Routine-biased technical change, structure of employment, and cross-country income differences*

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Abstract

We investigate links between routine-biased technical change, the structure of occupational employment, and cross-country income differences. To implement this, we combine several data sources, including national labour force surveys and the Penn World Tables. In our novel dataset spanning 92 countries, we document a negative relationship between the employment share of routine occupations and GDP per hour worked. We then conduct a development accounting exercise in which we differentiate labour inputs by occupation and allow for occupation-specific technologies. We find a systematic relationship between occupation-specific productivities and development. Labour in routine occupations tends to be much more productive in richer countries, with effective productivity in the top 25 percent being about 14 times higher than in the bottom 25 percent of countries ranked by GDP per hour worked. Cross-country gaps in routine technology alone account for about 17 percent of the 90–10 ratio of GDP per hour worked, whereas differences in abstract labour technology do not contribute to the observed GDP dispersion. Eliminating all occupations' and capital's technology differences would compress the GDP distribution by 32 to 40 percent.

Keywords: biased technical change; employment structure; income differences; development accounting
JEL Codes: O10, O33, O41, J21, J24

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1 Introduction

A large literature has investigated cross-country differences in incomes per capita or per worker. Most studies find a rather modest role for production factors explaining these differences but assign a large role to technologies (e.g. Klenow and Rodriguez-Clare (1997), Hall and Jones (1999), Caselli (2005), Caselli (2016)). That technology differences are the biggest force behind income differences has also been supported by more recent papers that break up the labour input and allowing for imperfect substitutability between unskilled and skilled labour and factor-biased technologies (e.g. Hendricks (2002), Caselli and Coleman (2006), Caselli and Ciccone (2013)). While distinguishing workers based on their education has a long tradition and is relatively easy to implement in the data, it potentially misses out on important non-neutral productivity differences at the level of workers' tasks or occupations.

Occupation-specific productivity changes, such as routine-biased technical change (RBTC), have played an important role in labour markets of developed economies in recent decades (e.g. Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), Goos, Manning, and Salomons (2014), Michaels, Natraj, and Van Reenen (2014)). But is such occupation-biased technical change similar across countries at different stages of development, and do differences in occupational technologies and employment structures matter for cross-country GDP disparities? To address these questions, we split labour inputs by occupation. Our results suggest that RBTC is not only a time-series phenomenon but also increases with development across countries. In fact, we find that differences in routine productivity explain a sizeable part of cross-country GDP differences, highlighting its central role in development.

Using micro and macro data from several sources, we construct a unique dataset with information on occupational outcomes for two cross-sectional samples, the 1990s and 2010s. This spans 92 countries across the development spectrum, ranging (in the 2010s sample) from output per hour worked as low as 1.50 to values up to 116.85 (in 2017 USD at chained PPPs in PWT 10.0). Apart from the breadth of coverage, our assembled data goes beyond prior literature in two dimensions: (i) we measure employment in terms of hours worked, and (ii) we bring in data on occupational wages. To measure employment in hours is not just interesting for occupational trends, but also important when accounting for productivity differences across countries. Bick, Fuchs-Schündeln, and Lagakos (2018) argue that an analysis of productivity in per worker terms understates the true extent of differences between rich and poor countries since hours worked decline with development. In our data, we see such a pattern of hours worked also within occupations, and we therefore construct productivities in terms of hours worked. Moreover, having data on wages by occupation is what enables us to analyse occupation-biases in technology.

We classify occupations into manual, routine, and abstract groups based on their dominant task content in the United States, following Autor et al. (2003) and Autor and Dorn (2013). This classification is held fixed across countries, reflecting the notion that the set of underlying tasks, which can be assigned to workers in different occupations or to capital, is common across countries. The actual allocation of tasks (at a finer level) to workers may differ across countries. We interpret such variations as outcomes driven by differences in technology, for example, the capabilities of machines that automate particular tasks. This margin is therefore encompassed in the cross-country differences in occupational technologies that we aim to capture in the development accounting exercise.[1] Beyond distinguishing routine occupations, we separate occupations into manual and abstract groups, as this dimension is central to how technological change differentially affects labour inputs. We adopt this parsimonious three-group classification to capture the most salient variation in task content while keeping the model tractable and consistent with the available data.

With this dataset, we first document how the employment shares of manual, routine, and abstract occupations vary with economic development. In the 2010s cross-section (81 countries), richer countries have a considerably larger share of hours worked in abstract occupations, while manual and routine shares decline with GDP per hour worked. Comparing the 1990s and 2010s, richer countries have seen a larger decrease in routine employment and income shares, alongside a higher increase in abstract shares, relative to less developed countries.

We then conduct a development accounting exercise distinguishing occupational labour inputs. We set up a production function that allows for occupation-specific technologies and complementarity between the occupational inputs. In our framework each production factor, i.e. each occupation and capital, has its own technology. Our main interest is in technologies augmenting the occupational inputs and how they vary across countries and over time. Because we fix occupational assignments, variation in observed occupation-specific technologies can arise both from changes in task composition within occupations and from productivity changes in underlying tasks. We cannot disentangle these two channels. Both, however, reflect cross-country differences in technology, as the state of technology determines task allocation between workers and machines as well as productivity of each factor.[2] The GDP implications of technology differences at the occupational

[1] Our exercise is fundamentally different to papers like Lewandowski, Park, Hardy, Du, and Wu (2022) that disentangle differences in routine task intensities across labour markets. Nonetheless, it is interesting to note that Lewandowski et al. (2022) with a non-structural approach, which uses country-specific survey data to construct task-intensities, find that technology is by far the most important factor behind cross-country differences in routine intensities.

[2] Caunedo, Keller, and Shin (2021) argue that the composition of tasks assigned to an occupation

group level are unaffected by this distinction.

Our approach infers occupation-specific technologies using firms' optimality conditions derived under the assumption of perfect competition. Conditional on values of the elasticity of substitution, this allows us to back out technologies from observables. This approach is standard in the literature (e.g., Caselli, 2005, Caselli and Coleman, 2006, Buera, Kaboski, Rogerson, and Vizcaino, 2022), but it ignores distortions, market power, and measurement issues. We focus on occupation-specific technologies following Bárány and Siegel (2021) but in the cross-country context, where additional factors, such as differential capital intensities, may further influence marginal products across occupations. Any factors absent from the model (e.g., distortions, market power, unobserved inputs) will be reflected in the inferred occupation-specific 'technologies'. Thus, while the model treats these terms as pure occupational technologies, what we infer from the data also captures contributions from other factors affecting the marginal products of labour in each occupation. Therefore, the results of the development exercise should be interpreted as measures of *effective occupation-specific productivities*.

Complementarities between types of labour have been studied in terms of skills (e.g., Jones (2014), Rossi (2022), Hendricks and Schoellman (2022)). We instead differentiate labour by occupation and specify a production function with complementarities between occupations. As advocated by Caselli and Ciccone (2019), in our setup a country's set of technologies impacts relative (occupational) wages. Our paper is also related to Vizcaino (2021), who uses occupational data to improve the measurement of unskilled and skilled labour. Unlike Vizcaino, we take each broad occupational group as the relevant factor and allow for occupation-specific technologies to study cross-country variation, in the spirit of Bárány and Siegel (2021).

In our analysis we infer occupation-specific technologies from the observed allocation of workers into occupations and wages. Under our assumption that the data we observe are equilibria, the observed outcomes describe points on the labour demand curves (and are on labour supply curves as well). That the equilibrium allocations reflect occupational choices and not underlying endowments, does not pose a problem to backing out technologies, as these map the observed (occupational) inputs to output. However, to fully evaluate the consequences of occupation-biased technology differences across countries, we conduct model counterfactuals where we endogenize occupational choice to allow for changes in technology to affect labour supply.

We find that higher real GDP per hour worked is associated with higher relative productivity in routine occupations compared to abstract occupations. If other factors

varies with development, while Caunedo, Jaume, and Keller (2023) highlight that the productivity of underlying tasks varies as well due to technology and occupational exposure to capital. A further possibility are variations in occupation-specific skills.

affecting marginal products are uniform across occupations, these differences can be interpreted as technological. In this case, the result suggests that more developed economies use technologies that are more routine-biased than less developed economies, indicating —borrowing from Caselli and Coleman (2006)'s terminology— *occupation-biased cross-country technology differences*. Specifically, we find that in the 2010s, countries in the top quartile of GDP per hour worked have routine productivity 160 percent above the world average, whereas bottom-quartile countries are 82 percent below average. This implies that workers in routine occupations in the top 25 percent of countries are about 14 times as productive as those in the bottom 25 percent. Additionally, we document that routine productivity growth has been faster in the top 50 percent of countries.

Through model counterfactuals, where we interpret inferred productivity differences as technological differences, we show that variations in routine and capital productivities account for most of the disparity in GDP per hour worked across countries, assuming constant inputs. While the dispersion in manual productivities across countries is considerably larger than that of routine productivities, manual productivity plays a smaller role in explaining GDP differences due to the relatively small share of manual employment. In contrast, closing routine productivity gaps has the largest equalizing effect on GDP disparities, as poorer countries tend to have a higher share of routine employment. If all countries had access to the frontier productivity levels for all inputs, the gap between the 10th and 90th percentiles of GDP per hour worked would be reduced by about a third. When occupational choice is allowed to vary with technologies, this effect becomes stronger, reducing cross-country disparities by approximately 40 percent.

In our analysis, we include workers in agricultural occupations in the routine category. While the labour market polarization literature for rich countries typically omits these workers, we want our data to cover the entire economy to consistently use aggregate data when decomposing GDP. We classify agricultural occupations as routine because in high-income countries these tasks have been largely mechanized over the past century, aligning with the definition of routine task content.

Because the agricultural employment share declines with development (e.g., Herrendorf, Rogerson, and Valentinyi, 2014) and agricultural productivity is lower in poorer countries (Caselli, 2005, Duarte and Restuccia, 2010), one might wonder whether our findings on the central role of routine technology merely reflect agriculture. We show this is not the case: excluding agriculture from all data (for a subsample of 47 countries) to decompose non-agricultural value added yields very similar results, with routine productivity still accounting for most cross-country differences.

In the next section, we describe our data sources and document occupational employment and wage patterns across countries. Section 3 introduces the model framework and implements the development accounting exercise. Section 4 explores implications for GDP dispersion through counterfactuals. Section 5 shows that results hold outside agriculture. Section 6 demonstrates robustness to alternative parametrizations and accounting for human capital. The final section concludes.

2 Documenting Empirical Facts

As we want to analyse relationships between occupational employment structure, sectoral composition, technologies, and GDP differences across countries, we need a large array of data. While data on aggregate or average income such as GDP per hour worked or per capita for a large set of countries is readily available from commonly used data sources, we need more disaggregated information as we want to distinguish between different occupational labour inputs at the aggregate and sectoral level. Our development accounting exercise requires data on occupational average wages, within a country and sector, as well as macro data on real GDP and sectoral real value added. We therefore combine multiple sources of micro and macro data. Our final dataset spans 92 countries across the development spectrum. In the following we describe its construction in detail.

2.1 Data Sources

Using micro data from several sources we have complete information on persons engaged (employees and self-employed), hourly wages or earnings[3], and weekly hours worked, all by occupation, for at least one year for 113 countries from 1970 to 2020.[4] As we also want to single out individual sectors, we have gathered sectoral-occupational information for a subset of countries. We have complete information on sectoral-occupational persons engaged, sectoral-occupational hourly wages or earnings, and sectoral-occupational weekly hours worked for at least one year for 81 countries from 1970 to 2020.

[3]For some countries, we have information on hourly wages by occupation; for others, only on earnings. Our development accounting exercise requires relative occupational wages within each country. When we cannot construct relative wages across occupations, we use relative earnings instead, implicitly assuming these ratios are similar. In a subset of 32 countries with both measures, the correlation between relative wages and relative earnings ranges from 0.78 to 0.83 across occupation pairs (M/R, A/R, M/A), suggesting that this is a reasonable approximation.

[4]Despite the common problems related to the measurement of proprietors' income, in the development accounting exercise we use persons engaged (employees and self-employed) instead of employees. The reason is that our measure of GDP per hour worked includes in the denominator persons engaged. While in developed countries employees represent a high share of persons engaged, in developing countries this is not the case; for instance, in our sample for the 2010s those countries in the bottom 25 percent of countries ranked by GDP per hour worked have a share of 43%, compared to the 88% in the top 25 percent. Thus, using employees instead of persons engaged would not be consistent with our production measure in a cross-country setting.

The sources for the micro data are the statistical database of the International Labour Organization (ILO) (2020) (ILOSTAT), Occupational Wages around the World (OWW) by Freeman and Oostendorp (2012), IPUMS International by the Minnesota Population Center (2020), IPUMS USA by Ruggles, Flood, Goeken, Grover, Meyer, Pacas, and Sobek (2020), the European Labour Force Survey (EU-LFS) by Eurostat (2021a), the European Statistics on Income and Living Conditions (EU-SILC) by Eurostat (2021b), the Harmonized Microdata Center for Household Surveys in Latin America and the Caribbean (CMAEH) provided by Inter-American Development Bank (IADB) (2021), and the International Income Distribution Data Set (World Bank I2D2) by Montenegro and Hirn (2009).

When combing these various sources at the aggregate and sectoral level we have to ensure comparability of the data. At the aggregate level, we take the following steps. First, we select regional harmonized household surveys (EU-LFS, EU-SILC and CMAEH) as the base datasets for the number of persons engaged, since they allow us to construct this indicator from raw data and we can use other variables from the same source to minimise comparability and noise issues in our analysis. We construct this indicator following ILOSTAT and thus taking the same definition for persons engaged,[5] the same one-digit ISCO classification and the same age-range (from 15 to 65+ years of age). To complement this information we use I2D2, IPUMS international and finally ILOSTAT. As the hourly wages/earnings for persons engaged is a key variable for our analysis, we select EU-SILC, CMAEH, I2D2 and IPUMS international as the base datasets, using local currency units (LCU) for the current hourly wages or earnings based on individuals that match our definition of persons engaged. To complement information not available in these sources, we use the LCU current hourly wages or earnings for employees available in OWW and ILOSTAT datasets. For the weekly hours worked we follow the same procedure as per wages/earnings, and restrict the maximum number of hours worked per week to 86, which is the maximum of weekly hours worked in ILOSTAT.[6] For the US we use micro data from the 5% State Sample 1990 and the American Community Survey (ACS), as they contain more complete information compared to the surveys available for this country in the IPUMS international dataset.[7] Appendix A gives further details on

[5]ILOSTAT uses the term employment, which is analogous to the term persons engaged, and defines it as "(...) all persons of working age who, during a specified brief period, were in one of the following categories: a) paid employment (whether at work or with a job but not at work); or b) self-employment (whether at work or with an enterprise but not at work)".

[6]The ILOSTAT and OWW datasets do not provide occupational wages/earnings or hours worked for persons engaged, so we use employee data instead. This implicitly assumes that occupational wages/earnings and hours-worked shares do not differ between employees and persons engaged. In Appendix Figure A4, we plot inferred relative technologies when restricting the sample to countries with data on persons engaged; the results are very similar to those obtained in our full dataset.

[7]We use the 5% State Sample 1990 and the ACS of 2005, 2011 and 2014. Occupations are classified

the data sources.

The occupations contained in our dataset are classified to one digit according to ISCO-08, ISCO-88 and ISCO-08(COM), ISCO-88(COM) which are used by Eurostat.[8] At the one digit level, the four classifications contain broadly the same occupations and it is therefore possible to combine data across the various sources. We assign each occupation to the group of manual, routine, or abstract occupations. Following Autor et al. (2003) and Autor and Dorn (2013), we first classify occupations by their task-content in the United States into routine and non-routine. The non-routine occupations are split according to their cognitive skill requirements further into manual (non-routine and non-cognitive) and abstract (non-routine cognitive) occupations. As noted in the introduction, our classification of occupations is held fixed across countries. We consider the set of underlying tasks, which can be assigned to workers in different occupations or to capital, as common to all countries, and interpret variations in the actual task intensities of occupations as outcomes driven by differences in technologies. Consistent with this, we do not drop agricultural workers, unlike Autor and Dorn (2013), but include them in the routine category, reflecting that in high-income countries these tasks have been largely mechanized over the past century (Autor, 2015). As all workers contribute to GDP, retaining them ensures consistency between the occupational data and the aggregate data used in the decomposition. Table 1 lists the classification of occupations.

For the 113 countries with complete information on persons engaged, hourly wages or earnings and weekly hours worked, we collect macro data from the Penn World Tables (PWT) version 10.0 by Feenstra, Inklaar, and Timmer (2015), the World Development Indicators of the World Bank (2021), and ILOSTAT on GDP, GDP per worker, capital stock, the labour share in GDP, and other relevant variables. For GDP we use the output-side real GDP at chained PPPs (in mil. 2017US$) from the PWT, as constant PPP allows for cross-country and cross-time comparisons. Our capital stock data also comes from PWT 10.0, which is measured at constant local currency units and current PPP (in mil. 2017US$). We use the GDP deflator between output-side real GDP at current PPPs and at chained PPPs to convert capital stock from current to constant PPP (2017US$).

When collecting the sectoral-occupational information, we follow the same steps as for the aggregate level with some differences worth to point out. First, we classify each of the occupations defined earlier into one of the four broad sectors shown in Appendix

using the harmonized coding scheme based on the Census Bureau's 2010 ACS classification in IPUMS USA. We apply the four-digit crosswalk from SOC to ISCO-08 by the Bureau of Labor Statistics to map IPUMS-USA codes into ISCO-08, and then aggregate to the one-digit level to match our groupings.

[8]The occupational codes in the OWW dataset are those used by the ILO October Inquiry, which includes 161 codes. We crosswalk these codes to the ISCO-08 at 2 digits and finally we collapse the 2 digits into the ISCO-08 1 digit.

Table 1: Classification of Occupations

ISCO-88/ISCO-88(COM)	ISCO-08/ISCO-08(COM)	Grouping
Legislators, Senior Officials and Managers	Managers	Abstract
Professionals	Professionals	Abstract
Technicians and Associate Professionals	Technicians and Associate Professionals	Abstract
Clerks	Clerical Support Workers	Routine
Service Workers and Shop and Market Sales Workers	Services and Sales Workers	Routine
Skilled Agricultural and Fishery Workers	Skilled Agricultural, Forestry and Fishery Workers	Routine
Craft and Related Workers	Craft and Related Trades Workers	Routine
Plant and Machine Operators and Assemblers	Plant and Machine Operators and Assemblers	Routine
Elementary Occupations	Elementary Occupations	Manual

Note: In ISCO-08, the elementary occupations classification includes the following groups (previous versions of the ISCO roughly contain the same groups): cleaners and helpers; agricultural, forestry and fishery labourers; labourers in mining, construction, manufacturing and transport. While some of the tasks performed by these kinds of workers are repetitive, most of them require basic skills and situational adaptability, which make them difficult to be automated. These characteristics allow us classify them as manual and to differentiate them from abstract (tasks require problem solving skills and creativity) and routine occupations (tasks are repetitive, well defined and prone to be codifiable).

Table A1.[9] Second, for the analysis excluding agriculture in Section 5, we aggregate all other sectors. For the sectoral analysis in Appendix Section E, we alternatively consider either two sectors (goods and services) or four sectors, where the goods sector is split into agriculture and industry, and the services sector into high- and low-skilled services, based on the skill or educational composition of labour in each industry, as is standard in the recent structural transformation literature (Buera and Kaboski (2012), Duernecker, Herrendorf, and Valentinyi (2024), Bárány and Siegel (2021)).

For sectoral macro data, we draw on multiple sources. First, we use the World Input-Output Database (WIOD) by Timmer, Dietzenbacher, Los, Stehrer, and de Vries (2015) and World KLEMS[10] to obtain data on sectoral nominal gross value added, sectoral nominal capital stock, sectoral nominal factor compensations and sectoral number of total hours worked by persons engaged. We prioritise World KLEMS where available, followed by WIOD (which covers data up to 2014). To deflate these nominal values, we use the GGDC Productivity Level Database 2023 (PLD 2023) by Inklaar, Marapin, and Gräler (2023), which provides value added, employment, and PPP conversion factors

[9]As each dataset has a specific classification scheme for industries, we focus on broader sectors that can be consistently constructed across datasets by mapping them into our broad sector classifications.

[10]This is a dataset compiled by World KLEMS consortium that includes EU KLEMS, LA (Latin American) KLEMS and Asia KLEMS.

for 12 sectors across 84 countries. Using the method developed by Inklaar and Diewert (2016), we aggregate value added, factor compensations and capital stock data from World KLEMS and WIOD, converted to 2017 PPPs using PLD2023 conversion factors, into both broad sectors (e.g., non-agriculture) and more detailed categories such as goods and services.[11]

For countries not covered by KLEMS or WIOD, we use the PLD2023 to get each country's non-agricultural value added in purchasing power parities. Then we use Eora National IO Tables by Lenzen, Kanemoto, Moran, and Geschke (2012) to construct sectoral labour income shares and capital allocations. Specifically, we use sectoral value-added components from the input–output tables to derive labour compensation and labour income shares by sector, which we then apply to sectoral value added from PLD2023 to obtain total factor compensation by sector. We approximate sectoral capital stocks by allocating the aggregate capital stock from the Penn World Tables using sectoral shares of consumption of fixed capital (CFC) derived from Eora.[12] To deflate the Eora-derived values and aggregate them into our sectors of interest, we follow the procedure outlined above. Given differences in coverage between the various datasets, we select 2011 as the reference year for our sectoral analysis, as this maximises country coverage.[13]

In documenting cross-sectional patterns and in conducting our development accounting exercise at the aggregate and sectoral level, we want to include as many countries as possible. One complication is that data availability sometimes differs across countries by a few years. At the aggregate level we try to overcome this issue by assigning each country-year full set of information to two cross-sectional samples, the "1990s" and the "2010s". We include in the "2010s" ("1990s") sample for each country the most recent full set of main data points (i.e. all required information on occupational outcomes) –as long as it is from the year 2010 (1990) or newer. This results in having 96 (68) countries of the 2010s (1990s) sample, with about 82 (84) percent of observations corresponding to 2015 (1995) or more recent years.[14]

[11]To integrate WIOD and World KLEMS with the PLD 2023 database, we harmonise their data to match the 12 industries defined in PLD 2023. We then follow Inklaar and Diewert (2016) to aggregate the data into the broad sector of non-agriculture, as well as into goods and services, and to further disaggregate the latter into agriculture, industry, high-skilled services, and low-skilled services.

[12]CFC reflects the depreciation of the existing capital stock and is therefore broadly proportional to its size. Assuming similar depreciation rates across sectors, sectoral CFC shares provide a reasonable proxy for the sectoral distribution of capital. To test this assumption, we use a sample of 25 countries for which sectoral capital shares (agriculture, industry, high-skilled services and low-skilled services) can be computed using both KLEMS and WIOD data, as well as our approximation based on CFC. The two measures are highly positively correlated, with a correlation coefficient of 0.84.

