $(A_s L_s)$ and $(B_s K_s)$ are the *effective* labor and capital inputs in sector s, respectively.

Under competitive markets, input factors are paid their marginal products, such that the ratio of factor shares is

$$\frac{\lambda_s}{\kappa_s} = \frac{\phi_s}{1 - \phi_s} \left(\frac{B_s}{A_s}\right)^{\frac{1-\sigma}{\sigma_s}} \left(\frac{K_s}{L_s}\right)^{\frac{1-\sigma_s}{\sigma_s}}, \tag{B.3}$$

with κ_s and λ_s denoting the capital and labor share in sector s, respectively. Under the standard assumption that ϕ_s does not systematically vary with development, Equation (B.3) clearly predicts when sectoral labor shares will increase with the capital-labor ratio. There are two different sets of conditions, depending on whether the input factors are gross substitutes or complements. Taking logs and differentiating yields

$$\Delta \log\left(\lambda_s / \kappa_s\right) = \frac{1 - \sigma_s}{\sigma_s} \Delta \log\left(B_s / A_s\right) + \frac{1 - \sigma_s}{\sigma_s} \Delta \log\left(K_s / L_s\right). \tag{B.4}$$

Under gross complementarity, $\sigma_s < 1$, an increase in the capital-labor ratio will lead to a rising labor share as long as $\Delta \log\left(K_s / L_s\right) > -\Delta \log\left(B_s / A_s\right)$. In this case, effective capital inputs grow

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relatively faster than effective labor inputs, which increases effective capital per effective unit of labor. This induces a *more than proportional* increase in the ratio of the marginal product of labor to the marginal product of capital. Since production factors are paid their marginal products, this causes an increase in the labor share. Under gross substitutability, $\sigma_s > 1$, the sign of the inequality reverses.

How could the finding that the labor shares of the manufacturing and market services sectors increase at a significantly faster rate with the capital-labor ratio than those of the other goods sector be explained in this framework? Under gross complementarity, this requires

$$\Delta \log \left(\frac{B_M K_M}{A_M L_M} \right) > \Delta \log \left(\frac{B_{OG} K_{OG}}{A_{OG} L_{OG}} \right), \tag{B.5}$$

and

$$\Delta \log \left(\frac{B_{MS} K_{MS}}{A_{MS} L_{MS}} \right) > \Delta \log \left(\frac{B_{OG} K_{OG}}{A_{OG} L_{OG}} \right), \tag{B.6}$$

which say that the ratio of effective capital to effective labor must increase faster in the manufacturing and market services sectors than in the other goods sector. This would be the case, for instance, if capital-augmenting technological change was relatively slower in the other goods sector, all else equal. The case of gross substitutes reverses the sign. In this case, the ratio of effective capital to effective labor must increase more slowly in the manufacturing and market services sectors than in the other goods sector.

Alternatively, if one were to assume that the ratio B_s/A_s were constant across sectors, both over time and across countries, then $\Delta \log (B_s/A_s) = 0$ in Equation (B.4). Consequently, the labor income share would increase with the capital-labor ratio as long as $\sigma_s < 1$, and the labor share would decline when $\sigma_s > 1$. In the case of a constant ratio B_s/A_s, the finding that the labor shares of the manufacturing and market services sectors decrease at a significantly slower rate with the capital-labor ratio than those of the other goods sector could be explained by lower values of σ in the manufacturing and market services sectors compared to the other goods sector.

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