[13]Due to data availability, we use the year closest to 2011 in our extended database for some countries: AUS (2016), TUR (2010), GHA (2013), MMR (2015), UGA (2012), BGD (2016), MWI (2013), and NAM (2012).

[14]For 55 (46) countries the most recent data we have is for 2018 or 2019 (1998 or 1999). For another 11 (3) countries we got data for 2017 (1997).

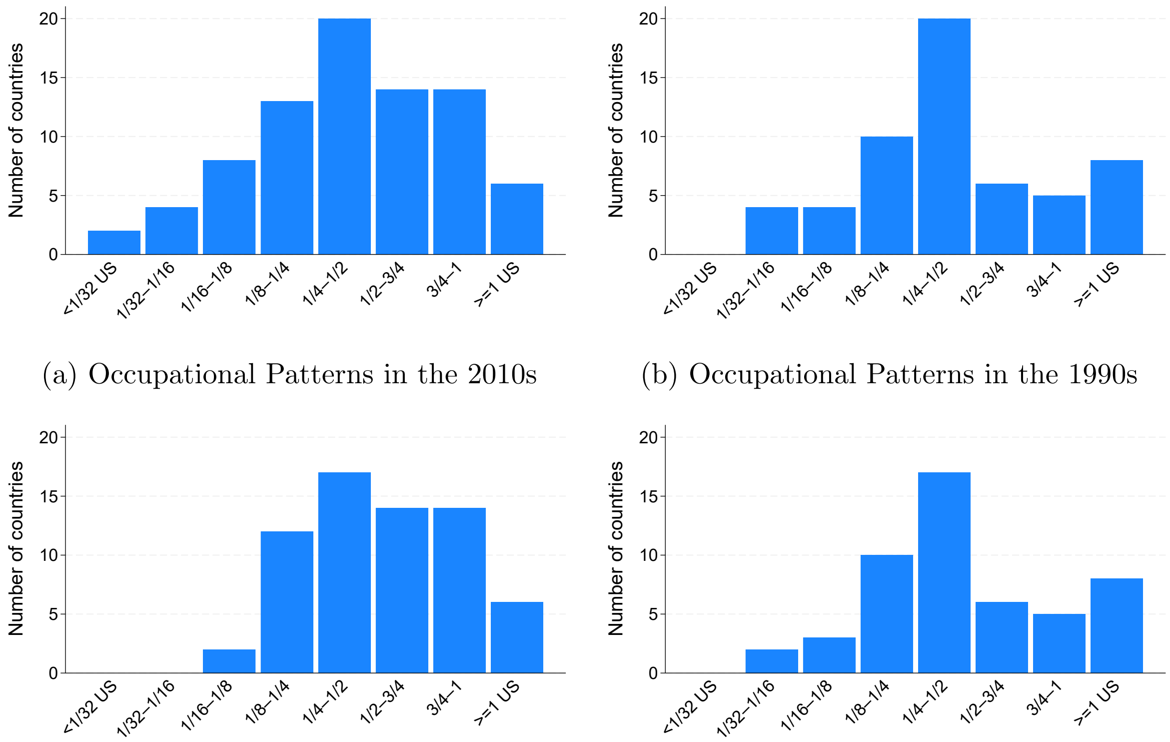
Once we have the micro data and the macro data at the sectoral and aggregate level, we proceed to merge the databases. From here we have 105 countries with the required aggregate and occupational data, whereas the sectoral dataset contains 73 countries. Finally, we conduct an exercise to detect outliers and exclude them from the analysis.[15] Thus, in the most basic setting, we are able to estimate absolute and relative labour augmenting technologies for 92 countries at the aggregate level (81 for the "2010s" and 57 for the "1990s"). At the sectoral level for the non-agricultural economy, we are able to estimate factor-augmenting technologies for 47 countries (all for 2011). At a finer level of sectoral disaggregation (e.g., goods and services), these estimates are obtained for 34 countries (also for 2011).[16] The list of countries included in each sample as well as their corresponding variables and sources of the occupational micro data and the macro data are presented in Appendix Table A2 and Appendix Table A3.

Figure 1 shows the distribution of countries across different levels of GDP per hour worked relative to the United States. It shows the number of countries in various GDP brackets, highlighting the broad spectrum of development levels represented in our dataset. Panel (a) shows the distribution for the 2010s sample used to document occupational patterns, while panel (c) corresponds to the subset used in the main development accounting exercise (section 3.2), which requires additional data on capital stocks and capital-income shares. Panels (b) and (d) present the corresponding distributions for the 1990s cross-section.

[15]We perform a boxplot analysis to remove implausible looking values in our occupational and sectoral occupational data when at least one of the following conditions is met: 1) if the country is an outlier in more than one of our occupational data (hours worked, wages/earnings and labour shares; see Section 2.2), or 2) if the country is an outlier in the estimated labour augmenting technologies compared to other countries in the same quartile of GDP per hour worked (see Section 3).

[16]The smaller country coverage compared to the non-agriculture sector estimates reflects data requirements: for the latter, we do not need sector-specific occupational data, as we can simply exclude the 1-digit ISCO category corresponding to agriculture-related occupations. Also, notice that the scope of the data we have assembled also enables us to estimate finer sectoral absolute technology levels for 34 countries in 2005, along with sectoral relative technology measures for a similar number of countries in both the 1990s and 2010s samples.

Figure 1: Distribution of Countries' GDP per Hour Worked Relative to the United States



(a) Occupational Patterns in the 2010s

(b) Occupational Patterns in the 1990s

(c) Development Accounting in the 2010s

(d) Development Accounting in the 1990s

Notes: These bar charts show the distribution of countries by GDP per hour worked relative to the United States. Data coverage varies across exercises due to availability constraints. Panels (a) and (b) correspond to the samples used to document occupational patterns (section 2.2) for the 2010s and 1990s, respectively. Panels (c) and (d) correspond to the samples used in the main development accounting exercise (section 3.2) and the model counterfactuals (section 4).

2.2 Occupational Patterns in the Cross-section of Countries

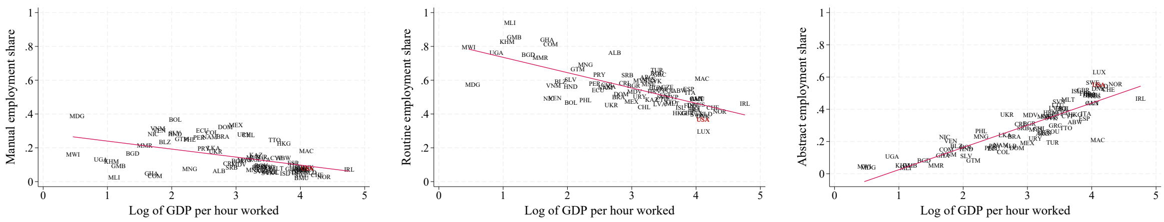
In this subsection we show various novel descriptive statistics on the relationship between occupational labour market outcomes and economic development. Throughout we measure employment in terms of hours worked. Figure 2 shows the cross-sectional patterns in the 2010s of the employment shares of manual, routine, and abstract occupations against the log of real GDP per hour worked. The plots show clear discernible patterns: the higher the countries average income, the lower is the employment share of manual and of routine occupations, and the higher the abstract employment share.[17] While a part

[17] We can compute in our data also the correlation between the employment shares in terms of occupations and in terms of skills as measured by years of education. In the 1990s, the correlation between abstract and skilled labour shares was 0.73, whereas the correlation between routine and unskilled was 0.41 (37 countries included). For the 2010s, these correlations are 0.83 and 0.39, respectively (47 countries included). While there is a strong correlation between skilled and abstract labour shares, the routine and unskilled labour shares depict a weaker association. This implies that the skilled-unskilled dimension

of the decline in the routine share with development in Figure 2 reflects the reduction in agricultural employment, the routine share also declines within non-agricultural employment, as shown in Appendix Figure A1. The cross-sectional behaviour of the routine and abstract occupational employment shares mimics the time-series behaviour for advanced economies over time (e.g. see Bárány and Siegel (2018) for the trends in the US since the 1950s).

In Table 2 (columns two to four) we show how the annual average percentage point change of the employment shares per occupation vary across the cross-country distribution of the GDP per hour worked. Countries at the top of the income distribution have experienced, on average, a faster annual decrease in the routine employment share compared with the bottom quartile. This suggest the existence of a process of substitution of routine occupations between the 1990s and the 2010s that has been faster in richer countries compared to less developed nations[18]. This decline goes hand in hand with an increase in the employment share of abstract occupations at the top of the average income distribution.

Figure 2: Occupational employment shares vs log of GDP per hour worked in the 2010s



(a) Manual share (b) Routine share (c) Abstract share

Notes: This figure plots the three occupational groups' employment share against log of real GDP per hour worked based on the cross-section of countries in the 2010s. In this figure the 2010s sample contains 81 countries.

We also document in Figure 3 the occupational income shares and their distribution in the cross-section of countries for the 2010s. The patterns resemble those observed in the employment shares: the higher the income of a country is, the lower the labour income shares of manual and routine occupations are; whereas the labour income share of abstract occupations increases with the level of GDP per hour worked. Table 2 (columns five to seven) contains the annual average percentage point variation of labour income share per occupation between the 1990s and 2010s.

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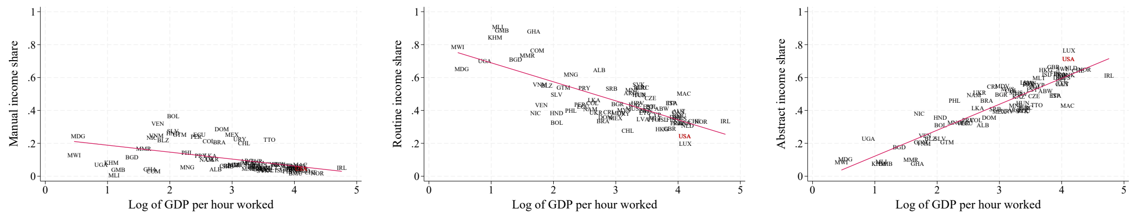
cannot fully capture the full dynamics associated with technical change biased against routine workers.

[18]Interestingly, Reijnders and de Vries (2018) take a task-based model of global value chains to data over 1999–2007 and find that technological change matters much more for the non-routine employment share than task reallocation across countries.

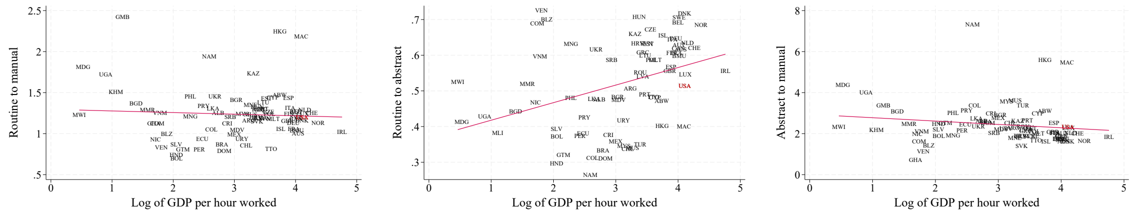
Figure 3: Occupational income shares vs log of GDP per hour worked in the 2010s



(a) Manual share (b) Routine share (c) Abstract share

Notes: This figure plots the three occupational groups' occupational income share against log of real GDP per hour worked based on the cross-section of countries in the 2010s. In this figure the 2010s sample contains 81 countries.

Figure 4: Relative occupational wages vs log of GDP per hour worked in the 2010s



(a) Routine to manual (b) Routine to abstract (c) Abstract to manual

Notes: This figure plots the relative average occupational wages against log real GDP per hour worked based on the cross-section of countries in the 2010s. In this figure the 2010s sample contains 81 countries.

The results are similar to the change of the employment shares; however, we document that the speed at which the labour income share of routine (abstract) occupations decreases (increases) in richer countries is faster than the one observed in the employment shares. In Figure 4 we show how relative wages across the three occupational groups vary with GDP per hour worked across countries. Relative wages do vary with GDP per hour worked, but the relationships are weaker than those observed for the occupational employment and income shares. While higher GDP tends to be associated with lower wages for routine occupations relative to manual, there is a positive association between GDP per hour worked and routine wages relative to abstract occupations. When we compare wages of abstract to manual occupations, there exists a negative association with the GDP per hour worked.

Table 2: Cross-country comparison of the annual average percentage point changes of occupational employment, occupational income shares and relative wages (1990s-2010s)

Quartile of	Occupational employment shares			Occupational income shares			Relative wages	
GDP p.h.w	Manual	Routine	Abstract	Manual	Routine	Abstract	R-to-M	R-to-A
1	-0.13	0.17	-0.04	-0.01	0.20	-0.19	-0.15	0.15
2	-0.15	-0.27	0.42	-0.11	-0.47	0.58	-0.43	0.00
3	0.03	-0.43	0.40	-0.07	-0.58	0.65	0.82	-0.47
4	-0.04	-0.38	0.42	-0.08	-0.53	0.60	0.36	-0.54

Notes: This table reports by quartile of GDP per hour worked (of the 2010s) the annual average percentage point change of occupational employment, income shares and relative wages. This table contains 46 countries. For each country we take the absolute variation of the employment and income shares and relative wages and divide them by the year difference between the two observation points.

Table 2 reports over time changes of these occupational outcomes by quartiles of the world GDP per hour worked distribution. Relative wages of routine to manual occupations have increased in richer countries over the last three decades. Relative wages of routine to abstract labour have decreased at the top of the income distribution, while there has been a positive evolution in the poorest countries. We observe that in the range where labour income share of routine labour decreases, behind of it there is a decrease of the employment share in routine occupations combined with a drop in relative routine to abstract wages. We document the opposite when the labour income share of routine labour increases, which is the case at the bottom of the income distribution.

Overall these figures suggest that there are substantial systematic differences in the occupational employment structure across countries. In the remainder of the paper we analyse to what extent differences in the occupational composition and in occupational technologies can explain cross-country differences in average income per hour worked. We focus on GDP per hour worked, rather than per worker, as this is a more precise measure of productivity. Bick et al. (2018) show that in terms of aggregate trends hours worked at the intensive margin decline with development. Using our dataset, we show in Appendix Figure A2 that this patterns holds within occupation as well.

3 Analysis with an Aggregate Production Function

We assume a production function in occupational labour for an economy's output. Using firms' profit-maximizing conditions, which equate each occupation's marginal product to its wage, we invert these relationships to back out factor-augmenting technologies from observed employment shares and wages. Conditional on a value for the elasticity of substitution, this approach allows us to infer relative technologies of occupational labour within a country. When capital is included, the relative technology of capital is pinned down by capital per hour worked and its share in total value-added. Given the observed inputs and inferred relative technologies, we solve for technology levels that match each country's GDP per hour worked.[19] The method follows Bárány and Siegel (2021) but adapted to the cross-country context.[20] Any factors absent from the model such as distortions or unobserved inputs are reflected in the inferred occupation-specific "technologies". What we back out from the data are occupation-specific factors capturing effective occupation-specific productivities, encompassing both technology and additional factors that affect occupational marginal products.

In this analysis, we interpret the observed data, including occupational wages and employment, as reflecting equilibrium outcomes. As noted in the introduction, endogeneity of occupational choices with respect to technology does not pose a problem to backing out technologies, but it matters for evaluating their GDP impact. Accordingly, in Section 4 we conduct two types of counterfactuals: one keeping inputs fixed, and one allowing occupational employment to adjust to technology changes.

We first present a framework distinguishing manual, routine, and abstract occupational labour, allowing for occupation-specific technologies.[21] In section 3.2 we add capital with its own technology. This is our preferred specification, as it remains parsimonious and avoids further assumptions, for instance about human capital transferability across occupations. In an extension in Section 6.2, we account for human capital differences as efficiency units, but as this does not materially change the results for the occupation-bias in technologies and data limitations reduce the sample, we report it as a robustness check.[22]

3.1 Routine, Manual and Abstract Labour as Distinct Inputs

Following Bárány and Siegel (2021) we allow for the technologies of all three occupational groups to differ and assume for the aggregate production function

$$Y_i = \left(\alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}} + \beta(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha-\beta)(\mu_{A,i}A_i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{1}$$

where R_i, M_i, A_i respectively denote the employment share of routine, manual and abstract occupations, and $\mu_{R,i}, \mu_{M,i}, \mu_{A,i}$ respectively denote their technologies in country i.

[19]Note, the occupation-specific technologies are different to occupations' marginal products, which depend also on the other occupations' technologies and the occupational employment structure. Given the observables, our model allows to infer the occupation-specific technologies.

[20]Unlike Bárány and Siegel (2021) we do not distinguish ICT and non-ICT capital as we do not have such data for our (large) sample of countries.

[21]Appendix B.1 shows a simpler two-group setup for routine and non-routine labour.

[22]Our baseline analysis focuses on the aggregate economy. In section E we show that the general patterns also holds at the sectoral level.

These factor-augmenting technologies are allowed to differ across countries and we will use model relationships to infer their values from the data. The parameters α and β are invariant across countries and capture occupational intensities. Y_i is the real GDP per hour worked and σ the elasticity of substitution between occupational labour. In this formulation substitutability is the same across any pair of the three occupations. In Section 6 we show that the main conclusions go through when relaxing this assumption.

Assuming perfect competition in labour markets, we can derive by inverting the optimality conditions for occupational labour demand (see Appendix C) expressions for relative technologies within a country as

$$\frac{\mu_{M,i}}{\mu_{A,i}} = \left(\frac{1-\alpha-\beta}{\beta}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{w_{M,i}}{w_{A,i}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{M_i}{A_i}\right)^{\frac{1}{\sigma-1}}, \tag{2}$$

$$\frac{\mu_{R,i}}{\mu_{M,i}} = \left(\frac{\beta}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{w_{R,i}}{w_{M,i}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{R_i}{M_i}\right)^{\frac{1}{\sigma-1}}, \tag{3}$$

where $w_{O,i}$ is the wage rate for occupation O in country i. The first equation pins down the relative technology of manual compared to abstract labour and the second equation the technology of routine relative to manual labour.

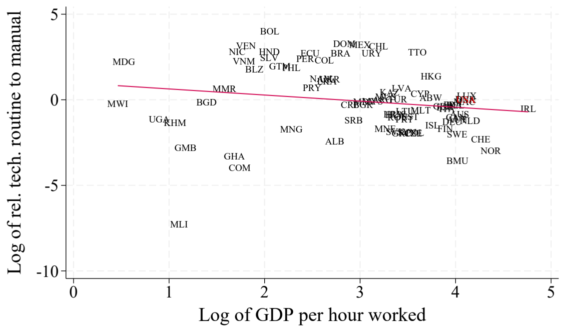
The level of each country's technology is such that the observed inputs and inferred technologies are in line with the data for real GDP per hour worked and thus must satisfy

$$\mu_{M,i} = \left(\frac{Y^{\frac{\sigma-1}{\sigma}} w_{M,i} M_i^{\frac{1}{\sigma}}}{\beta(w_{R,i}R_i + w_{M,i}M_i + w_{A,i}A_i)}\right)^{\frac{\sigma}{\sigma-1}}. \tag{4}$$

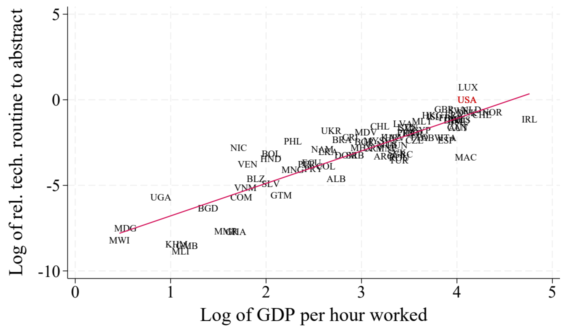
After specifying a value for the elasticity of substitution σ, every term on the right-hand side of (2) to (4) is observable, apart from the parameter α and β. We set, as in Bárány and Siegel (2021), the substitution elasticity $\sigma = 0.6$. To obtain a value for the two remaining parameters, we impose that for a benchmark country, all factors' technologies to take the same value, i.e. $\mu_{R,benchmark} = \mu_{M,benchmark} = \mu_{A,benchmark}$, allowing us to use equations (2) and (3) to obtain values for α and β using the observable information for the benchmark country. We implement this by taking the US as the benchmark economy. Given this normalisation, α and β capture a combination of the occupational intensities and the relative occupational productivities of the US. However, this normalisation does not drive any of our results as everything will be derived from relative technologies, either between factors within a country or for a given factor across countries. Equipped with the values for α and β, we use data for all other countries to compute their technologies using equations (2) to (4). This gives us all countries factor-augmenting technologies, $\mu_{R,i}, \mu_{M,i}, \mu_{A,i}$ relative to the US economy.

To note is that here we do not account for capital at all. As such, the variation in the inferred technologies across countries and across occupations might capture differences in technology, organization of tasks, or in capital services.[23]

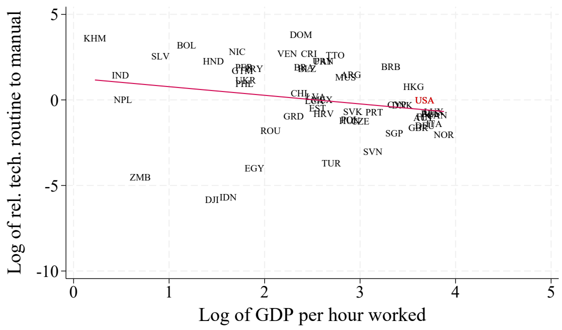
Figure 5: Relative technologies based on (1) vs real GDP per hour worked



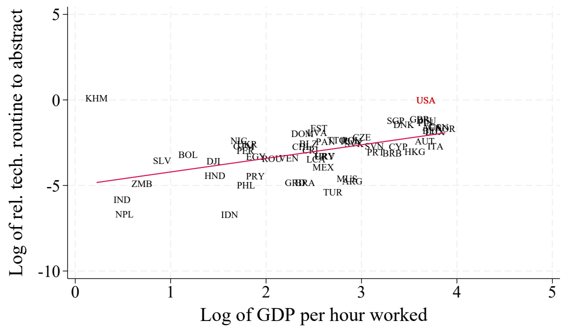
(a) Routine to manual technologies (2010s)



(b) Routine to abstract technologies (2010s)



(c) Routine to manual technologies (1990s)



(d) Routine to abstract technologies (1990s)

Notes: This figure plots the relative technologies inferred based on the aggregate production function (1) with $\sigma = 0.60$ against log GDP per hour worked in the cross-section of countries in the 2010s and the 1990s. In this figure the 2010s sample contains 81 countries and the 1990s 57 countries.

Figure 5 plots the inferred relative technologies against GDP per hour worked for the 1990s and 2010s. Several main patterns emerge. First, relative occupational productivities vary systematically with economic development, indicating that richer countries are not uniformly more productive across occupations but there is a bias in the occupational dimension. Second, the inferred technology of routine relative to abstract labour increases with GDP per hour worked, suggesting that the routine-bias in technologies increases with development. This relationship is statistically highly significant. Third, the technology of routine relative to manual labour shows a slight negative relationship

[23] In the next subsection we account for capital in an occupation-neutral way, where capital differences across countries are netted out but technology gaps between occupations might still reflect (country-specific) differences in capital intensities across occupations. As a robustness check we present in section 6.3 results from a very different production function where capital is good substitute for routine labour but not for the other labour inputs.

with GDP, although this pattern is not statistically significant (not even at the 10% level). Taken together, these differing trends highlight the importance of distinguishing occupations also outside the routine category.

Qualitatively, the 1990s and 2010s exhibit similar patterns. Quantitatively, however, the productivity bias between routine and abstract occupations has increased over time.[24] The slope of the fitted relationship between the routine-to-abstract inferred technology ratio and GDP per hour worked is 2.4 times larger in the 2010s than in the 1990s (statistically significant at the 1% level in both periods), whereas the gradient for routine-to-manual technologies barely changed (and is not statistically significant in either period).

These results suggest that routine-biased technical change may be an increasingly important driver of cross-country GDP differences. We assess this in Section 4 using two sets of counterfactuals: one holding production inputs fixed, and another allowing occupational employment to adjust to changes in technology. In fact, in a model with endogenous labour assignment under complementarities between the occupational inputs ($\sigma < 1$), an improvement in an occupation's technology causes a reduction in the equilibrium employment share of that occupation.[25] This mechanism rationalizes the joint patterns of occupational employment shares (Figure 2) and occupation-specific productivities (Figure 5). Moreover, improvements in routine technology affect GDP both directly and indirectly, by reallocating labour toward other occupations.

Finally, distinguishing between manual, routine, and abstract labour yields insights beyond the standard skilled–unskilled framework. While abstract employment might be closely related to college attainment, our results reveal differential technology patterns between manual and routine occupations that would be missed in a two-factor model. In fact, in section 6.2 we additionally account for worker's human capital and the patterns in the occupation-bias of technologies prevail.

3.2 Routine, Manual and Abstract Labour and Capital as Inputs in a Nested CES Specification

The previous production function is the most parsimonious way to study complementarity between routine, abstract and manual labour allowing for routine-biased technical change. Yet, as it does not take into account capital whose stocks differ vastly across countries, it is not suitable for comparing technology levels across countries. We therefore augment

[24] Due to data availability the set of countries differs between the 1990s and the 2010s cross-sections. However, the increase in routine bias over time is also evident in the balanced panel of 43 countries. Between the 1990s and the 2010s, growth in routine technologies has been the highest, see Table 4.

[25] The effects of biased technical change on labour allocations are well known in the literature, see for instance Ngai and Pissarides (2007) for an application to structural transformation or Bárány and Siegel (2018) for a case without wage equalization.

this framework by adding capital as a further production factor. As we do not have cross-country data on capital use by occupation or on different types of capital, we assume a nested CES structure, where the inner layer consists of a CES labour aggregator akin to (1), and the outer nesting combines the labour aggregate with capital.

Introducing capital in this way is 'occupation-neutral' — cross-country differences in capital (or its efficiency) do not alter the relative productivities of occupational labour within a country. When inferring the occupational technologies, capital differences across countries are netted out. However, technology gaps between occupations might still reflect (country-specific) differences in capital intensities across occupations. If there are differences in the amounts or types of capital available to the various occupations, these differences will be loaded in our framework on the occupation-specific technologies. We also cannot disentangle the effects of capital that is heterogeneous across occupations due to differences in substitution elasticities, as in Caunedo et al. (2023), from directly occupational labour augmenting technologies.

Specifically, we adopt the structure of the nested formulation used by Bárány and Siegel (2021) and assume[26]

$$\begin{aligned} Y_i = \Bigg(\phi\Big[\alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}} + \beta(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha-\beta) \\ \times (\mu_{A,i}A_i)^{\frac{\sigma-1}{\sigma}}\Big]^{\frac{\sigma}{\sigma-1}\frac{\eta-1}{\eta}} + (1-\phi)(\mu_{K,i}K_i)^{\frac{\eta-1}{\eta}}\Bigg)^{\frac{\eta}{\eta-1}} \end{aligned} \tag{5}$$

where $\mu_{K,i}$ is the factor-augmenting technology for capital K_i in country i, and η is the elasticity of substitution between the labour aggregate and capital. In this formulation the most inner nesting is the combination of effective routine, abstract and manual labour. As before, labour inputs are aggregated according to an elasticity of substitution $\sigma < 1$. The most external layer of the CES function combines the aggregate labour and effective capital using an elasticity of substitution $\eta < 1$ to produce the final output.

A special case of this is one with a unitary elasticity in the outer nesting, such that the production function becomes Cobb-Douglas in capital and the labour aggregate. We present this case in Appendix B.2, but focus on the non-unitary specification, which allows for cross-country differences not only in capital quantities but also in capital-augmenting technologies. This is important for capturing the fact that the capital income share tends to fall in GDP across countries. Moreover, with $\eta < 1$, the model implies smaller cross-country differences in occupational technologies than the Cobb–Douglas case, as richer countries tend to exhibit higher inferred capital-augmenting technologies. In this sense,

[26] In section 6.3, as robustness check, we use an alternative specification of the nested production function in which there are different substitution elasticities between different pairs of occupations, and the complementarity of capital varies across the occupational labour inputs.

the CES specification in (5) is more conservative, as it attenuates the role of occupation-biased technological differences.

Given the production function (5) we can back out the countries' technologies from observables conditional on σ and η from the following expression (see Appendix C for derivations):

$$\frac{\mu_{K,i}}{\mu_{R,i}} = \left(\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{1}{\eta-1}} \frac{r_i}{w_{R,i}} \left(\frac{\phi}{1-\phi}\right)^{\frac{\eta}{\eta-1}} \alpha^{\frac{\sigma}{\sigma-1}} \left(\frac{1}{\theta_{R,i}}\right)^{\frac{\eta-\sigma}{(\sigma-1)(\eta-1)}} \tag{6}$$

$$\frac{\mu_{R,i}}{\mu_{A,i}} = \left(\frac{\theta_{R,i}}{\theta_{A,i}}\right)^{\frac{1}{\sigma-1}} \frac{w_{R,i}}{w_{A,i}} \left(\frac{1-\alpha-\beta}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \tag{7}$$

$$\frac{\mu_{R,i}}{\mu_{M,i}} = \left(\frac{\theta_{R,i}}{\theta_{M,i}}\right)^{\frac{1}{\sigma-1}} \left(\frac{\beta}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \frac{w_{R,i}}{w_{M,i}} \tag{8}$$

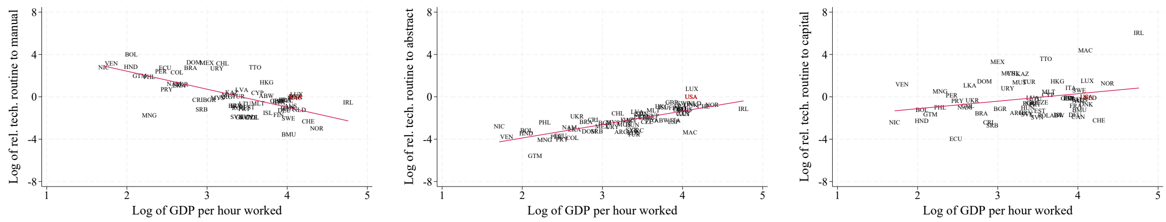
$$\mu_{K,i} = \frac{Y_i}{K_i(1-\phi)^{\frac{\eta}{\eta-1}} \left(\frac{(1-\Theta_{K,i})}{\Theta_{K,i}}+1\right)^{\frac{\eta}{\eta-1}}}, \tag{9}$$

where $\Theta_{K,i} = \frac{r_i K_i}{Y_i}$ is the non-labour share in GDP, r_i is the rental price of capital[27] and $\theta_{o,i} = \frac{w_{o,i} o_i}{\sum_{o'} w_{o',i} o'_i}$ the share of labour income going to occupation $o \in \{R, M, A\}$, all in country i. We take the US as the benchmark economy to normalise all factors' technologies by imposing $\mu_{R,benchmark} = \mu_{M,benchmark} = \mu_{A,benchmark} = \mu_{K,benchmark}$. This allows us to obtain α, β and ϕ, using equations (6), (7) and (8). We set the elasticity parameters to $\sigma = 0.60$ and $\eta = 0.84$, which are the values Bárány and Siegel (2021) use in their calibration against US data, implying that all factors are gross complements. Figure 6 plots the relative routine labour augmenting technologies for the 2010s and 1990s.

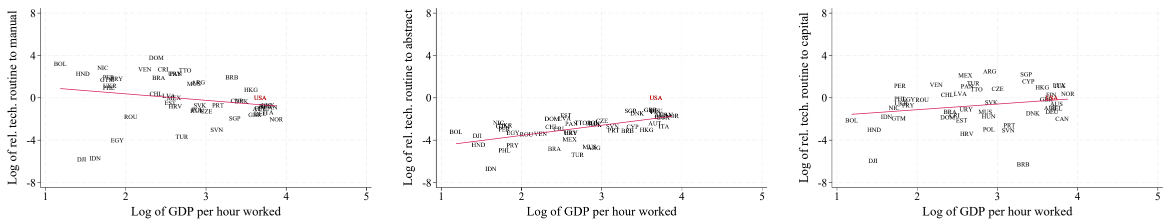
The inferred relative technologies of routine to manual and abstract occupations display the same patterns as documented earlier. This is not a surprise, as the occupational labour inputs are aggregated using the same structure as in equation (1). However, the results here are based on the subset of countries with data on the non-labour share in GDP, and this smaller sample yields a more pronounced negative relationship between the routine-to-manual technology ratio and development. A new result in Figure 6 is the ratio of routine to capital technologies, which exhibits a positive gradient with GDP (statistically significant at the 5% level) in both cross-sections.

[27] We back out the rental price of capital from the GDP identity as $r_i = \frac{Y_i - \sum_o w_{o,i} o_i}{K_i}$, where $o \in \{R, M, A\}$.

Figure 6: Relative technologies based on (5) vs real GDP per hour worked



(a) Routine to manual tech. (2010s) (b) Routine to abstract tech. (2010s) (c) Routine to capital tech. (2010s)



(d) Routine to manual tech. (1990s) (e) Routine to abstract tech. (1990s) (f) Routine to capital tech. (1990s)

Notes: This figure plots the relative technologies inferred based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$ against log GDP per hour worked. In this figure the 2010s sample contains 65 countries and the 1990s 51 countries, where the sub-samples contain only the countries for which we have data on the capital share in GDP.

We also compare inferred technologies across the development spectrum in the 2010s by grouping countries by GDP per hour worked. Table 3 reports, for each quartile and production input, the ratio of the quartile's average technology to the world average. Dispersion is highest for manual occupations, exceeding that of GDP per hour worked. Routine workers in the top 25 percent of countries are on average 14 times more productive than those in the bottom 25 percent, while the gap for abstract technologies is much smaller, with a factor of only 2.6. This result is perhaps quite intuitive: abstract workers might use very similar software packages across the world, whereas manual and routine workers are much more subjected to local modes of production. Finally, capital-augmenting technology shows the least dispersion across the quartiles in the 2010s cross-section.

Finally, we conduct a comparison over time. For the 43 countries where we can compute technologies for both the 1990s and 2010s, Table 4 presents the annual geometric growth rates for each country and technology. Across the distribution, growth in manual and routine technologies has outpaced that of abstract technologies, while there has been a reduction in capital-augmenting technologies. More developed countries have experienced somewhat faster routine-augmenting technical change, particularly in the third GDP quartile, though the variation across quartiles is modest. As shown in Table 2, countries in the third quartile also saw the fastest decline in routine employment and a

Table 3: Cross-country comparison of occupation-augmenting technologies in 2010s

Quartile of GDP p.h.w.	GDP p.h.w. rel. to world	Technology relative to world avg.			
		Manual	Routine	Abstract	Capital
1	0.33	0.04	0.18	0.71	0.84
2	0.75	0.21	0.57	0.90	0.62
3	1.14	0.42	0.70	0.56	1.00
4	1.82	3.38	2.60	1.85	1.55

Notes: This table reports by quartile of real GDP per hour worked the average inferred technology of routine, manual and abstract labour and capital relative to the world average, as inferred from the data based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

Table 4: Cross-country comparison of occupation-specific technology changes

Quartile of GDP p.h.w	Growth (%) 1990s-2010s				
	M	R	A	C	GDP phw
1	4.26	4.90	1.22	-2.37	2.36
2	4.64	5.50	-1.00	-1.49	2.86
3	6.95	6.88	0.65	-2.17	2.70
4	5.44	5.45	-0.33	-1.87	1.65

Notes: This table reports by quartile of real GDP per hour worked (2010s) the geometric rate of growth of inferred technology of routine, manual and abstract labour and capital, as inferred from the data based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$ and using the factor input-intensities of production of the US in the 2010s. The sample in this table contains 43 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

pronounced drop in routine wages relative to abstract occupations; therefore, the model assigns a high role to RBTC in these countries.

4 Implications for GDP Per Hour Disparities

To assess the role of effective productivity differences in shaping cross-country disparities in GDP per hour worked, we conduct a series of counterfactual exercises. Using the results from Section 3.2, we explore how the cross-country GDP distribution would change if all countries had access to the same technology for one or more production factors.

We refer to these exercises as providing countries with access to common technology. However, since the inferred technologies may reflect not only pure technological differences but also the impact of other not-modelled factors, these experiments simulate what would happen if all input-specific productivity differences were eliminated across countries.

In the first set of experiments, we hold inputs constant when assigning counterfactual technologies. In the second set, we allow occupational employment shares to adjust in response to technological changes by modelling endogenous occupational choice.

4.1 Implications of technology differences at given inputs

In this exercise, we assign each technology the highest value found across all countries in the 2010s, while leaving other technologies and inputs unchanged. We then compute the implied ratio of GDP per hour worked at the 90th percentile to the 10th percentile, as well as the 90-to-50 and 50-to-10 percentile ratios. By keeping occupational employment and capital at their actual values, this exercise gauges the direct effects of technology differences across countries. Table 5 shows the results.[28]

Table 5: Data and Counterfactual Inequality of GDP per hour worked in the 2010s at Given Inputs

Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 Ratio	6.20	5.76	5.13	9.38	5.45	4.20
90-50 Ratio	1.96	1.90	1.67	2.63	1.90	1.62
50-10 Ratio	3.17	3.03	3.07	3.57	2.87	2.60

Note: This table reports the percentile ratios of GDP per hour worked in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

While assigning the frontier manual technology to all countries, given the other technologies and all inputs, would have lowered international differences in income per hour worked as measured by the 90-10 ratio, the effect would have been relatively modest (a reduction by 7 percent). A larger effect would occur if all economies had access to the best routine technology (17.3 percent), even though the dispersion in routine technologies is smaller than the one of manual (see Table 3). This is likely to be due to the fact that the routine share in employment is relatively large and exceeds the one of manual occupations considerably. Perhaps somewhat surprising, if all economies had access to the highest level of abstract technology, given the current inputs and other technologies, cross-country dispersion in GDP per hour worked would have been higher. This occurs because more developed economies have a larger employment share in abstract occupations (recall Figure 2), so they gain more when having access to the best abstract technology than poorer economies do. Assigning the best capital technology to all countries would have the second most equalizing effect on international income differences among all the factor augmenting technologies, this is in spite that capital technology is the one that shows less dispersion across the income distribution. In these counterfactuals that vary only one technology at a time, the largest effect comes from the routine technology.

[28]In Figures A4 and A5, and Tables A4 and A5 we show that these results are qualitatively the same when we use information solely coming from persons engaged or male workers.

On the other hand, if all countries could use the best possible technology for each occupational input and capital, GDP per hour worked differences would be much reduced, the 90-10 ratio by about 32 percent. To see where in the distribution of countries inequality is reduced, investigating the 90-50 and the 50-10 ratios is useful. Eliminating cross-country differences in all technologies reduces inequality rather evenly across the distribution, with bottom and top inequality falling by about 18 and 17 percent respectively. On the contrary, eliminating differences in routine technologies only, compacts the distribution of GDP per hour worked more at the top (by about 15 percent) than at the bottom. Yet these numbers are considerably smaller than what the literature has found when not differentiating labour by occupation. The reason we find smaller gains from eliminating cross-country differences in technology are the complementaries between the different labour inputs in the production function. Because of these complementaries, differences in the occupational composition of the workforce matter. If convergence in technologies were to imply an assimilation of the occupational employment structure, eliminating technical differences might have larger effects, as we will explore next.

4.2 Implications of technology differences under endogenous occupational choice

Here, we allow the equilibrium assignment of labour to occupations to respond to technological changes, unlike in the previous counterfactuals where all inputs, including occupational employment shares, were held constant. To fully evaluate the impact of technologies on cross-country GDP differences, we account for how technology shapes both occupational wages and employment shares in equilibrium. To do this, we adapt the model of Bárány and Siegel (2020) to the cross-country context.[29]

A change in technologies will alter firms' optimal occupational labour demand and therefore occupational wages. Workers face costs to enter each occupation and decide optimally which one to enter, and thereby react to changing occupational wages. In equilibrium, the set of wages clears the labour market for all occupations; technical change will result in a new equilibrium with a new occupational employment mix. The model is described in Appendix D. The distribution of occupational entry costs is calibrated country-by-country such that the observed occupational employment structure is consistent with the observed relative wages. Note, this implies that the cost distributions are

[29]A key feature of this model is that workers choose occupations based on (idiosyncratic) entry costs only. This is not a Roy-type selection model, e.g. like Lagakos and Waugh (2013) or Bárány and Siegel (2018), since there is no selection on unobserved worker productivity. The assumptions made here, and as in Bárány and Siegel (2020) and Bárány and Siegel (2021), enables us to compute the occupation-augmenting technologies directly from the data and in a way where the observed wages are consistent with the model's labour market equilibrium.

country-specific, which is needed to fully replicate the data and might reflect differences in institutions or in (multi-dimensional) skills due to education. As such, assigning equal technologies to all countries does not necessarily imply convergence in occupational employment. In our counterfactuals we see, however, a tendency towards such convergence (as we will show in Table 7).

Table 6: Data and Counterfactual Inequality of GDP per hour worked in the 2010s under Endogenous Occupational Labour Shares

Range of GDP	Actual	Counterfactual: Best Technology				
per hour worked	Data	Manual	Routine	Abstract	Capital	All
90-10 Ratio	6.20	4.85	5.20	10.41	5.45	3.71
90-50 Ratio	1.96	1.88	1.64	2.58	1.90	1.57
50-10 Ratio	3.17	2.58	3.17	4.03	2.87	2.37

Note: This table reports the percentile ratios of GDP per hour worked in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the general equilibrium model described in Appendix D. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

In this model with endogenous occupational employment structure, we then re-run our counterfactual exercises that vary the technologies across countries. Table 6 reports the resulting inequality measures and Table 7 the underlying occupational labour shares. Any differences in results relative to our analysis of Section 4.1 stem from the endogenous adjustment of the occupational composition. Due to complementarities in production, an improvement in one occupation's technologies reduces the equilibrium employment share of that occupation. Therefore, in the counterfactual exercises here occupation-specific technologies have a direct effect on GDP and a further indirect effect through reallocating employment across occupations.

By large our conclusions are unchanged but with one notable exception; we now find a larger role of manual technology differences. In equilibrium manual augmenting technologies account for most of the observed GDP per hour worked differences across countries (measured by the 90-10 ratio in Table 6), while under constant occupational employment structure routine technologies were the most equalising (Table 5). As seen in the 50-10 ratio, this stems mainly from the effects on poorer countries who have a particular high share of manual workers. For them improvements in manual technologies are particularly important as these allow labour to reallocate towards the other occupations where technology gaps tend to be smaller, as shown in Table 3. When using the best manual technology, the employment share of manual occupations amongst the least productive countries decreases considerably, allowing for a substantive increase in routine and manual work, see Table 7. Therefore, the effects through occupational assignment on the

GDP distribution across countries is particular important for manual technologies.

The other occupational technologies, of course, affect the employment structure too, but there the reallocation effect has a much smaller impact on GDP differences and often goes in the other direction. For instance, assigning the best routine technology to all countries reallocates labour towards manual and abstract work, but this reallocation tends to modestly increase lower-tail productivity inequality as the cross-country gaps in manual technologies are larger than in routine. The model with endogenous occupational choice therefore implies that the current differences in manual technologies are a larger detriment to productivity in poorer countries than differences in routine technologies are. However, routine augmenting technologies still have the highest equalising effect on the 90-50 ratio amongst the richer countries.

Table 7: Cross-country Comparison of Endogenous Occupational Labour Shares in 2010s Counterfactuals

Q. GDP	Actual Data			Best Routine			Best Abstract			Best Manual			Best All		
p.h.w.	M	R	A	M	R	A	M	R	A	M	R	A	M	R	A
1	0.26	0.55	0.20	0.38	0.30	0.32	0.30	0.61	0.08	0.05	0.66	0.29	0.13	0.56	0.31
2	0.15	0.56	0.29	0.22	0.31	0.47	0.19	0.67	0.13	0.04	0.62	0.34	0.11	0.54	0.35
3	0.10	0.50	0.40	0.14	0.25	0.61	0.15	0.69	0.16	0.03	0.53	0.44	0.10	0.50	0.40
4	0.07	0.44	0.49	0.09	0.24	0.67	0.12	0.66	0.22	0.03	0.45	0.52	0.09	0.48	0.43

Note: This table reports by quartile of real GDP per hour worked (2010s) the average occupational labour share in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only and all best technologies. This is based on the general equilibrium model described in Appendix D. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

In the other experiments we continue to see qualitatively what we had under constant occupational shares. Assigning the best abstract technology to all countries increases cross-country income disparities. Here, this effect is even larger and comes with a widening in cross-country differences in the occupational employment structure. When we eliminate all technology differences across countries, the dispersion of GDP per hour worked is compressed the most. In terms of the 90-10 ratio, differences are reduced by approximately 40 percent (compared to 32 percent at given inputs, see Table 5). While the 90-50 ratio changes under endogenous occupational composition are rather similar to under constant inputs, changes in the 50-10 ratio are much more pronounced here. This indicates that the effects of technology on GDP differences are amplified through the employment structure, especially at the bottom of the income distribution.[30]

[30]As Table 7 shows, when we assign all occupations' best technologies at once to all countries, there is an assimilation of the occupational employment structure across the GDP distribution, towards the one of countries in the top quartile. This assimilation process drives the higher reduction in GDP differences. However, when assigning only one occupation's best technology, the employment composition can become more unequal across countries. A better technology lowers across the development spectrum the employment share of that occupation due to the complementarities in production, but which other

In Appendix Table A9, we also examine the role of cross-country differences in the distribution of occupational entry costs given the current country-specific technologies. We contrast the data, which the model under country-specific occupational entry costs replicates perfectly, to the model's prediction under common occupational entry costs given by the one of the US. We see that cross-country differences in the entry costs do contribute to productivity differences across countries,[31] but only to a very small degree; eliminating cost differences reduces the 90-10 dispersion of GDP per hour worked by only 4.8 percent. This is a much smaller reduction than what we found in the counterfactuals in Table 6, highlighting the importance of productivity gaps for cross-country disparities.

5 Role of Technologies in Non-Agricultural GDP

In this section, we exclude agriculture from the analysis to assess whether the central role of routine technologies in the aggregate economy is primarily driven by agriculture. This is an important validation exercise, as we classify agricultural occupations as routine in our baseline analysis, and prior literature has documented large productivity gaps in agriculture in poorer countries, which also tend to have disproportionately large agricultural employment shares (Caselli, 2005, Duarte and Restuccia, 2010). We therefore replicate our analysis excluding agriculture.

To do so consistently, we remove agriculture not only from occupational data but from all components of the economy. Removing agriculture implies that we can no longer use aggregate data for GDP, capital, or factor-income shares, but must instead construct these measures from sectoral data. Specifically, we drop agriculture as an occupation (ISCO code 6) when constructing occupational employment shares and wages, and we build non-agricultural measures of value added, capital stock, and capital income shares from sectoral data, as described in section 2.1. This ensures that our development accounting framework, which relies on consistency between the production and income sides, can be applied to an economy excluding agriculture. Data limitations restrict this exercise to a subsample of 47 countries.

We then back out occupation-specific technologies using the same production function as in the baseline analysis (equation (5) with $\sigma = 0.60$ and $\eta = 0.84$) and conduct the same counterfactual exercises, but now applied to non-agricultural value added per hour

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occupations see the biggest increase in employment depends on the other country-specific technologies and the distribution of entry costs.

[31] Appendix Table A10 shows the occupational composition that arises in this counterfactual and that is the reason for the compression of the GDP distribution. Having access to the US occupational entry costs reallocates workers out of manual occupations in all quartiles, but especially so in the countries in the lowest quartile where the abstract employment share rises.

worked. Table 8 reports the resulting cross-country dispersion in non-agricultural GDP per hour worked in the data and under the counterfactual scenarios, assuming constant inputs.

Table 8: Excluding agriculture: Data and Counterfactual Inequality of GDP per hour worked in the 2010s at Given Inputs

Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 Ratio	8.30	7.30	6.41	17.78	6.33	3.71
90-50 Ratio	1.78	1.77	1.60	2.31	2.18	1.23
50-10 Ratio	4.67	4.13	4.01	7.69	2.90	3.02

Note: This table reports the percentile ratios of non-agricultural GDP per non-agricultural hour worked in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$. In this table the sample contains 47 countries, which is restricted by the availability of data that allows to exclude agriculture consistently from all data objects.

Despite differences in sample composition, the results closely mirror those of the baseline analysis (Table 3).[32] Eliminating routine technology differences yields the largest reduction in cross-country inequality, followed by capital and manual technologies, while equalizing abstract technologies would increase dispersion.

These findings show that our main results are not driven by agriculture. Whether focusing on the overall economy or the non-agricultural sector, differences in routine productivity have the largest effect on cross-country disparities in value added per hour worked.

In Appendix E, we conduct further sectoral analyses, distinguishing between goods and services. The occupation-bias in productivity patterns persists within sectors.[33] This demonstrates that incorporating occupations into the analysis of economic development provides new insights beyond the well-known sectoral patterns.

[32]The sample of countries in Table 8 differs from that in Table 3, as we can construct consistent non-agricultural data for only 47 countries. Consequently, the dispersion in non-agricultural GDP per hour is higher than in the baseline, aggregate data.

[33]Figure A8, for instance, plots the inferred relative technologies, which by and large echo our baseline results. The occupational bias of technology remains qualitatively consistent across broad sectors, with routine productivity relative to abstract increasing with development.

6 Further Robustness Checks and Extensions

We conduct several further robustness checks and extensions. First, we recalibrate our preferred specification of the aggregate production function using alternative substitution elasticities to assess sensitivity. Second, we account for cross-country differences in human capital by including efficiency units of labour in the calibration. Finally, we explore a different specification of the nested CES function.

6.1 Alternative and heterogeneous substitution elasticities

Our results using the benchmark equation (5) are based on two elasticities: $\sigma = 0.60$ and $\eta = 0.84$. We examine the impact of varying these elasticities individually. Changing the elasticities impacts the values we get for the factor input intensities of production and the inferred factor augmenting technologies, as these variables adjust to perfectly recover the GDP per hour worked. Alternative elasticity values are guided by the literature, where most studies find values below one for both substitution between occupations (e.g., Goos et al. (2014), Lee and Shin (2017), Aum, Lee, and Shin (2018)) and between capital and labour (e.g., Lawrence (2015), Herrendorf, Herrington, and Valentinyi (2015), Oberfield and Raval (2021)). Like Bárány and Siegel (2021), we consider $\sigma = 0.70$ and 0.50, and $\eta = 0.75$ and 0.65. Table 9 reports the correlations between relative factor-augmenting technologies and GDP per hour worked under each scenario. The correlation between relative factor augmenting technologies and GDP per hour worked is very similar across parameterizations, with virtually no changes in the patterns of the occupation-bias and no qualitative changes in the capital to routine labour bias. This indicates the patterns we identify are robust to different parametrisations.

Table 9: Correlation between factor augmenting technologies based on (5) vs real GDP per hour worked with alternative substitution elasticities for the 2010s

Scenario	Routine to manual		Routine to abstract		Routine to capital	
	corr. coef.	p-value	corr. coef.	p-value	corr. coef.	p-value
Baseline: $\sigma = 0.60$ & $\eta = 0.84$	-0.66	0.00	0.75	0.00	0.28	0.00
Alternative: $\sigma = 0.70$	-0.66	0.00	0.74	0.00	0.31	0.01
Alternative: $\sigma = 0.50$	-0.66	0.00	0.76	0.00	0.25	0.04
Alternative: $\eta = 0.75$	-0.66	0.00	0.75	0.00	0.57	0.00
Alternative: $\eta = 0.65$	-0.66	0.00	0.75	0.00	0.76	0.00

Notes: This table presents the relative technologies inferred based on the aggregate production function (5) against log GDP per hour worked with alternative and heterogeneous substitution elasticities. In this figure the 2010s sample contains 65 countries, where the sub-samples contain only the countries for which we have data on the capital share in GDP.

We also explore the effects on our counterfactual analysis of GDP per hour inequality (Appendix Table A6). First, when σ changes to 0.70 or 0.50, routine and manual technologies remain the strongest equalising labour-augmenting technologies. When σ is reduced to 0.50, there is a decrease in the dispersion effect of assigning the best abstract technology. Second, when η is reduced to 0.75 or 0.65, the equalizing effect of routine and abstract labour technologies increases. Overall, our results are robust to variations in substitution elasticities between labour inputs and between labour inputs and capital.

6.2 Nested CES with efficiency units of labour

In our baseline equation (5), labour inputs are measured by hours worked per occupation, implicitly assuming that workers in all countries have the same efficiency. Ignoring cross-country differences in human capital could obscure the role of routine-biased technical change in explaining productivity differences. To account for this, we augment the model with efficiency units of labour derived from Mincer log wage regressions.

We adopt two strategies. In the first one, we run a country-specific Mincer regression for all countries with available data. We adopt this strategy as it has been documented that Mincerian wage returns differ across rich and poor countries (e.g. due to quality of human capital accumulation) and this may matter for accounting for technology differences (Manuelli and Seshadri (2014), Lagakos, Moll, Porzio, Qian, and Schoellman (2018)). In the second strategy, we run the Mincer wage regression only for one benchmark country and apply its coefficients to data from all countries to predict each country's human capital. We select the US as our benchmark country and run the following regression

$$\log(w_j) = \beta_0 + \beta' X_j + \epsilon_j, \tag{10}$$

where X_j is a vector of worker j's characteristics, which includes years of schooling s_j, a second order polynomial for potential work experience $potexp_j$ interacted with a dummy for college education (15 or more years of education) *college* and a gender dummy $female$.[34]

To ensure comparability of the Mincerian returns across countries, we use a harmonised definition for years of schooling based on the International Standard Classification of Education (ISCED). In addition, we deflate the nominal wages or earnings in LCU using the price level of household consumption (price level of USA GDPo in 2017=1) and the exchange rate (national currency/USD), both available in PWT version 10.0.[35] We then predict the workers' efficiency units using formula (11) and compute averages by occupation and country.

[34] We define potential work experience as $potexp_j = age_j - s_j - 6$.

[35] The former transformation makes wages comparable over time within a country, and the second transformation allows for cross-country comparisons of the predicted efficiency units.

In our second strategy we run these regressions using cross-sectional data from the American Community Survey for 2014. Then, we obtain the estimated coefficients for each regressor and predict the average worker's efficiency units by country i and occupation o using formula (11)

$$e_j = \exp(\hat{\beta}_1\, s_j + \hat{\beta}_2\, female_j + \hat{\beta}_3\, potexp_j + \hat{\beta}_4\, potexp_j^2 + \hat{\beta}_5\, college_j + \hat{\beta}_6\, college_j * potexp_j + \hat{\beta}_7\, college_j \times potexp_j^2). \tag{11}$$

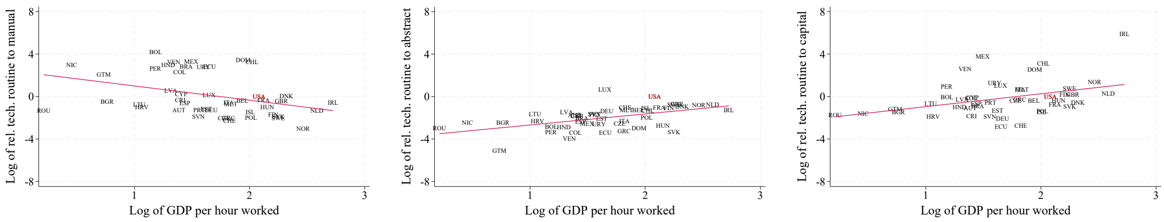
Table 10 reports how the predicted efficiency units of labour vary across countries in the 2010s. We see that there is quite some variation. While richer countries tend to have more human capital than poorer countries (but by a factor that is considerably smaller than the dispersion for capital per hour worked), there is also vast dispersion across occupations, in particular with workers in abstract occupations having higher efficiency units. While qualitatively we get similar results with our two strategies, the use of country-specific Mincer returns gives a wider dispersion of labour efficiency units between countries at the bottom and at the top of the income distribution. Equipped with the value of $\bar{e}_{o,i}$, we can include efficiency units of labour into our model by modifying the amount of labour that the firm optimally chooses to $oe_i = o_i * \bar{e}_{o,i}$, where $o \in \{R, M, A\}$. Thus, we can obtain an estimate of the occupational efficiency wages per hour in country i as $\hat{w}_{o,i} = \frac{\bar{w}_{o,i}}{\bar{e}_{o,i}}$.

Table 10: Data on average efficiency units of labour by occupation in the 2010s

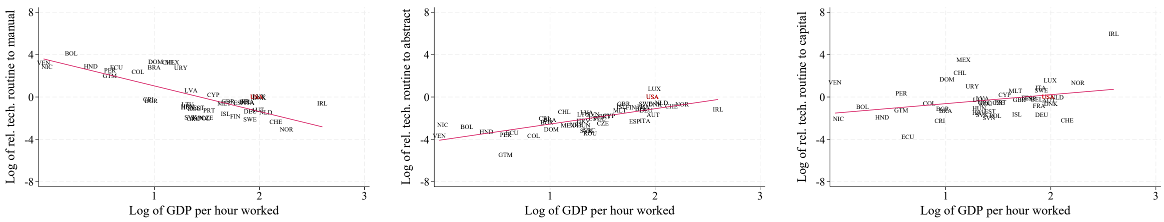
Quartile of	Capital	Country-specific Mincer regression			Benchmark country Mincer regression		
GDP p.h.w	p.h.w	Manual	Routine	Abstract	Manual	Routine	Abstract
1	50.16	2.79	2.64	5.41	5.52	5.28	9.09
2	162.08	5.67	6.94	11.21	6.27	6.70	9.71
3	232.26	5.55	6.33	8.37	6.22	6.86	9.54
4	327.09	6.48	7.18	9.13	5.97	6.73	9.66
USA	214.26	5.77	6.14	8.80	6.66	6.86	9.75

Notes: This table reports by quartile of real GDP per hour worked the average efficiency units of labour by occupation predicted from (11) based on estimating (10) in each country (columns 3 to 5) and on estimating (10) in a benchmark country (columns 6 to 8). The second column reports capital per hour worked for comparison. In this table the 2010s sample contains 46 countries (both panels contain the same countries), where the sub-samples contain only the countries for which we have data on the capital share in GDP, gender, age and years of schooling.

Figure 7: Relative technologies with efficiency units of labour based on (5) vs real GDP per hour worked in the 2010s



(a) Routine to manual – cntry-specific (b) Routine to abstract – cntry-specific (c) Routine to capital – cntry-specific



(d) Routine to manual – benchmark (e) Routine to abstract – benchmark (f) Routine to capital – benchmark

Notes: This figure plots the relative technologies with efficiency units of labour inferred based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$ against log GDP per hour worked. The first panel plots the efficiency units of labours obtained using country-specific Mincer regressions. The second panel is obtained using the US as the benchmark country to run the Mincer regression. In this figure the 2010s sample contains 46 countries (both panels contain the same countries), where the subsamples contain only the countries for which we have data on the capital share in GDP, gender, age and years of schooling. For each country and sample we take the most recent full observation we have.

With these efficiency units, we re-calibrate equation (5) to obtain the factor-augmenting technologies for the 2010s. In the first panel of Figure 7 the efficiency units of labour are obtained from country-specific Mincer regressions, while in the second panel they are derived from US Mincer returns. Notice, that Figure 7 includes fewer countries than our baseline analysis (Figure 6), as we can only include countries for which efficiency units can be computed using these strategies. The sample drops from 65 to 46 countries, which is a limitation and one reason we prefer the framework in Section 3.2. Nonetheless, despite the smaller sample, the technology patterns in both panels are qualitatively and quantitatively similar to those in our baseline results.

6.3 Different nested CES specification

As a robustness check to our baseline specification (5), we consider an alternatively nested CES production structure. This specification allows for (i) different substitution elasticities between different pairs of occupations and (ii) for the complementarity of capital to vary across the occupational labour inputs. The structure of the nested formulation follows vom Lehn (2020), but we allow for factor-augmenting technologies of each input. We thus assume here for the aggregate production function

$$Y_i = \Bigg(\alpha(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\Big[\beta(\mu_{A,i}A_i)^{\frac{\gamma-1}{\gamma}} + (1-\beta) \times \left(\phi(\mu_{R,i}R_i)^{\frac{\eta-1}{\eta}} + (1-\phi)(\mu_{K,i}K_i)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta(\gamma-1)}{(\eta-1)\gamma}}\Big]^{\frac{\gamma(\sigma-1)}{(\gamma-1)\sigma}}\Bigg)^{\frac{\sigma}{\sigma-1}} \tag{12}$$

where in the most inner nesting routine labour and effective capital are combined and considered to be gross substitutes, i.e. $\eta > 1$. This gives a routine-task aggregate that is then combined with abstract labour with an elasticity of substitution $\gamma < 1$, such that routine and abstract tasks are complements. This routine-abstract task bundle, in turn, is in the most outer layer combined with manual labour under a substitution elasticity σ to produce final output.[36]

Given (12), technologies can be inferred from observables (again conditional on elasticities) according to the following equations (see Appendix C for derivations):

$$\frac{\mu_{K,i}}{\mu_{R,i}} = \frac{r_i}{w_{R,i}}\left(\frac{\phi}{1-\phi}\right)^{\frac{\eta}{\eta-1}}\left(\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{1}{\eta-1}} \tag{13}$$

$$\frac{\mu_{A,i}}{\mu_{R,i}} = \left(\frac{\theta_{A,i}}{\theta_{R,i}}\right)^{\frac{1}{\gamma-1}}\left(\frac{1-\beta}{\beta}\right)^{\frac{\gamma}{\gamma-1}}\left(\frac{w_{A,i}}{w_{R,i}}\right)\phi^{\frac{\eta}{\eta-1}}\left(1+\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{\gamma-\eta}{(\eta-1)(\gamma-1)}} \tag{14}$$

$$\frac{\mu_{M,i}}{\mu_{A,i}} = \left(\frac{\theta_{M,i}}{\theta_{A,i}}\right)^{\frac{1}{\sigma-1}}\left(\frac{w_{M,i}}{w_{A,i}}\right)\left(\frac{1-\alpha}{\alpha}\right)^{\frac{\sigma}{\sigma-1}}\beta^{\frac{\gamma}{\gamma-1}}\left(1+\frac{\theta_{R,i}}{\theta_{A,i}}+\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{A,i}}\right)^{\frac{\sigma-\gamma}{(\gamma-1)(\sigma-1)}} \tag{15}$$

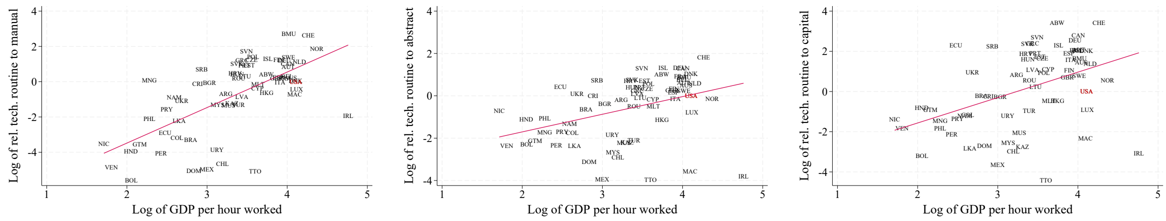
$$\mu_{M,i} = \frac{Y_i}{\alpha^{\frac{\sigma}{\sigma-1}}M_i\left(1+\left(\frac{\theta_{A,i}}{\theta_{M,i}}\right)\left(1+\frac{\theta_{R,i}}{\theta_{A,i}}+\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{A,i}}\right)\right)^{\frac{\sigma}{\sigma-1}}}, \tag{16}$$

As in the previous specifications, we take the US as the benchmark economy and set the elasticity parameters to $\sigma = 1.49, \gamma = 0.31, \eta = 1.3$, which are the values vom Lehn (2020) obtained in his calibration against US data. Figure 8 plots the inferred relative technologies in the 2010s and the 1990s cross-sections of countries.

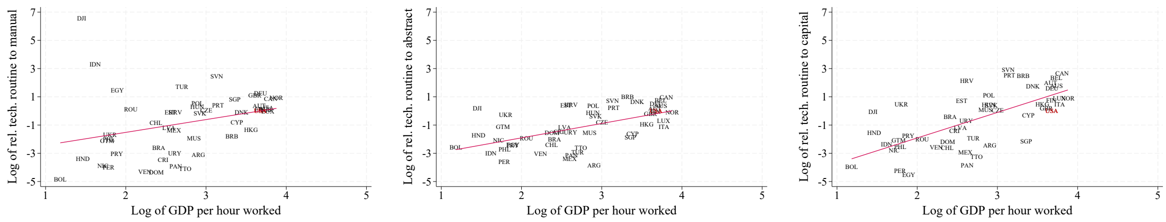
This figure displays, just as Figure 6, systematic relationships between GDP per hour worked and relative technologies. According to this figure, the technology of routine labour compared to the one of any input, manual or abstract labour or capital, increases with GDP per hour worked. The patterns in technology of routine compared to abstract labour are qualitatively the same as in our baseline, whereas the relationship between

[36]This structure implies that capital accumulation affects labour demand differently across occupations, consistent with Kehrig (2018)'s finding that the degree of substitutability between computer equipment and labour varies across occupations.

Figure 8: Relative technologies based on (12) vs real GDP per hour worked



(a) Routine to manual tech. (2010s) (b) Routine to abstract tech. (2010s) (c) Routine to capital tech. (2010s)



(d) Routine to manual tech. (1990s) (e) Routine to abstract tech. (1990s) (f) Routine to capital tech. (1990s)

Note: This figure plots the relative technologies inferred based on the aggregate production function (12) with $\sigma = 1.49, \gamma = 0.31, \eta = 1.30$ against log GDP per hour worked in the 2010s. In this figure the 2010s sample contains 65 countries and the 1990s 51 countries, where the sub-samples contain only the countries for which we have data on the capital share in GDP.

GDP per hour worked and the technology of routine relative to manual labour changes signs. This is due to the parametrisation of the elasticities of substitution. In Figure 6 we set $\sigma = 0.60$ implying that routine and manual workers are gross complements. In Figure 8, based on the vom Lehn (2020) parametrisation, $\sigma = 1.49$ implying that these two groups of workers are gross substitutes. As the elasticity of substitution changes from below to above one, the opposite bias in relative technologies is needed to match the data. However, the effect that a decrease in the routine to manual technology has for $\sigma < 1$ is qualitatively equivalent to the effect an increase in the routine to manual technology has for $\sigma > 1$.[37] In contrast, the pattern of relative routine to abstract technologies is qualitatively the same in Figures 6 and 8 as in both cases routine and abstract occupations are gross complements. The relative technology of routine labour to capital exhibits the same pattern as in Figure 6, despite that in equation (12) both inputs are considered to be gross substitutes. This is due to the nested structure of the production function, where inputs are combined in multiple layers with different elasticities. In fact, even if we consider routine labour and effective capital to be gross complements ($\eta < 1$) the relative technology between these two inputs continues to increase with GDP per hour worked. Overall, the results from the nested specification (12) are in line with what we found under our preferred specification (20).

[37] See for instance Ngai and Pissarides (2007) who discuss how the effects of changing relative productivities depend on whether the elasticity substitution is above or below one.

Table 11: Alternatively Nested CES – Counterfactual Inequality of GDP per worker in the 2010s

Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 ratio	6.20	5.33	3.78	6.79	4.38	2.80
90-50 ratio	1.96	1.89	1.57	2.02	1.70	1.43
50-10 ratio	3.17	2.83	2.42	3.36	2.58	1.96

Note: This table reports the ratio of GDP per hour worked at the 90 percentile to the 10th percentile in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the the aggregate production function (12) with $\sigma = 1.49, \gamma = 0.31, \eta = 1.30$. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

When we evaluate the implications of technical differences for cross-country dispersion, we draw very similar conclusions. Table 11 reports the effects of eliminating cross-country differences in factor-augmenting technologies based on the nested specification (12). The patterns resemble those in Table 5, with occupation-specific technologies playing an even larger quantitative role. Routine technology remains the most equalizing technology, reducing the 90–10 ratio by 39 percent. Assigning all countries the best technology for all inputs further compresses the GDP distribution, just as in Table 5, but here by 55 percent. Overall, we see that the results are robust across alternative specifications of the aggregate production function.

7 Conclusions

This paper investigates the links between routine-biased technical change, the structure of occupational employment, and cross-country income differences. To carry out our analysis, we construct a novel dataset containing occupational employment, wages, weekly hours worked and macro aggregates, such as real GDP, for two cross-sectional samples (2010s and the 1990s) containing 92 countries, and for a subset of 47 countries with data also at the sector-occupation level.

We establish a series of new facts of economic development. We document that the employment shares of routine and manual occupations decrease with GDP per hour worked, while the share of abstract occupations increases. We further show that since the 1990s the routine employment share has declined faster in more developed than in less developed countries, while the share of abstract occupations exhibits the opposite pattern.

Drawing on our model framework with three occupational labour inputs in a development accounting exercise, we document systematic patterns in relative occupation-specific productivities across countries. In countries with higher GDP per hour worked, routine productivity tends to be higher relative to abstract productivity, while it is lower relative to manual productivity. In terms of dispersion, manual productivities vary the most, followed by routine productivities, whereas capital productivities are the least dispersed. Our results suggest that routine productivity in the top quartile of countries ranked by GDP per hour worked is about 14 times higher than in the bottom quartile, with even larger dispersion for manual productivities. As countries in the bottom quartile tend to have much higher routine and manual employment shares, these productivity gaps contribute substantially to cross-country income differences. Interestingly, we also find that countries in the upper half of the distribution have experienced a faster growth in routine technologies between the 1990s and the 2010s. These findings complement Rossi (2022), who documents that highly educated workers are relatively more productive in rich countries. While his results are based on differentiating labour by skills, we focus on occupational differences for which we see an inverse relation between abundance and productivity.

Through counterfactual experiments, we assess how eliminating cross-country differences in occupational productivities would affect GDP differences. Eliminating routine or manual productivity gaps leads to sizeable equalizing effects. At given employment structures, closing gaps in routine productivity has the largest impact, reflecting higher routine employment shares in poorer countries. When allowing occupational employment to adjust endogenously, differences in manual productivity become more important, as they limit the reallocation of labour towards occupations with smaller productivity gaps. In contrast, equalizing abstract productivity alone would increase cross-country disparities, due to higher abstract employment shares in more developed countries. When all productivity gaps are eliminated, cross-country differences in GDP per hour worked decline by about one third, and by around 40 percent when allowing for endogenous occupational choice.

Overall, our findings highlight that differences in occupation-specific productivities are systematically related to economic development, both in terms of overall GDP and non-agricultural value added. They suggest that there are occupation-biases in the technology differences across countries, and that closing gaps in routine and manual technologies is particularly important for reducing cross-country income differences.

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Appendix

A Data

A.1 Data Sources

In this subsection we describe the sources of the micro and macro data and our harmonization procedure in greater detail.

International Labour Organization (ILOSTAT)

ILOSTAT contains a wide range of information on labour market variables. We use the employment, working time, earnings and labour income modules. Specifically, we obtain the number of persons engaged (employment) by occupation (from 1968 to 2018), the mean weekly hours actually worked per persons engaged and by occupation (from 1991 to 2018) and the mean nominal hourly earnings (in LCU) of employees by occupation (from 1981 to 2018). These three datasets are collapsed into routine, non-routine, abstract and manual occupations. We repeat the process at the sectoral level for persons engaged (from 1992 to 2019), but classifying each of the occupations into one of the broad sectors shown in Table A1.[38]

Occupational Wages around the World (OWW)

This dataset, constructed by Freeman and Oostendorp (2012) and based on the International Labor Organization October Inquiry, contains information on occupational wages for 161 occupations and 49 industries, covering 171 countries from 1983 to 2008. We choose to use the standardised wage (LCU) with country-specific calibration and imputation and lexicographic weighting ($hw3wl$ -hourly wages- and $mw3wl$ -monthly wages-) as it provides the widest sample of countries. We collapse the 161 occupations into the following categories: routine, non-routine, abstract and manual occupations. First, we codify the 161 occupations at two digits using the ISCO-08, then we collapse this to the one digit ISCO-08, with the one-digit classification we assigned the occupations to routine, non-routine, abstract and manual occupations. We apply this procedure to reduce subjectivity when classifying the 161 occupations between routine and non-routine occupations and to standardize the classification process with the other datasets that do not have such an extensive list of occupations. Finally, we obtain an approximation for the average weekly hours worked knowing that $mw3wl \equiv hw3wl * monthly\_hours\_worked$, thus $weekly\_hours\_worked \equiv mw3wl/hw3wl/52/12$. We repeat the process at the sectoral level using the industry classification presented in Table A1 to classify the occupations into one of our broad sectors.

IPUMS International

IPUMS International, provided by Minnesota Population Center (2020), is a standardized dataset that collects information on censuses and household surveys for more than

[38]For some countries and years ILOSTAT provides occupational information from two or more different surveys. We select only one survey using the following hierarchy: 1. Labour force surveys with national representativeness, 2. household surveys with national representativeness, 3. administrative data.

90 countries. We collect information on occupational employment, occupational earnings/wages, occupational weekly hours worked for 78 countries from 1962 to 2018. In this dataset, the variable for occupations is codified to the ISCO-88 (one digit). This allows us to collapse the database to routine, non-routine, abstract and manual occupations. For labour income, this dataset contains two variables: (i) earned income and (ii) wage and salary income. These two variables are computed on monthly or annual basis, so we proceed to construct the hourly wages using the weekly hours worked and applying the same procedure as we do for the OWW data. When possible, we use the wage and salary income. However, when this variable is not available, we use earned income. These two variables are adjusted using a modified weight, including the number of hours worked during the week. To harmonize this dataset with ILOSTAT, we use the same definitions for persons engaged and remove weekly hours worked above 86. We repeat the process described using the sectoral classification shown in Table A1. Finally, using the occupational and the sectoral-occupational differentiation, we get the average age and average years of schooling.

IPUMS USA

The IPUMS USA by Ruggles et al. (2020) is a database that contains decennial censuses for the US from 1790 to 2010 and American Community Surveys (ACS) from 2000 to 2019. We use the 5% State Sample 1990 and the American Community Survey for the years 2005 and 2014, provided by Ruggles et al. (2020) in order to get data at the sectoral level for the US. We use the "harmonized occupation coding scheme based on the Census Bureau's 2010 ACS occupation classification scheme" available in IPUMS USA to group the occupations into routine, non-routine, abstract and manual occupations. We use the four-digit crosswalk between the Standard Occupational Classification (SOC) and the ISCO-08, developed by the Bureau of Labor Statistics, to generate a four-digit ISCO-08 representation of the IPUMS-USA codification. Subsequently, we collapse this into a one-digit ISCO classification to match our grouping of occupations presented in Table 1. We also get the sectoral-occupational wage and salary income per hour and the usual hours worked per week. We adopt the same definition as ILOSTAT to obtain the number of persons engaged and we remove weekly hours worked above 86. We also get the sectoral-occupational average age and years of schooling.

European Labour Force Survey (EU-LFS)

The EU-LFS (Eurostat, 2021a) contains information on persons engaged by occupation and occupational weekly hours worked for 31 countries from 1993 to 2018. The occupations are classified according the ISCO-08 (COM) from 2011 onwards and the ISCO-88 (COM) from 1993 to 2010. This allows us to collapse the dataset to our classification of routine, non-routine, abstract and manual occupations (the same procedure applies for the sectoral level, in which we group industries according to Table A1). A drawback of the EU-LFS is that it does not contain information on labour income. Thus, we are not able to retrieve information on wages/earnings from this dataset. We adopt the same definition as ILOSTAT to obtain the number of persons engaged and we remove weekly hours worked above 86. Finally, using the occupational and the sectoral-occupational differentiation, we get the average age and average years of schooling.

European Statistics on Income and Living Conditions (EU-SILC)

The EU-SILC (Eurostat, 2021b) is a comparable database that contains information on 32 countries within the EU and some non-EU member countries. This survey targets individuals of age 16 or older and was launched in 2003, initially in six countries. We use the gross employee cash or near cash income, the gross non-cash employee income and the cash profits or losses from self-employment to construct our earnings variable. In the EU-SILC, the labour income variables are computed for the reference period of the EU-SILC, which is one year. Therefore, we convert them to hourly wages using the weekly hours worked and applying the same methodology as for the OWW data. The earnings are adjusted using a modified weight, which includes the number of hours worked during the week. The EU-SILC classifies occupations according to the ISCO-88 (COM) and the ISCO-2008 (COM). We use these codes to collapse the dataset into routine, non-routine, abstract and manual occupations. In addition, we assign to reported weekly hours worked above 86 the maximum value found in the ILOSTAT database. Finally, the process is repeated at the sectoral level, grouping industries as presented in Table A1.

Harmonized Microdata Center for Household Surveys in Latin America and the Caribbean (CMAEH)

The Inter-American Development Bank (IADB) (2021) compiles this dataset that contains harmonized information based on household surveys for 23 countries from the LAC region.[39] The CMAEH allows us to get information from 1990 to 2019 for the majority of LAC countries. We include information for all individuals aged 16 and above that were working as paid employees or as self-employed to construct the variable for persons engaged, following the definitions of ILOSTAT. For the labour income information, we use the monetary wage in the principal activity, which is computed on a monthly and hourly basis. For the weekly hours worked, we remove those hours above 86. In the CMAEH, the occupations are harmonized to one digit using the ISCO-88 and ISCO-08. Thus, we are able to collapse the dataset into routine, non-routine, abstract and manual occupations. To get the occupational data at the sectoral level, we apply the same procedure using the industry classification presented in Table A1. The wages are adjusted using a modified weight, which includes the number of hours worked during the week. Finally, using the occupational and the sectoral-occupational differentiation, we get the average age and average years of schooling.

The International Income Distribution Data Set (I2D2)

This database was initially constructed by Montenegro and Hirn (2009) and thereafter maintained by the World Bank. The I2D2 includes standardized information along several dimensions such as: (i) demography, (ii) education, (iii) labour markets and iv) welfare. According to Montenegro and Hirn (2009), the database contains information on more than 120 countries. This dataset is not publicly available, thus, following Kunst (2019), we asked for access to some statistics. World Bank staff shared with us information on

[39] During the construction of our database, we accessed to the CMAEH through the following link: https://microdatos.iadb.org/node/11. This website allowed us to upload Stata routines to retrieve data extracts directly from the household surveys. During 2022, the website was updated under the name of 'Social Data-Household Socio-Economic Surveys'. Now it can be accessed through the link https://microdatos.iadb.org/en/public and provides access to pre-defined indicators.

a subsample of 20 countries from 1970 to 2016. This includes information on labour market, demographic and educational variables. As part of the standardization process followed by the World Bank, the occupations have been codified to one digit following the ISCO-88. The hourly wages are in local currency units. For the weekly hours worked, numbers above 86 hours are removed, following ILOSTAT, and only employees and self-employed individuals aged 15 or above are considered. We implement the same procedure at the sectoral level in order to get the occupational data required at this level. Finally, we adjust the hourly wages using a modified weight, resulting from the individual weight and the number of hours worked during the week.

Penn World Tables (PWT), World Development Indicators and International Labour Organization (ILOSTAT)

PWT version 10.0, provided by Feenstra et al. (2015), is a well-known macro dataset with information on GDP, capital stock, investment, price levels and other macroeconomic variables. For our product variable, we use the output-side real GDP at chained PPPs (in mil. 2017 USD), as it allows to make comparison across countries and across time. The PWT estimates the capital stock at constant 2017 national prices (which allows comparison across time for a given country) and the capital stock at current PPPs (which allows comparison across countries at a specific point in time). In order to be able to make comparison across countries and across time, we deflate the capital stock at current PPPs with a GDP deflator obtained from the PWT with the aim to obtain a measurement of capital stock at chained PPPs (in mil. 2017USD). In addition, we obtain the labour income share, population, number of persons engaged, and prices levels from this dataset. From WDI and ILOSTAT, we obtain data on GDP per capita and per worker at constant 2011 PPPs and 2017 PPPs and unemployment shares.

World Input-Output Database (WIOD), World KLEMS, GGDC Productivity Level Database and Eora National IO Tables For the sectoral macro data we use the World KLEMS, the WIOD by Timmer et al. (2015), the GGDC Productivity Level Database 2023 (PLD2023) by Inklaar et al. (2023) and Eora National IO Tables by Lenzen et al. (2012). The WIOD contains information on national accounts and macroeconomic variables for 43 countries, specifically, we use the Socio Economic Accounts (Release 2016) to collect industry data on nominal gross value added, number of persons engaged, labour compensation and nominal capital stock. The World KLEMS is a data repository compiled by the World KLEMS consortium, which includes the EU KLEMS (See Jäger (2017) for a detailed description of the dataset), LAKLEMS (This is the regional dataset for Latin American and the Caribbean, see Mas and Benages (2020)) and ASIA KLEMS. World KLEMS contains data on output, inputs and productivity at the sector level. We give priority to World KLEMS, as it provides a comparable methodology and longer series which allow us to increase data comparability between high-income countries and middle-low-income countries. The data from WIOD and World KLEMS are in nominal values of LCU, then, to deflate these values we use the GGDC Productivity Level Database (2023 Edition). This dataset provides information for value added, persons engaged and PPP conversion rates by 12 sectors for 84 countries and for three PPP base years: 2005, 2011 and 2017.[40]

The combination of micro data and macro data from World KLEMS, WIOD, and the GGDC PLD2023 enables the estimation of baseline sectoral factor-augmenting technologies, albeit with a bias toward developed countries. To extend coverage to developing countries with available micro data and PLD2023 sectoral value added, employment, and PPPs, we supplement missing inputs –factor shares and capital stock– using the Eora National IO Tables. Eora provides country-level input–output tables for 190 countries, with series for some countries starting in 1970. In particular, we use the sectoral value added components from the input–output tables. This allows us to get the sectoral labour compensations, which we use to compute the sectoral labour income shares. We multiply these shares by the sectoral value added available in the GGDC Productivity Level Database to obtain the sectoral factor compensation in LCU. We approximate the sectoral distribution of capital stocks using consumption of fixed capital (CFC). Under the assumption of similar depreciation rates across sectors, CFC shares proxy for capital shares, which we apply to the aggregate capital stock (current LCU) from the Penn World Tables.

[40]The sectors are: agriculture, mining, manufacturing, utilities, construction, trade, transport, business, finance, real estate, government, and other services.

Table A1: Classification of industries into sectors

Industries		ILOSTAT: ISIC Rev 3.1	ILOSTAT & OWW:ISIC Rev 4	I2D2: ISIC Rev 3.1	IPUMS International: ISIC Rev 3.1
Goods	Agriculture	• Agriculture, hunting and forestry • Fishing	• Agriculture; forestry and fishing	• Agriculture	• Agriculture, fishing, and forestry
	Industry	• Mining and quarrying • Manufacturing • Construction	• Mining and quarrying • Manufacturing • Construction	• Mining • Manufacturing • Construction	• Mining and extraction • Manufacturing • Construction • Other industry, n.e.c.
Services	High-Skilled Services	• Electricity, gas and water supply • Financial intermediation • Real estate, renting and business activities • Public administration and defence; compulsory social security • Education • Health and social work	• Electricity; gas, steam and air conditioning supply • Water supply; sewerage, waste management and remediation activities • Information and communication • Financial and insurance activities • Real estate activities • Professional, scientific and technical activities • Administrative and support service activities • Public administration and defence; compulsory social security • Education • Human health and social work activities	• Public utilities • Financial and business services • Public administration	• Electricity, gas, water and waste management • Financial services and insurance • Public administration and defense • Business services and real estate • Education • Health and social work
	Low-Skilled Services	• Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods • Hotels and restaurants • Transport, storage and communications • Other community, social and personal service activities • Activities of private households as employers and undifferentiated production activities of private households	• Wholesale and retail trade; repair of motor vehicles and motorcycles • Transportation and storage • Accommodation and food service activities • Arts, entertainment and recreation • Other service activities • Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	• Commerce • Transport and communications • Other services, unspecified	• Wholesale and retail trade • Hotels and restaurants • Transportation, storage, and communications • Services, not specified • Other services • Private household services

Table A1: Classification of industries into sectors (Continued)

Industries		IPUMS USA: IND1990	CMAEH: ISIC Rev 3.1 & ISIC Rev 4	EULFS & EUSILC: NACE Rev 1.1	EULFS & EUSILC: NACE Rev 2
Goods	Agriculture	• Agriculture, forestry, and fisheries	• Agriculture, hunting, forestry, and fishing	• Agriculture and fishing	• Agriculture, forestry and fishing
	Industry	• Mining • Construction • Manufacturing	• Mining and quarries • Manufacturing • Construction	• Mining and quarrying, manufacturing, electricity, gas and water supply • Construction	• Mining and quarrying, manufacturing, electricity, gas, steam and air-conditioning supply and water supply, sewerage, waste management and remediation • Construction
Services	High-Skilled Services	• Communications • Utilities • Finance, insurance, and real estate • Business and repair services • Professional and related services • Public administration	• Electricity, gas, and water • Financial services, insurance, and real estate • Social, community and personal services	• Financial intermediation • Real estate, renting and business activities • Public administration and defence; compulsory social security • Education • Health and social work	• Communication • Financial and insurance activities • Real estate activities and business • Public administration and defence, compulsory social security • Education • health services
	Low-Skilled Services	• Transportation • Wholesale trade • Retail trade • Business and repair services • Personal services • Entertainment and recreation services	• Wholesale & Retail, restaurants, and hotels • Transport and storage	• Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods • Hotel and restaurants • Transport, storage and communication • Other community, social and personal service activities, activities of households	• Wholesale and retail trade, repair of motor vehicles and motorcycles • Transportation and storage • Accommodation and food service activities • Arts, entertainment and recreation, • Other services, activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Table A1: Classification of industries into sectors (Continued)

Industries		WIOD: ISIC Rev. 4 & NACE Rev. 2	KLEMS: ISIC Rev. 4 & NACE Rev. 2	PLD 2023 (Eora IO tables): ISIC Rev. 4
Goods	Agriculture	• Crop and animal production, hunting and related service activities • Forestry and logging • Fishing and aquaculture	• Agriculture, forestry and fishing	• Agriculture
	Industry	• Mining and quarrying • Manufacture of food products, beverages and tobacco products • Manufacture of textiles, wearing apparel and leather products • Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials • Manufacture of paper and paper products • Printing and reproduction of recorded media • Manufacture of coke and refined petroleum products • Manufacture of chemicals and chemical products • Manufacture of basic pharmaceutical products and pharmaceutical preparations • Manufacture of rubber and plastic products • Manufacture of other non-metallic mineral products • Manufacture of basic metals • Manufacture of fabricated metal products, except machinery and equipment • Manufacture of computer, electronic and optical products • Manufacture of electrical equipment • Manufacture of machinery and equipment n.e.c. • Manufacture of motor vehicles, trailers and semi-trailers • Manufacture of other transport equipment • Manufacture of furniture; other manufacturing • Construction	• Construction • Mining and quarrying • Total manufacturing	• Mining • Manufacturing • Construction
Services	High-Skilled Services	• Electricity, gas, steam and air conditioning supply • Water collection, treatment and supply • Publishing activities • Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities • Telecommunications • Computer programming, consultancy and related activities; information service activities • Financial service activities, except insurance and pension funding • Insurance, reinsurance and pension funding, except compulsory social security • Activities auxiliary to financial services and insurance activities • Real estate activities • Legal and accounting activities; activities of head offices; management consultancy activities • Architectural and engineering activities; technical testing and analysis • Scientific research and development • Advertising and market research • Other professional, scientific and technical activities; veterinary activities • Administrative and support service activities • Public administration and defence; compulsory social security • Education • Human health and social work activities	• Electricity, gas and water supply • Education • Financial and insurance activities • Health and social work • Information and communication • Professional, scientific, technical, administrative and support service activities • Public administration and defence; compulsory social security • Real estate activities	• Utilities • Business • Finance • Real estate • Government
	Low-Skilled Services	• Repair and installation of machinery and equipment • Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services • Wholesale and retail trade and repair of motor vehicles and motorcycles • Wholesale trade, except of motor vehicles and motorcycles • Retail trade, except of motor vehicles and motorcycles • Land transport and transport via pipelines • Water transport • Air transport • Warehousing and support activities for transportation • Postal and courier activities • Accommodation and food service activities • Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use • Other service activities	• Accommodation and food service activities • Activities of households as employers; undifferentiated goods-and services-producing activities of households for own use • Arts, entertainment and recreation • Other service activities • Transportation and storage • Wholesale and retail trade; repair of motor vehicles and motorcycles	• Trade • Transport • Other services

Table A2: Data sources by year and country- Aggregate

Country	Year	Persons engaged	Wages-earnings	Weekly hours worked	Age	Schooling	Output	Persons engaged (overall economy)	Capital stock	Labour share
ABW	2010	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
ALB	2017	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	N.D.
ARG	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
ARG	2018	ILOSTAT	ILOSTAT	ILOSTAT	CMAEH	CMAEH	PWT	PWT	PWT	PWT
AUS	1998	ILOSTAT	OWW	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
AUS	2016	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
AUT	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
AUT	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
BEL	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
BEL	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
BGD	2017	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	N.D.
BGR	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
BLZ	1995	ILOSTAT	OWW	OWW	CMAEH	CMAEH	PWT	PWT	PWT	N.D.
BLZ	2017	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	N.D.
BMU	2010	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
BOL	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
BOL	2018	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
BRA	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
BRA	2015	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
BRB	1995	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	PWT
CAN	1999	ILOSTAT	OWW	OWW	IPUMS-I	IPUMS-I	PWT	PWT	PWT	PWT
CAN	2014	ILOSTAT	ILOSTAT	ILOSTAT	IPUMS-I	IPUMS-I	PWT	PWT	PWT	PWT
CHE	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
CHL	1992	IPUMS-I	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
CHL	2017	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
COL	2018	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	N.D.
COM	2014	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
CRI	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
CRI	2019	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
CYP	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
CYP	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
CZE	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
CZE	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
DEU	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
DEU	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
DJI	1996	I2D2	OWW	OWW	I2D2	I2D2	PWT	PWT	PWT	PWT
DNK	1992	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
DNK	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
DOM	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
DOM	2019	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
ECU	2019	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
EGY	1996	IPUMS-I	OWW	OWW	I2D2	I2D2	PWT	PWT	PWT	PWT
ESP	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
EST	1997	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
EST	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
FIN	1999	EULFS	OWW	OWW	EULFS	EULFS	PWT	PWT	PWT	PWT
FIN	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
FRA	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
GBR	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
GBR	2018	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	N.D.
GHA	2017	ILOSTAT	ILOSTAT	ILOSTAT	I2D2	I2D2	PWT	PWT	PWT	N.D.
GMB	2012	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
GRC	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	N.D.
GRD	1994	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	PWT
GTM	1998	CMAEH	OWW	OWW	CMAEH	CMAEH	PWT	PWT	PWT	PWT
GTM	2018	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
HKG	1999	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	PWT
HKG	2016	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
HND	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
HND	2019	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
HRV	1996	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	PWT
HRV	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
HUN	1999	ILOSTAT	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
HUN	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
IDN	1995	IPUMS-I	IPUMS-I	IPUMS-I	IPUMS-I	IPUMS-I	PWT	PWT	PWT	PWT
IND	1994	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	PWT
IRL	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
ISL	2018	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
ITA	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
ITA	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	N.D.
KAZ	2017	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	N.D.
KHM	1999	ILOSTAT	OWW	OWW	I2D2	I2D2	PWT	PWT	PWT	N.D.
KHM	2016	ILOSTAT	ILOSTAT	ILOSTAT	I2D2	I2D2	PWT	PWT	PWT	PWT
LCA	1991	IPUMS-I	OWW	IPUMS-I	IPUMS-I	IPUMS-I	PWT	PWT	PWT	PWT
LKA	2016	I2D2	ILOSTAT	ILOSTAT	I2D2	I2D2	PWT	PWT	PWT	PWT
LTU	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
LUX	1995	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
LUX	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
LVA	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
LVA	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	N.D.
MAC	2016	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	N.D.
MDG	2015	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
MDV	2016	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
MEX	1999	ILOSTAT	OWW	OWW	CMAEH	CMAEH	PWT	PWT	PWT	N.D.
MEX	2018	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
MLI	2016	ILOSTAT	ILOSTAT	ILOSTAT	I2D2	I2D2	PWT	PWT	PWT	N.D.
MLT	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	N.D.
MMR	2018	ILOSTAT	ILOSTAT	ILOSTAT	I2D2	I2D2	PWT	PWT	PWT	PWT

Country	Year	Persons engaged	Wages-earnings	Weekly hours worked	Age	Schooling	Output	Persons engaged (overall economy)	Capital stock	Labour share
MNE	2011	I2D2	I2D2	I2D2	I2D2	I2D2	PWT	PWT	PWT	PWT
MNG	2018	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
MUS	1995	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	N.D.
MUS	2018	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
MWI	2013	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
MYS	2018	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
NAM	2018	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
NIC	1998	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
NIC	2014	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
NLD	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
NOR	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	N.D.
NOR	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
NPL	1998	I2D2	I2D2	I2D2	I2D2	I2D2	PWT	PWT	PWT	PWT
PAN	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
PER	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
PER	2019	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
PHL	1997	IPUMS-I	OWW	I2D2	I2D2	I2D2	PWT	PWT	PWT	PWT
PHL	2018	ILOSTAT	ILOSTAT	ILOSTAT	I2D2	I2D2	PWT	PWT	PWT	PWT
POL	1999	EULFS	OWW	ILOSTAT	EULFS	EULFS	PWT	PWT	PWT	PWT
POL	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	N.D.	N.D.	N.D.	N.D.
PRT	1999	EULFS	OWW	OWW	EULFS	EULFS	PWT	PWT	PWT	PWT
PRT	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
PRY	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
PRY	2018	ILOSTAT	ILOSTAT	ILOSTAT	CMAEH	CMAEH	PWT	PWT	PWT	PWT
ROU	1999	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
ROU	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
SGP	1999	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	PWT
SLV	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	N.D.
SLV	2019	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	N.D.
SRB	2018	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
SVK	1999	EULFS	OWW	OWW	EULFS	EULFS	PWT	PWT	PWT	PWT
SVK	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
SVN	1997	EULFS	OWW	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
SVN	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
SWE	2019	EULFS	EUSILC	EULFS	EULFS	EULFS	PWT	PWT	PWT	PWT
TTO	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	N.D.	N.D.	N.D.	N.D.
TTO	2013	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
TUR	1990	IPUMS-I	OWW	OWW	IPUMS-I	IPUMS-I	PWT	PWT	PWT	PWT
TUR	2014	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
UGA	2017	ILOSTAT	ILOSTAT	ILOSTAT	I2D2	I2D2	PWT	PWT	PWT	PWT
UKR	1999	ILOSTAT	OWW	OWW	N.D.	N.D.	PWT	PWT	PWT	N.D.
UKR	2016	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
URY	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
URY	2019	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
USA	1990	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	PWT	PWT	PWT	PWT
USA	2014	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	PWT	PWT	PWT	PWT
VEN	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
VEN	2015	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	PWT	PWT	PWT	PWT
VNM	2018	ILOSTAT	ILOSTAT	ILOSTAT	N.D.	N.D.	PWT	PWT	PWT	PWT
ZMB	1990	IPUMS-I	OWW	OWW	I2D2	I2D2	PWT	PWT	PWT	N.D.

Note: N.D.= No data. IPUMS-I = IPUMS International. IPUMS-U = IPUMS USA. PWT = PWT V. 10.0. Ouput = Output side real GDP at chained PPP (2017 US$). Capital stock = Capital stock at chained PPP (2017 US$).

Table A3: Data sources by year and country- Sectors

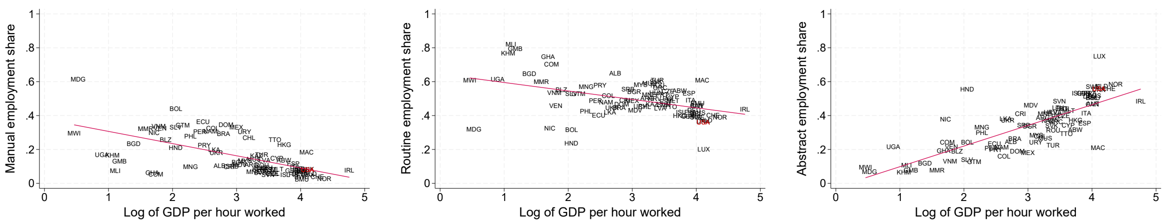
Country	Year	Persons engaged	Wages-earnings	Weekly hours worked	Gross value added	Persons engaged (overall economy)	Capital stock	Labour share	PPP
ARG	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
AUS	2011	ILOSTAT	ILOSTAT	ILOSTAT	WIOD	WIOD	WIOD	WIOD	PLD 2023
AUT	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
AUT	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
BEL	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
BEL	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
BGD	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
BGR	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
BGR	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
BRA	2005	ILOSTAT	ILOSTAT	ILOSTAT	WIOD	WIOD	WIOD	WIOD	PLD 2023
BRA	2011	CMAEH	CMAEH	CMAEH	WIOD	WIOD	WIOD	WIOD	PLD 2023
CAN	2005	IPUMS-I	OWW	IPUMS-I	WIOD	WIOD	WIOD	WIOD	PLD 2023
CAN	2011	IPUMS-I	ILOSTAT	IPUMS-I	WIOD	WIOD	WIOD	WIOD	PLD 2023
CHE	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
CHL	2011	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
CRI	2005	CMAEH	OWW	OWW	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
CRI	2011	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
CYP	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
CYP	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
CZE	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
CZE	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
DEU	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
DEU	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
DNK	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
DNK	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
ESP	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
ESP	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023

Country	Year	Persons engaged	Wages-earnings	Weekly hours worked	Gross value added	Persons engaged (overall economy)	Capital stock	Labour share	PPP
EST	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
EST	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
FIN	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
FIN	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
FRA	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
FRA	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
GBR	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
GBR	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
GRC	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
GRC	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
HRV	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
HUN	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
HUN	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
IRL	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
IRL	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
ITA	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
ITA	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
KHM	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
KOR	2005	ILOSTAT	OWW	OWW	WIOD	WIOD	WIOD	WIOD	PLD 2023
LKA	2011	I2D2	I2D2	I2D2	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
LTU	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
LTU	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
LUX	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
LUX	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
LVA	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
LVA	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
MMR	2011	I2D2	I2D2	I2D2	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
MUS	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
MWI	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
MYS	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
NLD	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
NLD	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
NOR	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
NOR	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
PER	2005	I2D2	I2D2	I2D2	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
PER	2011	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
POL	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
POL	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
PRT	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
PRT	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
ROU	2005	EULFS	OWW	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
ROU	2011	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
SVK	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
SVK	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
SVN	2005	EULFS	EUSILC	EULFS	WIOD	WIOD	WIOD	WIOD	PLD 2023
SVN	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
SWE	2005	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
SWE	2011	EULFS	EUSILC	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
TUR	2005	ILOSTAT	OWW	OWW	WIOD	WIOD	WIOD	WIOD	PLD 2023
TUR	2011	ILOSTAT	ILOSTAT	ILOSTAT	WIOD	WIOD	WIOD	WIOD	PLD 2023
UGA	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023
USA	2005	IPUMS-U	IPUMS-U	IPUMS-U	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
USA	2011	IPUMS-U	IPUMS-U	IPUMS-U	KLEMS	KLEMS	KLEMS	KLEMS	PLD 2023
VNM	2011	ILOSTAT	ILOSTAT	ILOSTAT	PLD 2023	PLD 2023	Eora	Eora	PLD 2023

Note: N.D.= No data. IPUMS-I = IPUMS International. IPUMS-U = IPUMS USA. Gross value added = Gross value added at current basic prices (in mill, of LCU). Capital stock = Nominal capital stock (in mill. of LCU).

A.2 Additional Data Figures

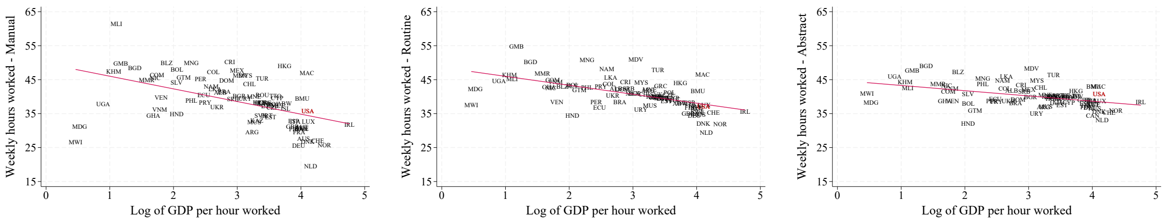
Figure A1: Occupational employment shares, excluding agriculture, vs log of GDP per hour worked in the 2010s



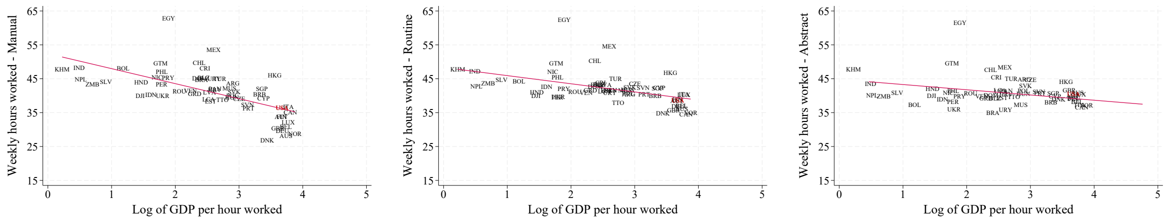
(a) Manual share (b) Routine share (c) Abstract share

Notes: This figure plots the three occupational groups' employment share against log of real GDP per hour worked based on the cross-section of countries in the 2010s, where agricultural occupations are dropped. In this figure the 2010s sample contains 81 countries.

Figure A2: Occupational average weekly hours worked vs log of GDP per hour worked



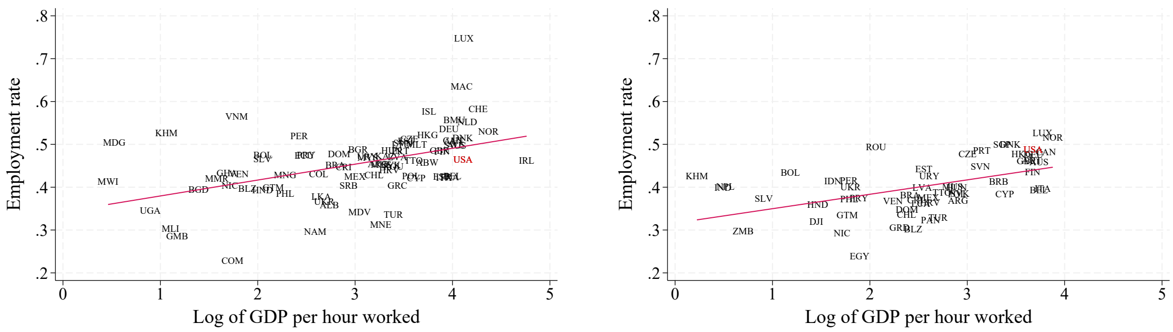
(a) Manual (2010s) (b) Routine (2010s) (c) Abstract (2010s)



(d) Manual (1990s) (e) Routine (1990s) (f) Abstract (1990s)

Note: This figure plots the three occupational groups' average weekly hours worked against log of real GDP per hour worked based on the cross-section of countries in the 2010s and the 1990s. In this figure the 2010s sample contains 81 countries and the 1990s 57 countries.

Figure A3: Relative occupational employment rates vs real GDP per worker

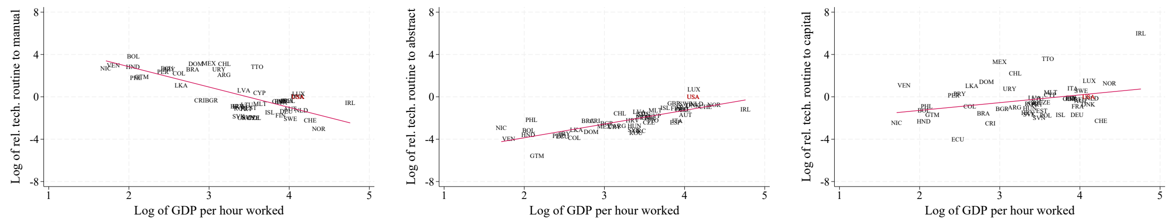


(a) Employment rate (2010s) (b) Employment rate (1990s)

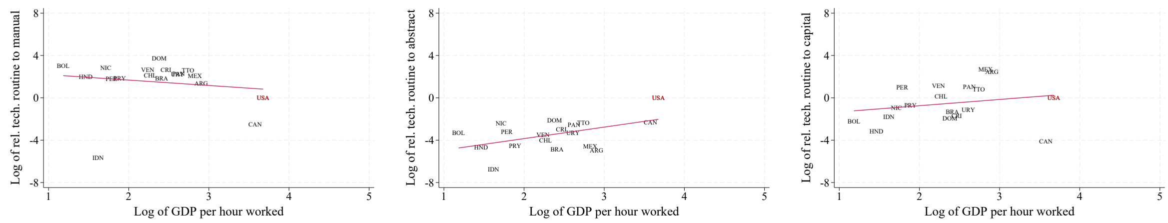
Note: This figure plots the employment rates against log GDP per worker in the cross-section of countries in the 2010s and the 1990s. In this figure the 2010s sample contains 81 countries and the 1990s 57 countries.

A.3 Additional Baseline Model Results

Figure A4: Relative technologies based on (5) vs real GDP per hour worked using information exclusively for persons engaged



(a) Routine to manual tech. (2010s) (b) Routine to abstract tech. (2010s) (c) Routine to capital tech. (2010s)



(d) Routine to manual tech. (1990s) (e) Routine to abstract tech. (1990s) (f) Routine to capital tech. (1990s)

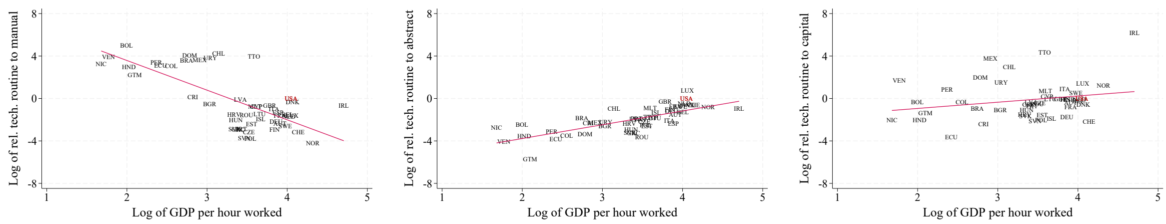
Note: This figure plots the relative technologies inferred based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$ against log GDP per hour worked. In this plot we use non-adjusted hourly wages and the information on employment shares, hourly wages and weekly hours worked comes entirely from persons engaged. In this figure the 2010s sample contains 51 countries and the 1990s 18 countries, where the sub-samples contain only the countries for which we have data on the capital share in GDP.

Table A4: Data and Counterfactual Inequality of GDP per hour worked in the 2010s using information exclusively for persons engaged

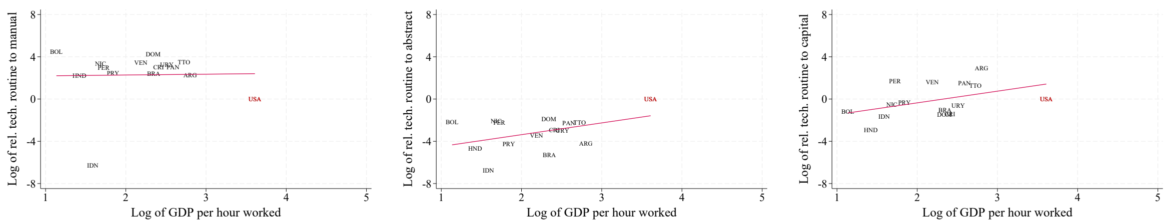
Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 ratio	7.02	5.95	5.59	10.56	5.35	4.39
90-50 ratio	1.90	1.90	1.64	2.34	1.71	1.62
50-10 ratio	3.69	3.13	3.41	4.50	3.13	2.71

Note: This table reports the ratio of GDP per hour worked at the 90 percentile to the 10th percentile in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$. In this table we use non-adjusted hourly wages and the information on employment shares, hourly wages and weekly hours worked comes entirely from persons engaged. In this table the 2010s sample contains 51 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

Figure A5: Relative technologies based on (5) vs real GDP per hour worked using information exclusively for males



(a) Routine to manual tech. (2010s) (b) Routine to abstract tech. (2010s) (c) Routine to capital tech. (2010s)



(d) Routine to manual tech. (1990s) (e) Routine to abstract tech. (1990s) (f) Routine to capital tech. (1990s)

Notes: This figure plots the relative technologies inferred based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$ against log GDP per hour worked. In this plot the information on employment shares, hourly wages and weekly hours worked comes entirely from males. In this figure the 2010s sample contains 47 countries and the 1990s 15 countries, where the sub-samples contain only the countries for which we have data on the capital share in GDP.

Table A5: Data and Counterfactual Inequality of GDP per hour worked in the 2010s using information exclusively for males

Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 ratio	7.11	5.04	6.11	12.88	6.41	4.72
90-50 ratio	1.71	1.74	1.45	2.31	1.93	1.48
50-10 ratio	4.16	2.90	4.22	5.59	3.33	3.18

Note: This table reports the ratio of GDP per hour worked at the 90 percentile to the 10th percentile in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$. In this table the information on employment shares, hourly wages and weekly hours worked comes entirely from males. In this table the 2010s sample contains 47 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

Table A6: Data and Counterfactual Inequality of GDP per hour worked in the 2010s with alternative substitution elasticities

Baseline: $\sigma = 0.60$ & $\eta = 0.84$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.20	5.76	5.13	9.38	5.45	4.20
90-50 ratio	1.96	1.90	1.67	2.63	1.90	1.62
50-10 ratio	3.17	3.03	3.07	3.57	2.87	2.60
Alternative: $\sigma = 0.70$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.20	4.98	5.08	11.20	5.45	4.20
90-50 ratio	1.96	1.89	1.66	2.69	1.90	1.62
50-10 ratio	3.17	2.63	3.07	4.16	2.87	2.59
Alternative: $\sigma = 0.50$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.20	5.92	5.22	8.16	5.45	4.24
90-50 ratio	1.96	1.92	1.71	2.53	1.90	1.61
50-10 ratio	3.17	3.09	3.04	3.22	2.87	2.64
Alternative: $\eta = 0.75$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.20	5.76	5.00	9.02	4.38	4.67
90-50 ratio	1.96	1.90	1.66	2.60	1.58	1.67
50-10 ratio	3.17	3.03	3.01	3.47	2.77	2.80
Alternative: $\eta = 0.65$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.20	5.76	4.98	8.36	5.13	5.14
90-50 ratio	1.96	1.90	1.66	2.50	1.78	1.73
50-10 ratio	3.17	3.03	3.01	3.35	2.89	2.98

Note: This table reports the ratio of GDP per hour worked at the 90 percentile to the 10th percentile in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the the aggregate production function (5) with alternative and heterogeneous substitution elasticities. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

B Alternative Parsimonious Models

B.1 Most Simple Model: Routine and Non-routine Labour Only

The most basic way to conduct the development accounting exercise allowing for routine-biased technical change is to specify the following labour-only production function

$$Y_i = \left(\alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\mu_{N,i}N_i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} . \tag{17}$$

It stipulates that the real GDP per hour worked in country i, Y_i, is the result of combining routine labour R_i and non-routine labour N_i (both measured in terms of their labour input share), according to an elasticity of substitution σ. Routine and non-routine labour inputs are augmented by factor-specific technologies $\mu_{R,i}$ and $\mu_{N,i}$ respectively, which are allowed to differ across countries. The parameter α is invariant across countries and captures the routine-intensity of production. Assuming perfect competition in the occupational labour markets, as we show in Appendix C the optimality conditions of the representative firm's profit maximisation problem can be rearranged to give

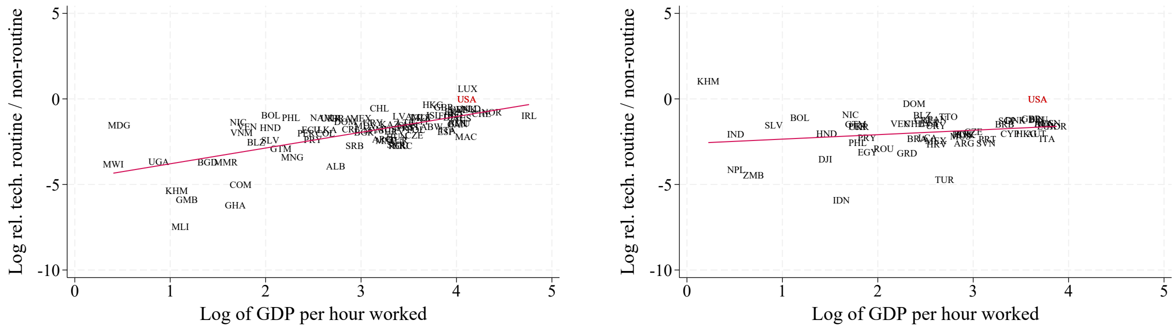
$$\frac{\mu_{R,i}}{\mu_{N,i}} = \left(\frac{1-\alpha}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{w_{R,i}}{w_{N,i}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{R_i}{N_i}\right)^{\frac{1}{\sigma-1}} , \tag{18}$$

where $w_{R,i}$ and $w_{N,i}$ denote the routine and the non-routine wage rates respectively. This condition informs us about the optimal relative occupational productivities within a country. Equation (18) together with (17) allows us to derive country i's routine technology as

$$\mu_{R,i} = \left(\frac{Y_i^{\frac{\sigma-1}{\sigma}} w_{R,i} R_i^{\frac{1}{\sigma}}}{\alpha(w_{R,i}R_i + w_{N,i}N_i)}\right)^{\frac{\sigma}{\sigma-1}} , \tag{19}$$

where Y_i is real GDP in purchasing power parities and per hour worked in country i. After specifying a value for the elasticity of substitution σ, every term on the right-hand side is observable, apart from the parameter α. To obtain a value for α, we impose that for a benchmark country, $\mu_{R,benchmark} = \mu_{N,benchmark}$. We can then use equation (18) to solve for α using the observable information for the benchmark country. Once we have found a value for α, we infer from all countries' data their technologies; (19) gives us $\mu_{R,i}$ and $\mu_{N,i}$ follows from (18). Note that α then reflects both the routine-intensity and the relative productivity of routine-labour in the benchmark country, whereas $\mu_{R,i}$ and $\mu_{N,i}$ capture the factor-augmenting technologies of country i relative to the benchmark economy. As throughout the paper our results are based on relative technologies, either between factors within a country or for a given factor across countries, this does not pose any problem for the analysis. To implement this approach on our dataset, we take the United States as the benchmark economy and set $\sigma = 0.56$, following Duernecker and Herrendorf (2022) who obtain this value for the substitution elasticity when differentiating labour into two occupational categories and allowing for occupation-specific technical change. We plot the inferred labour-augmenting relative technologies for the 2010s and 1990s in Figure A6.

Figure A6: Relative routine to non-routine technologies based on (17) vs real GDP per hour worked



(a) Routine to non-routine technologies (2010s) (b) Routine to non-routine technologies (1990s)

Notes: This figure plots the relative routine to non-routine technologies inferred based on the aggregate production function (17) with $\sigma = 0.56$ against log GDP per hour worked in the cross-section of countries in the 2010s and 1990s. In this figure the 2010s sample contains 81 countries and the 1990s 57 countries.

While there is some dispersion in the implied relative routine to non-routine technologies, Figure A6a shows a discernible pattern to them. The higher an economy's real GDP per hour worked is, the higher tends to be the relative technology of routine labour. Since the occupational labour inputs are complements (since $\sigma = 0.56 < 1$), this implies that countries that have higher average labour productivity, as measured by GDP per hour worked, tend to have technologies that are more biased against routine workers. These results complement the decline observed in the routine labour shares with respect to countries' GDP (Figure 2). Figure A6 also reveals that the relationship between relative routine to non-routine technologies and GDP per hour worked is also positive in the 90s decade (based on smaller set of countries due to data availability). It is worth to note that the slope of the regression line in Figure A6a is statistically significant and is approximately 3.5 times higher than the slope in the regression line of Figure A6b (which is not statistically significant), suggesting that the technical bias against routine workers in more developed economies has increased over time.

B.2 Routine, Manual and Abstract Labour and Capital as Inputs

The simple production function in (1) is the most parsimonious framework to study complementarity between routine, abstract and manual labour allowing for routine-biased technical change. Yet, as it does not take into account capital whose stocks differ vastly across countries, it is not suitable for comparing technology levels across countries. It is straightforward to augment this framework to allow for capital to be a further input to production. The simplest framework with capital is a Cobb-Douglas production function in capital and a CES labour aggregator of the following form:

$$Y_i = K_i^{\gamma} \left(\left(\alpha(\mu_{R,i} R_i)^{\frac{\sigma-1}{\sigma}} + \beta(\mu_{M,i} M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha-\beta)(\mu_{A,i} A_i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \right)^{1-\gamma}. \tag{20}$$

Since profit maximisation requires the cost minimal combination of the different occupational labour inputs, the optimality conditions for the relative labour demands remain unchanged. Therefore equations (2) and (3), which pin down relative technologies within a country, continue to hold. Accounting for capital in the neutral way assumed in (20) affects only the level we infer for a country's technology, which is now given by

$$\mu_{M,i} = \left(\frac{Y^{\frac{1}{1-\gamma}\frac{\sigma-1}{\sigma}} w_{M,i} M_i^{\frac{1}{\sigma}}}{\beta K_i^{\frac{\gamma}{1-\gamma}\frac{\sigma-1}{\sigma}} (w_{R,i}R_i + w_{M,i}M_i + w_{A,i}A_i)} \right)^{\frac{\sigma}{\sigma-1}}. \tag{21}$$

But since (2) and (3) still apply, relative occupational productivities within countries are identical to Figure 5. However, the level of the inferred technologies become now meaningful as –otherwise potentially confounding– differences in capital per worker have been taken into account. In Table A7 we show how the technology of manual, routine, and of abstract labour varies across the cross-country distribution of GDP per hour worked. We do this by reporting the ratios of the quartile average of a technology relative to the world average for each occupation-specific technology.[41]

Table A7: Cross-country comparison of occupation-augmenting technologies in 2010s based on (20)

Quartile of GDP p.w.	GDP p.w. rel. to world	Technology relative to world avg. Manual	Routine	Abstract
1	0.33	0.03	0.26	1.17
2	0.75	0.17	0.49	1.05
3	1.14	0.65	0.97	0.78
4	1.82	3.22	2.33	0.99

Notes: This table reports by quartile of real GDP per hour worked the average inferred technology of routine, manual, and abstract labour relative to the world average, as inferred from the data based on the aggregate production function (20) with $\sigma = 0.6$ and γ equal to the value of capital share in the US. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

As one would expect, the ranking of GDP per hour worked maps into differences in technologies augmenting the various forms of occupational labour. However, the table demonstrates clearly that the dispersion of technologies is not the same for the three occupational groups. While the top 25 percent countries in terms of GDP per hour worked have an abstract technology that is 1 percent below the cross-country average, the bottom 25 percent have abstract technologies that are 17 percent above the world average. This does not mimic the distribution of GDP per hour worked. In contrast, across GDP per hour worked quartiles manual technologies are ranked like GDP and much more dispersed, ranging from 0.03 at the bottom to 3.22 at the top. Also the dispersion in routine technologies is larger than the dispersion of GDP per hour worked, but smaller than the one in manual technologies.

[41]We restrict our sample to countries for which we have data on the capital share in GDP, as we want to compare the results in Table A7 with the results provided by the nested CES specification we present in section 3.2 of the main text.

C Derivations

CES aggregator in routine and in non-routine labour (Section B.1)

Under the aggregate production function 17, the profit maximization problem of the representative firm in country i is given by

$$\max_{R_i, N_i} \pi_i = pY_i - w_{N,i}N_i - w_{R,i}R_i$$

where Y_i is the production function specified in 17. The first order conditions for routine and non-routine occupational labour are

$$\frac{\partial \pi_i}{\partial R_i} = pY_i^{\frac{1}{\sigma}} \alpha (\mu_{R,i}R_i)^{-\frac{1}{\sigma}} \mu_{R,i} - w_{R,i} = 0$$
$$\frac{\partial \pi_i}{\partial N_i} = pY_i^{\frac{1}{\sigma}} (1-\alpha) (\mu_{N,i}N_i)^{-\frac{1}{\sigma}} \mu_{N,i} - w_{N,i} = 0$$

From these two FOCs, the relative occupational labour demand are as follows

$$\frac{N_i}{R_i} = \left(\frac{1-\alpha}{\alpha}\right)^{\sigma} \left(\frac{\mu_{N,i}}{\mu_{R,i}}\right)^{\sigma-1} \left(\frac{w_{R,i}}{w_{N,i}}\right)^{\sigma}$$

This equation can be solved for relative technologies as a function of observed labour inputs and relative wages, which gives equation (18) in the main text.

Symmetric CES aggregator in routine, manual, abstract labour (Section 3.1)

The profit maximization problem of representative firm in country i is now given by

$$\max_{R_i, A_i, M_i} pY_i - w_{R,i}R_i - w_{A,i}A_i - w_{M,i}M_i$$

where Y_i is the production function specified in equation 1. The first order conditions for routine, abstract, and manual occupational labour demands are:

$$\frac{\partial \pi_i}{\partial R_i} = pY_i^{\frac{1}{\sigma}} \alpha (\mu_{R,i}R_i)^{-\frac{1}{\sigma}} \mu_{R,i} - w_{R,i} = 0$$
$$\frac{\partial \pi_i}{\partial M_i} = pY_i^{\frac{1}{\sigma}} \beta (\mu_{M,i}M_i)^{-\frac{1}{\sigma}} \mu_{M,i} - w_{M,i} = 0$$
$$\frac{\partial \pi_i}{\partial A_i} = pY_i^{\frac{1}{\sigma}} (1-\alpha-\beta) (\mu_{A,i}A_i)^{-\frac{1}{\sigma}} \mu_{A,i} - w_{A,i} = 0$$

From these FOCs, relative labour demand for three occupations are given by

$$\frac{A_i}{M_i} = \left(\frac{1-\alpha-\beta}{\beta}\right)^{\sigma} \left(\frac{\mu_{A,i}}{\mu_{M,i}}\right)^{\sigma-1} \left(\frac{w_{M,i}}{w_{A,i}}\right)^{\sigma}$$
$$\frac{M_i}{R_i} = \left(\frac{\beta}{\alpha}\right)^{\sigma} \left(\frac{\mu_{M,i}}{\mu_{R,i}}\right)^{\sigma-1} \left(\frac{w_{R,i}}{w_{M,i}}\right)^{\sigma}$$

which can be can rearranged to give equations 2 and 3 in the main text.

Routine, Manual and Abstract Labour and Capital as Inputs in a Nested CES Specification (Section 3.2)

$$\max_{R_i,A_i,M_i,K_i} pY_i - w_{R,i}R_i - w_{A,i}A_i - w_{M,i}M_i - r_iK_i \tag{22}$$

where Y_i is production function specified in 5. defining the labour aggregate as $LA = \alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}} + \beta(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha-\beta)(\mu_{A,i}A_i)^{\frac{\sigma-1}{\sigma}}$, the first order conditions for routine, abstract and manual occupations and capital are given by

$$\begin{aligned}
\frac{\partial \pi_i}{\partial M_i} &= pY_i^{\frac{1}{\eta}}\phi LA^{\frac{\eta-\sigma}{(\sigma-1)\eta}}\beta(\mu_{M,i}M_i)^{\frac{-1}{\sigma}}\mu_{M,i} - w_{M,i} = 0\\
\frac{\partial \pi_i}{\partial R_i} &= pY_i^{\frac{1}{\eta}}\phi LA^{\frac{\eta-\sigma}{(\sigma-1)\eta}}\alpha(\mu_{R,i}R_i)^{\frac{-1}{\sigma}}\mu_{R,i} - w_{R,i} = 0\\
\frac{\partial \pi_i}{\partial A_i} &= pY_i^{\frac{1}{\eta}}\phi LA^{\frac{\eta-\sigma}{(\sigma-1)\eta}}(1-\alpha-\beta)(\mu_{A,i}A_i)^{\frac{-1}{\sigma}}\mu_{A,i} - w_{A,i} = 0\\
\frac{\partial \pi_i}{\partial K_i} &= pY_i^{\frac{1}{\eta}}(1-\phi)(\mu_{K,i}K_i)^{\frac{-1}{\sigma}}\mu_{K,i} - r_i = 0
\end{aligned}$$

From these FOCs, relative labour demand for three occupations are given by

$$\begin{aligned}
\frac{M_i}{R_i} &= \left(\frac{w_{R,i}}{w_{M,i}}\right)^{\sigma}\left(\frac{\beta}{\alpha}\right)^{\sigma}\left(\frac{\mu_{M,i}}{\mu_{R,i}}\right)^{\sigma-1}\\
\frac{A_i}{R_i} &= \left(\frac{w_{R,i}}{w_{A,i}}\right)^{\sigma}\left(\frac{1-\alpha-\beta}{\alpha}\right)^{\sigma}\left(\frac{\mu_{A,i}}{\mu_{R,i}}\right)^{\sigma-1}
\end{aligned}$$

which can be can rearranged to give equations 7 and 8 in the main text. The process to obtain equations 6 and 9 follows the same logic; however, some additional steps are needed. Defining $\theta_{o,i}$ as the share occupation o has in the non-capital income of country i, we can obtain the optimum relative labour inputs:

$$\begin{aligned}
\frac{\mu_{M,i}M_i}{\mu_{R,i}R_i} &= \left(\frac{\theta_{M,i}}{\theta_{R,i}}\right)^{\frac{\sigma}{\sigma-1}}\left(\frac{\alpha}{\beta}\right)^{\frac{\sigma}{\sigma-1}}\\
\frac{\mu_{A,i}A_i}{\mu_{R,i}R_i} &= \left(\frac{\theta_{A,i}}{\theta_{R,i}}\right)^{\frac{\sigma}{\sigma-1}}\left(\frac{\alpha}{1-\alpha-\beta}\right)^{\frac{\sigma}{\sigma-1}}
\end{aligned}$$

The expressions above allow us to express the labour aggregate as:

$$LA = \alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}} + \beta(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha-\beta)(\mu_{A,i}A_i)^{\frac{\sigma-1}{\sigma}} = \alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}}\left(\frac{1}{\theta_{R,i}}\right)$$

Substituting LA in the expression for the relative price of routine labour to capital, $\frac{w_{R,i}}{r_i}$ (obtained from the FOCs), and defining the capital share in GDP as $\Theta_{K,i} = \frac{r_i K_i}{Y_i}$ give the relative labour demand of routine occupations to capital and the optimum relative input of routine labour to capital:

$$\frac{R_i}{K_i} = \left(\frac{r_i}{w_{R,i}}\right)^{\eta}\left(\frac{\phi}{1-\phi}\right)^{\eta}\left(\frac{\mu_{R,i}}{\mu_{K,i}}\right)^{\eta-1}\alpha^{\frac{\sigma(\eta-1)}{\sigma-1}}\left(\frac{1}{\theta_{R,i}}\right)^{\frac{\eta-\sigma}{\sigma-1}}$$

$$\frac{\mu_{K,i}K_i}{\mu_{R,i}R_i} = \left(\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{\eta}{\eta-1}}\left(\frac{\phi}{1-\phi}\right)^{\frac{\eta}{\eta-1}}\alpha^{\frac{\sigma}{\sigma-1}}\left(\frac{1}{\theta_{R,i}}\right)^{\frac{\eta-\sigma}{(\sigma-1)(\eta-1)}}$$

Using the relative demand of routine labour to capital we can arrive to expression 6 in the main text. Finally, plugging the optimum relative input of routine labour to capital and LA in equation 5 allows us to obtain equation9 in the main text.

Routine, Manual and Abstract Labour and Capital as Inputs in a Nested CES Specification (Section 6.3) The profit maximization problem of the firm is given by:

$$\max_{R_i,A_i,M_i,K_i} pY_i - w_{R,i}R_i - w_{A,i}A_i - w_{M,i}M_i - r_iK_i \tag{23}$$

where Y_i is production function specified in 12. Defining the routine aggregate as $RA = \phi(\mu_{R,i}R_i)^{\frac{\eta-1}{\eta}} + (1-\phi)(\mu_{K,i}K_i)^{\frac{\eta-1}{\eta}}$ and the complex aggregate as $CA = \beta(\mu_{A,i}A_i)^{\frac{\gamma-1}{\gamma}} + (1-\beta)RA^{\frac{\eta}{(\eta-1)}\frac{(\gamma-1)}{\gamma}}$, the first order conditions for routine, abstract and manual occupations and capital are given by

$$\begin{aligned}
\frac{\partial\pi_i}{\partial M_i} &= pY_i^{\frac{1}{\sigma}}\alpha(\mu_{M,i}M_i)^{-\frac{1}{\sigma}}\mu_{M,i} - w_{M,i} = 0\\
\frac{\partial\pi_i}{\partial A_i} &= pY_i^{\frac{1}{\sigma}}(1-\alpha)CA^{\frac{\sigma-\gamma}{(\gamma-1)\sigma}}\beta(\mu_{A,i}A_i)^{-\frac{1}{\gamma}}\mu_{A,i} - w_{A,i} = 0\\
\frac{\partial\pi_i}{\partial R_i} &= pY_i^{\frac{1}{\sigma}}(1-\alpha)CA^{\frac{\sigma-\gamma}{(\gamma-1)\sigma}}(1-\beta)RA^{\frac{\gamma-\eta}{(\eta-1)\gamma}}\phi(\mu_{R,i}R_i)^{-\frac{1}{\eta}}\mu_{R,i} - w_{R,i} = 0\\
\frac{\partial\pi_i}{\partial K_i} &= pY_i^{\frac{1}{\sigma}}(1-\alpha)CA^{\frac{\sigma-\gamma}{(\gamma-1)\sigma}}(1-\beta)RA^{\frac{\gamma-\eta}{(\eta-1)\gamma}}(1-\phi)(\mu_{K,i}K_i)^{-\frac{1}{\eta}}\mu_{K,i} - r_i = 0
\end{aligned}$$

From these FOCs, relative demand of routine occupations to capital is given by

$$\frac{R_i}{K_i} = \left(\frac{r_i}{w_{R,i}}\right)^{\eta}\left(\frac{\phi}{1-\phi}\right)^{\eta}\left(\frac{\mu_{R,i}}{\mu_{K,i}}\right)^{\eta-1}$$

which can be can rearranged to give equation 13 in the main text. The process to obtain equations 14 to 16 follows the same logic, however, some additional steps are needed. Defining $\theta_{o,i}$ as the share occupation o has in the non-capital income of country i and the capital share in GDP in country i as $\Theta_{K,i} = \frac{r_i K_i}{Y_i}$, we can obtain the optimum relative capital input to routine labour input:

$$\frac{\mu_{K,i} K_i}{\mu_{R,i} R_i} = \left(\frac{\phi}{1-\phi}\right)^{\frac{\eta}{\eta-1}} \left(\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{r,i}}\right)^{\frac{\eta}{\eta-1}}$$

The expression above allows us to express the routine aggregate as:

$$RA = \phi (C_i R_i)^{\frac{\eta-1}{\eta}} + (1-\phi)(F_i K_i)^{\frac{\eta-1}{\eta}} = (\mu_{R,i} R_i)^{\frac{\eta-1}{\eta}} \phi \left(1 + \frac{\Theta_K}{(1-\Theta_K)\theta_{R,i}}\right)$$

substituting RA in the expression for the relative wages of routine labour to abstract, $\frac{w_{R,i}}{w_{A,i}}$ (obtained from the FOCs), gives the relative labour demand of routine to abstract labour and the optimum relative labour input of routine to abstract occupations:

$$\frac{R_i}{A_i} = \left(\frac{w_{A,i}}{w_{R,i}}\right)^{\gamma} \left(\frac{1-\beta}{\beta}\right)^{\gamma} \left(\frac{\mu_{R,i}}{\mu_{A,i}}\right)^{\gamma-1} \left(1 + \frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{\gamma-\eta}{\eta-1}} \phi^{\frac{\eta(\gamma-1)}{\eta-1}}$$

$$\frac{\mu_{R,i} R_i}{\mu_{A,i} A_i} = \left(\frac{\theta_{R,i}}{\theta_{A,i}}\right)^{\frac{\gamma}{\gamma-1}} \left(\frac{\beta}{1-\beta}\right)^{\frac{\gamma}{\gamma-1}} \left(1 + \frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{\eta-\gamma}{(\eta-1)(\gamma-1)}} \phi^{\frac{\eta(1-\gamma)}{(\eta-1)(\gamma-1)}}$$

where the relative labour demand of routine to abstract occupations gives equation 14 in the main text. The expression RA and the optimum relative labour input of routine to abstract occupations allows us to express the complex aggregate as:

$$CA = \beta (E_i A_i)^{\frac{\gamma-1}{\gamma}} + (1-\beta) RA^{\frac{\eta}{(\eta-1)} \frac{(\gamma-1)}{\gamma}} = \beta (\mu_{A,i} A_i)^{\frac{\gamma-1}{\gamma}} \left(1 + \frac{\theta_{R,i}}{\theta_{A,i}} + \frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{A,i}}\right)$$

plugging the CA in the expression for the relative wage of abstract labour to manual occupations, $\frac{w_{A,i}}{w_{M,i}}$, gives the relative labour demand of abstract to manual occupations and the optimum relative labour input of abstract to manual occupations:

$$\frac{A_i}{M_i} = \left(\frac{w_{M,i}}{w_{A,i}}\right)^{\sigma} \left(\frac{1-\alpha}{\alpha}\right)^{\sigma} \beta^{\frac{\gamma(\sigma-1)}{\gamma-1}} \left(\frac{\mu_{A,i}}{\mu_{M,i}}\right)^{\sigma-1} \left(1 + \frac{\theta_{R,i}}{\theta_{A,i}} + \frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{A,i}}\right)^{\frac{\sigma-\gamma}{\gamma-1}}$$

$$\frac{\mu_{M,i} M_i}{\mu_{A,i} A_i} = \left(\frac{\theta_{M,i}}{\theta_{A,i}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{1-\alpha}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \beta^{\frac{\gamma}{\gamma-1}} \left(1 + \frac{\theta_{R,i}}{\theta_{A,i}} + \frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{A,i}}\right)^{\frac{\sigma-\gamma}{(\gamma-1)(\sigma-1)}}$$

Then, using the relative demand of abstract labour to manual occupations we can get equation 15 in the main text. Finally, using the optimum relative labour input of abstract to manual occupations and CA to substitute in the corresponding terms in equation 12 allows us to obtain equation 16 in the main text.

D Equilibrium model with endogenous occupational choice (Section 4.2)

This appendix briefly describes the general equilibrium model constructed for each country and presented in Section 4.2. As Bárány and Siegel (2020) do, we assume an economy in which there is a continuum of heterogeneous workers that optimally choose an occupation based on idiosyncratic entry costs, drawn from a distribution.[42] In this economy firms operate under perfect competition and wages are such that they clear the markets. The assumptions made about the occupational choice, as in Bárány and Siegel (2020) and Bárány and Siegel (2021), is what allows us to compute the occupation-augmenting technologies directly from the data in the same way as in section 3 and in a way where the observed wages are consistent with the model's labour market equilibrium.

Production. The production function of this one-sector economy is represented by our benchmark equation (5). We take the output of this economy as given. Then the representative firm's problem is reduced to minimise the cost of choosing occupational labour inputs in a competitive setting.[43] This allows us to endogenize the occupational labour demands with respect to changes in technologies, as occupational labour demands are now expressed as a function of wages, technologies and output. These demands are pinned down by combining the expression for the optimal routine labour demand in country i (expression (24), where GDP per hour worked is given by 5)[44] and the optimal relative labour demands presented in Appendix C.[45]

$$R_i^d = \tag{24}$$
$$\frac{Y_i}{\left[\phi\left(\frac{\alpha^{\sigma}\mu_{R,i}^{\sigma-1}w_{M,i}^{\sigma-1}w_{A,i}^{\sigma-1}+\beta^{\sigma}\mu_{M,i}^{\sigma-1}w_{R,i}^{\sigma-1}w_{A,i}^{\sigma-1}+(1-\alpha-\beta)^{\sigma}\mu_{A,i}^{\sigma-1}w_{R,i}^{\sigma-1}w_{M,i}^{\sigma-1}}{w_{M,i}^{\sigma-1}w_{A,i}^{\sigma-1}\alpha^{\sigma-1}\mu_{R,i}^{\frac{(\sigma-1)^2}{\sigma}}}\right)^{\frac{\sigma(\eta-1)}{(\sigma-1)\eta}}+\frac{(1-\phi)^{\eta}\mu_{K,i}^{\eta-1}w_{R,i}^{\eta-1}\theta_{R,i}^{\frac{(1-\sigma)(\eta-1)}{(\sigma-1)\eta}}}{r_i^{\eta-1}\phi^{\eta-1}\mu_{R,i}^{\frac{(\eta-1)^2}{\eta}}\alpha^{\frac{\sigma(\eta-1)^2}{(\sigma-1)\eta}}}\right]^{\frac{\eta}{\eta-1}}}$$

[42]This is not a Roy-type selection model as there is no selection on unobserved worker productivity. All workers are equally productive. Changing wage rates affect the occupational employment shares, but not the productivity of workers in an occupation.

[43]Here, we assume that capital is fixed as we want to gain insights about the magnitude of changes in our counterfactual exercises due to occupational mix changes. In our counterfactual exercises the recovered level of the rental rate of capital complies with the FOCs, given the equilibrium in the occupational labour markets.

[44]We add the superscript d to indicate that this is the expression for the routine labour demand. In equilibrium, $O_i = O_i^d = O_i^s$.

[45]The rental rate of capital is obtained as $r_i = \frac{w_{R,i}}{K_i^{\frac{1}{\eta}}}\left(\frac{1-\phi}{\phi}\right)\left(\frac{\mu_{K,i}}{\mu_{R,i}}\right)^{\frac{\eta-1}{\eta}}\left(\frac{1}{\alpha^{\frac{\sigma(\eta-1)}{\sigma-1}}}\right)^{\frac{1}{\eta}}\theta_{R,i}^{\frac{\eta-\sigma}{(\sigma-1)\eta}}R_i^{\frac{1}{\eta}}$.

Households –occupational choice. We assume the existence of a unit measure of workers that face an idiosyncratic and country-specific cost when selecting one occupation.[46] This cost is redistributed in a lump-sum fashion and, given this cost, workers choose the occupation that provides them the highest income. Therefore, workers in country i will select occupation O if:

$$w_{O,i}\xi^{j}_{O,i} \geq w_{Q,i}\xi^{j}_{Q,i} \tag{25}$$

where $O_i \neq Q_i$, $O_i, Q_i \in \{R_i, M_i, A_i\}$ and $\xi^j_{O,i}$ represents the country specific net-of-cost multiplier faced by worker j to enter occupation O_i. By defining $\tilde{\xi}^j_{O,i} = ln(\xi^j_{O,i})$ it is possible to rewrite the previous inequality as $ln\left(\frac{w_{O,i}}{w_{Q,i}}\right) \geq \tilde{\xi}^j_{Q,i} - \tilde{\xi}^j_{O,i}$, and then the relevant occupational cost differences in country i are: $\tilde{\xi}^j_{1,i} = \tilde{\xi}^j_{A,i} - \tilde{\xi}^j_{R,i}$ and $\tilde{\xi}^j_{2,i} = \tilde{\xi}^j_{A,i} - \tilde{\xi}^j_{M,i}$.

Using this, the optimal labour supplies in each country i and occupation O are described by:[47]

$$M^s_i = \int_{-\infty}^{\infty}\int_{-\infty}^{min[ln(w_{M,i}/w_{R,i})+\tilde{\xi}_1, ln(w_{R,i}/w_{A,i})]} f_i(\tilde{\xi}_{1,i}, \tilde{\xi}_{2,i}) d\tilde{\xi}_{1,i} d\tilde{\xi}_{2,i}, \tag{26}$$

$$R^s_i = \int_{-\infty}^{ln(w_{R,i}/w_{A,i})}\int_{ln(w_{M,i}/w_{R,i})+\tilde{\xi}_1}^{\infty} f_i(\tilde{\xi}_{1,i}, \tilde{\xi}_{2,i}) d\tilde{\xi}_{1,i} d\tilde{\xi}_{2,i}, \tag{27}$$

$$A^s_i = \int_{ln(w_{R,i}/w_{A,i})}^{\infty}\int_{ln(w_{M,i}/w_{A,i})}^{\infty} f_i(\tilde{\xi}_{1,i}, \tilde{\xi}_{2,i}) d\tilde{\xi}_{1,i} d\tilde{\xi}_{2,i}. \tag{28}$$

The expression $f_i(\tilde{\xi}_{1,i}, \tilde{\xi}_{2,i})$ represents the joint probability density function of occupational cost differences.

Equilibrium. This economy is composed of four markets, namely the labour market for manual, abstract and routine occupations and one goods market. We normalize wages by assuming that $w_{R,i} = 1$. Then, the equilibrium is defined by the set of wages $w_{A,i}$ and $w_{M,i}$ that clear the markets, i.e. $R^d_i = R^s_i$, $M^d_i = M^s_i$ and $A^d_i = A^s_i$.

Calibration of the cost distribution and parameters Key for our model is the idiosyncratic and country-specific cost that workers face when selecting one occupation. To calibrate the distribution of occupational costs differences we assume a bivariate normal distribution to represent $f_i(\tilde{\xi}_{1,i}, \tilde{\xi}_{2,i})$. We further assume that $\tilde{\xi}_{1,i}$ and $\tilde{\xi}_{2,i}$ are uncorrelated.[48] With this set-up, we then calibrate the two means of this distribution (μ_1 and

[46] This cost distribution is calibrated country by country and arguably reflect differences in institutions, preferences and labour markets. Allowing for country-specific parameters is required to perfectly match each country's occupational employment structure given the observed wage rates.

[47] In the labour supplies $f(\tilde{\xi}_{1,i}, \tilde{\xi}_{2,i})$ is the joint probability density function of occupational cost differences. For a detailed description of this occupational choice setting see section 2.2 in Bárány and Siegel (2020).

[48] As Bárány and Siegel (2020) point out, the value of correlation coefficient does not have a significant impact on any model outcome.

μ_2) and the two elements of the main diagonal in the variance-covariance matrix (σ_1^2 and σ_2^2) such that the occupational cost difference distribution allows us to exactly match the employment shares. These four parameters allow us to choose two relative wages and two employment shares for a given country at a given point in time. The means of the cost differences ensure that wages and employment shares are consistent, while the two elements of the main diagonal in the variance-covariance matrix are chosen to exactly match the employment shares. Table A8 presents these calibrated parameters of our model.

Table A8: Calibrated parameters of occupational choice in the 2010s

Quartile of GDP p.h.w.	Mean of $\tilde{\xi}_1$	Variance of $\tilde{\xi}_1$	Mean of $\tilde{\xi}_2$	Variance of $\tilde{\xi}_2$
1	-1.83	8.63	-0.84	2.75
2	-1.27	4.13	-0.23	1.50
3	-0.67	2.04	0.09	1.07
4	-0.40	1.65	0.32	0.87

Notes: This table reports the additionally calibrated parameters for endogenizing the occupational choice. In this table the 2010s sample contains 65 countries, where the sub-sample contains only the countries for which we have data on the capital share in GDP.

Table A9: GDP per hour worked in the 2010s under counterfactual cost distribution

Range of GDP per hour worked	Data, i.e. Country-specific cost distribution	Counterfactual US cost distribution
90-10 Ratio	6.20	5.90
90-50 Ratio	1.96	1.88
50-10 Ratio	3.17	3.14

Note: This table reports the percentile ratios of GDP per hour worked given the extracted technologies under endogenous occupational labour shares considering two scenarios: 1) workers draw entry costs from country-specific distributions (note, in this case the model replicates the data), and 2) workers in all countries draw entry costs from the US distribution, which is a counterfactual exercise to evaluate consequences of differences in the cost distribution across countries. Same sample of countries and baseline technologies as in Table 6, extracted from the production function (5) with $\sigma = 0.60$ and $\eta = 0.84$.

Table A10: Occupational labour shares in 2010s under counterfactual cost distribution

Q. GDP p.h.w.	Data, i.e. Country-specific cost distribution			Counterfactual US cost distribution		
	M	R	A	M	R	A
1	0.26	0.55	0.20	0.19	0.58	0.22
2	0.15	0.56	0.29	0.12	0.59	0.29
3	0.10	0.50	0.40	0.08	0.56	0.35
4	0.07	0.44	0.49	0.06	0.53	0.41

Note: This table reports by quartile of real GDP per hour worked (2010s) the average occupational labour shares given the extracted technologies considering two scenarios: 1) workers draw entry costs from country-specific distributions (note, in this case the model replicates the data), and 2) workers in all countries draw entry costs from the US distribution, which is a counterfactual exercise to evaluate consequences of differences in the cost distribution across countries. Same sample of countries and baseline technologies as in Table 7.

E Sectoral Analysis

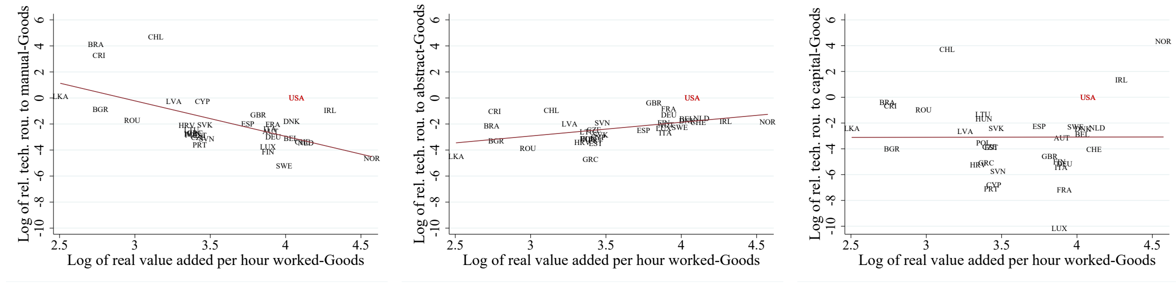
Here we conduct our analysis at the sectoral level. We use our benchmark equation (5) and our sectoral-occupational data already described in Section 2.1. We have collected data for both the goods and services sectors, allowing us to estimate the factor-augmenting technologies in each sector in both absolute and relative terms. We focus on the year 2011, as it allows us to compute absolute and relative technologies using a subsample drawn from the same pool of countries and period as in the cross-sectional sample and dataset used in Section 5.[49]

In Figure A7 we plot the inferred sectoral factor-augmenting relative technologies against the sectoral value added per hour worked at 2017 PPPs. While the results are based on a reduced sample of 34 countries,[50] the patterns generally resemble those observed for the aggregate economy. In both sectors the technology of routine compared to manual labour tends to decrease in the sector's average productivity. We observe that the higher a sector's real value added per hour worked is, the higher tends to be the relative technology of routine labour compared to abstract occupations. While in both sectors the relative routine to capital technology does not display a clear pattern in relation to average sectoral labour productivity, the majority of the results on the technology bias across occupations are echoing what we documented in section 3.2 in aggregate data (and in the much larger sample of countries). That is, our results on the occupation bias in technologies are generally upheld also within the sectors we consider here, and they also mimic the US time-series patterns found by Bárány and Siegel (2021), highlighting the robustness of our finding that higher development and increasing routine-bias go hand in hand.

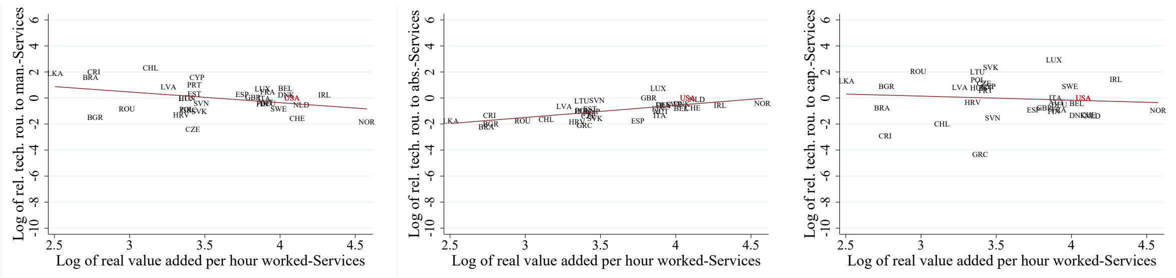
[49] As explained before, the sectoral results reported here are based on a smaller set of countries than those in Section 5, as the exercises in this section require sector-specific occupational data, unlike the analysis in Section 5.

[50] All countries in this sample are included in our 2010s sample.

Figure A7: Sectoral relative technologies based on (5) vs sectoral real value added per hour worked for 2011



(a) Goods: Routine to manual tech. (b) Goods: Routine to abstract tech. (c) Goods: Routine to capital tech.



(d) Services: Routine to manual tech. (e) Services: Routine to abstract tech. (f) Services: Routine to capital tech.

Note: This figure plots the sectoral relative technologies inferred based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$ against log sectoral real value added per hour worked in the 2011 for the goods and services sectors. In this figure the 2011 sample contains 34 countries, the sub-sample of the countries for which we have sectoral-occupational data.

In a further analysis we split these sectors finer into agriculture, industry, high-skilled services and low-skilled services. For these four sub-sectors, we compute relative factor augmenting technologies. Most technology patterns seen in the two sector classification of Figure A7 are discernible in the finer four sector classification of Figure A8 as well. As the average goods-sector productivity increases, technologies become more routine biased compared to abstract technologies in agriculture as well as in industry, and the opposite is true for the routine to manual technologies. These two patterns are in line to what we observe for the overall goods sector and the aggregate economy. However, the ratio of routine to capital technologies depicts a different pattern in the agriculture and industry sub-sectors: the most productive countries tend to use less routine labour augmenting technologies compared to capital technologies. The patterns in the two services sub-sector are rather similar to the overall services sector. The higher the average productivity in services, the lower is the ratio of routine to manual occupations' technology and the higher is ratio of routine to abstract occupations' technology. Similar to what we observe in the agriculture and industry sub-sectors, high-skilled and low-skilled services sectors tend to have slightly lower relative routine labour compared to capital technologies as the average sectoral productivity increases. Overall, these technology patterns identified suggest that our results derived at the aggregate economy level are not driven by substantial differences in the sectoral composition. Most importantly, while there are some sectoral differences in how the capital-augmenting technology compared to the routine occupational technology varies with development, the patterns of the occupational-bias in technology are qualitatively the same in all sectors, including agriculture, with the ratio of routine to abstract technology increasing in development.

Table A11: Sectoral Data and Counterfactual Inequality of VA per hour worked in 2011

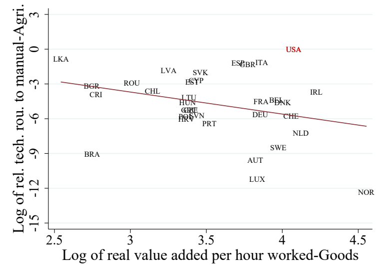
Goods- Counterfactual: Best Technology						
	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 Ratio	6.35	5.17	5.97	7.16	13.07	2.56
90-50 Ratio	3.04	2.60	2.07	3.08	4.42	1.40
50-10 Ratio	2.09	1.99	2.88	2.33	2.95	1.83
Services- Counterfactual: Best Technology						
	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 Ratio	2.13	2.12	2.21	3.09	2.92	1.84
90-50 Ratio	1.32	1.32	1.33	1.45	1.75	1.12
50-10 Ratio	1.61	1.61	1.66	2.13	1.67	1.65

Notes: This table reports the ratio of sectoral value added per hour worked at the 90 percentile to the 10th percentile in the data and in the following counterfactuals: best manual technology only, best routine technology only, best abstract technology only, best capital technology only and all best technologies. This is based on the the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$. In this table the 2011 sample contains 34 countries, where the sub-sample contain only the countries for which we have sectoral-occupational data.

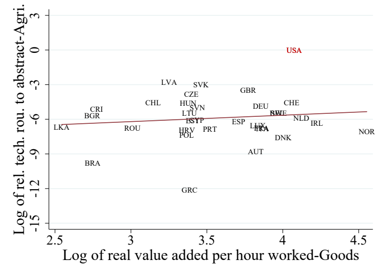
We replicate our counterfactual exercise of Section 4 to evaluate at the sectoral level how the cross-country distribution of value added per hour worked would have looked like if all countries had access to the best factor augmenting technology. As shown in Table A11, assigning the sector-specific technology frontier of routine occupations to all countries in the goods sector (leaving the other technologies and all inputs at their actual values) would have the second most equalising effect in the 90-to-10 ratio; however, it becomes the most equalizing in the 90-to-50 ratio. In the services sector assigning the best routine technology would increase the cross-country dispersion of output per hour between the 90th and the 10th percentiles. In fact, we observe that the majority of frontier factor augmenting technologies, considered one by one, tend to increase the dispersion of value added per hour worked in the services sector; the only equalizing effect is found for the 90-to-10 ratio in manual technologies. These results are explained by a smaller dispersion of factor augmenting technologies in the services sector compared to the goods sector. In this subset of countries and sectors, capital augmenting technologies increase the dispersion in value added across the sectoral average income distribution. This contrast to our finding at the aggregate level, where capital augmenting technologies reduce international differences labour productivity.[51] When we assign the technology frontier to all sectoral inputs we find the most equalizing effect in both sectors, echoing the results for the aggregate economy.

[51]However, if we restrict our sample at the aggregate level to countries with available sectoral data, we find that capital augmenting technologies increase the dispersion of the average income distribution. Since the majority of countries with sectoral data are developed, it seems that the equalising effect of capital augmenting technologies at the aggregate level disappears when we consider only richer countries.

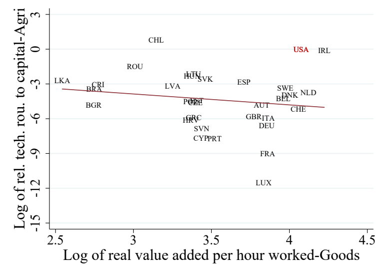
Figure A8: Sectoral relative technologies based on (5) vs sectoral real value added per hour worked for 2011



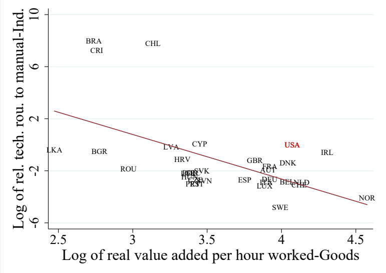
(a) Agriculture: Routine to manual tech.



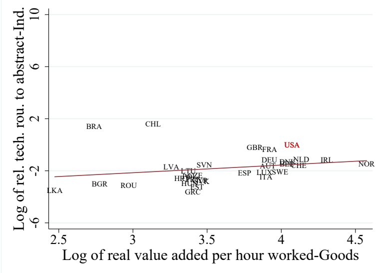
(b) Agriculture: Routine to abstract tech.



(c) Agriculture: Routine to capital tech.



(d) Industry: Routine to manual tech.



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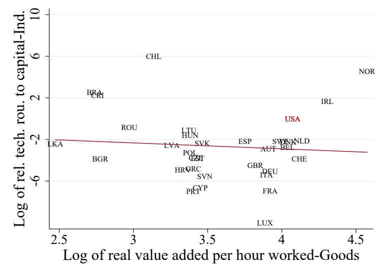
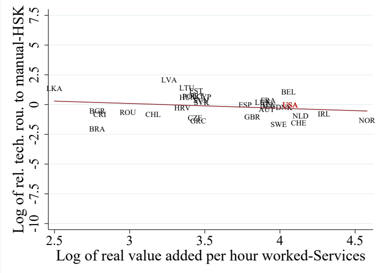
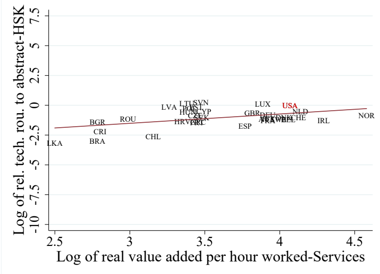


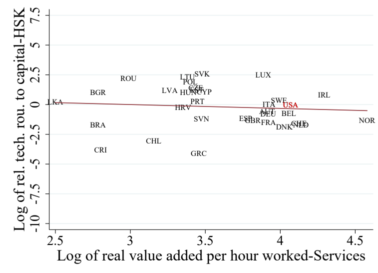
(f) Industry: Routine to capital tech.



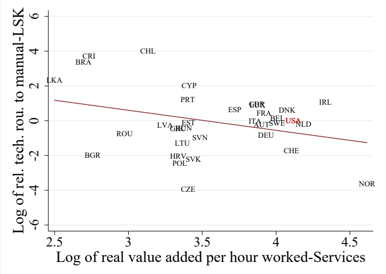
(g) HSK: Routine to manual tech.



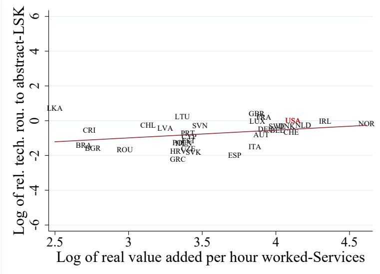
(h) HSK: Routine to abstract tech.



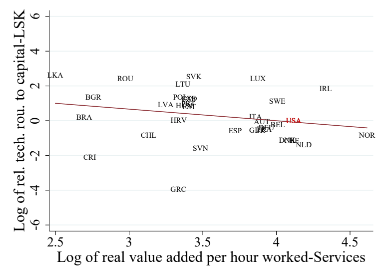
(i) HSK: Routine to capital tech.



(j) LSK: Routine to manual tech.



(k) LSK: Routine to abstract tech.



(l) LSK: Routine to capital tech.

Note: This figure plots the relative technologies inferred based on the aggregate production function (5) with $\sigma = 0.60$ and $\eta = 0.84$ against the log of goods sector's real value added per hour worked in the 2011 for agriculture and industry, and the the log of services sector's real value added per hour worked in the 2011 for high-skilled services (HSK) and low-skilled services (LSK). In this figure the 2011 sample contains 34 countries. The sub-sample contains only the countries for which we have sectoral-occupational data.