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

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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 Penn World Tables. We first document that in our novel dataset spanning 92 countries there is a negative relationship between the employment share of routine occupations and GDP per hour worked. We then conduct a development accounting exercise where we differentiate labour inputs by occupation and allow for occupation-specific technologies. We find a systematic relationship between occupation-specific technologies and GDP per hour worked. More developed economies use technologies that are more routine-biased. The productivity of routine labour is about 11 times higher in the top 25 percent than in the bottom 25 percent of countries ranked by GDP per hour worked. International differences in this routine labour technology by themselves account for about 13 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 across the world would compress the GDP distribution by 35 to 41 percent.

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

*Parts of this paper are based on data from the Penn World Tables; World Input-Output Database; World KLEMS; Eurostat, European Labour Force Survey 1992–2019 and European Statistics on Income and Living Conditions 2004–2019; International Labour Organization Statistics (ILOSTAT); Occupational Wages around the World (OWW); IPUMS International; IPUMS USA; Harmonized Microdata Center for Household Surveys in Latin America and the Caribbean (CMAEH); The International Income Distribution Data Set (I2D2). We thank Federico Rossi, Juan Ignacio Vizcaino, and Gaaitzen de Vries for many helpful suggestions as well as seminar and conference participants at University of Kent, Queen Mary University London, University of Trier, MMF-Bank of England-Kent 2021 Workshop Macroeconomic Consequences of Technological Change, ESADE, King's College London, the Society for Economic Dynamics (SED) Meetings in Minneapolis, and University of Mannheim. We also thank Claudio Montenegro and David Newhouse (both of the World Bank) for sharing with us I2D2 data. The responsibility for all conclusions drawn from the data lies entirely with the authors.

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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.

Indeed, occupation-specific productivity changes, such as routine-biased technical change, are known to have been important for developed economies' labour markets in recent decades (e.g. Autor et al. (2003), Autor et al. (2006), Goos et al. (2014), Michaels et al. (2014)). But is such occupation-biased technical change uniform across countries at varying stages of development, and do differences in occupational technologies and employment structure matter for international GDP differences? To investigate whether there are differences in occupation-biased technologies across countries and whether these matter for income differences across countries, the labour inputs need to be split by workers' occupation.

In this paper we first document how the employment shares of manual, routine, and abstract occupations vary across countries with economic development. Using micro and macro data from several sources, we construct a unique dataset with information on occupational employment, average occupational wages or earnings and occupational weekly hours worked for 92 countries for two cross-sectional samples: 1990s and 2010s. We show that, in a cross-section of the 2010s (which contains 81 countries), richer countries have a considerably larger share of their labour force employed in abstract occupations, whereas both the manual and the routine occupational employment shares decline with GDP per hour worked. This is also seen in the changes in the occupation shares between the cross-section of the 2010s and the cross-sectional sample of the 1990s: richer countries have experienced a larger decrease in routine employment and income shares and a higher increase in the share of abstract occupations vis-à-vis less developed countries.

We then conduct a development accounting exercise where we distinguish between the 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 occupations' labour input and capital, has its own factor-augmenting technology. Our main interest is in the technologies augmenting the various occupational labour inputs, the occupation-specific technologies, and how these vary across countries and over time. Such variation can stem from changes in the composition of tasks assigned to an occupation, which varies with development according to Caunedo et al. (2021), or from changes in the productivity of underlying tasks. In this paper we do not ask why cross-country differences in occupation-specific technologies arise. Instead, we document that there are systematic patterns in how technical change is biased in the occupation dimension across countries and then evaluate consequences for GDP.

We use firm optimality conditions to back out factor-specific technologies by country from the data, conditional on values of the elasticity of substitution. Similar methodology has been used extensively in the literature that studies the role of skill-biased technical change across countries, for example Caselli (2005), Caselli and Coleman (2006), and Buera et al. (2021). However, we focus on occupation-biased technologies and follow Bárány and Siegel (2021) in assuming a (location-invariant) CES production function that combines capital, manual, routine and abstract effective labour inputs. While Bárány and Siegel focus on the time series of the US economy and show that routine-biased technical change has been the first-order driver of labour productivity growth, we investigate in this paper the role of occupation-biased technologies in explaining cross-country differences in GDP per hour worked and find a large role.

Our framework features complementarity between the differentiated labour inputs. In the context of skills such complementarities have been investigated in the recent development accounting literature (e.g. Jones (2014), Rossi (2022), Hendricks and Schoellman (2022)), but unlike these papers we differentiate labour by occupation and thus focus on complementarities between occupations.[1] 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 detailed occupational data in a development accounting framework. However, while Vizcaino uses occupation information to improve the measurement of unskilled and skilled labour and then develops a model with two skill types, we take, as Bárány and Siegel (2021) do, each (broad) occupational group's labour supply directly as the relevant factor of production and allow for occupation-specific technologies to study how these vary across countries. In our analysis we infer occupation-specific technologies from the observed equilibrium allocation of workers into

[1] When calibrating the production function for our development accounting exercise we set the elasticity of substitution between occupations to a value below one, given the evidence in previous literature. As such, the degree of complementarities is much stronger than in the skilled vs. unskilled labour dimension where the typical elasticity is above one.

occupations and their wages. The fact that this allocation reflects occupational choices and not underlying endowments (for instance, such as skills) 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 technology changes to alter occupational choices.

We find that higher real GDP per hour worked is associated with higher relative productivities of labour in routine compared to abstract occupations. To put it differently, more developed economies use technologies that are more routine-biased than less developed economies do, implying –borrowing on Caselli and Coleman (2006)'s terminology– there are *occupation-biased cross-country technology differences*. Specifically we find that in the 2010s cross-section, countries in the highest quartile of income per hour worked have a routine labour productivity that is 142 percent above the world average, whereas countries in the lowest quartile are 78 percent below the average. This implies that routine labour in the top 25 percent of countries is about 11 times as productive as in the bottom 25 percent of the GDP per hour worked distribution. We also find that the growth rate of routine augmenting technologies is higher in the top 50 percent of countries, compared to the bottom 50 percent. Out of the four factor-specific technologies, the routine and manual technologies account for most of GDP per hour worked differences across countries. The dispersion in manual labour technology across countries is considerably larger than the one of routine, but plays a smaller role in explaining GDP dispersion as the manual employment share is rather small. On the other hand, giving all countries access to the best abstract technology would exacerbate the 90-10 ratio, since more developed economies have a larger abstract employment share and therefore would gain disproportionally. If all countries used the frontier technology for all inputs, the gap between the 10th and the 90th percentile of GDP per hour worked would be reduced by somewhat over a third. When we allow occupational choice to vary with technologies, this effect becomes stronger and income differences are reduced by approximately 41 percent.

These findings imply that declining routine employment shares, increasing routine-bias of technology (RBTC), and economic development go hand in hand. As richer economies also tend to have a smaller manufacturing sector (see Herrendorf et al. (2014) for an overview), this raises the question whether the patterns observed in the aggregate are due to the varying size of industrial sectors (e.g. Duarte and Restuccia (2010)) or are also a within-sector phenomenon.[2] We therefore conduct our accounting exercise

[2] There is a tight nexus between technical change, occupational employment structure, sectoral composition and economic development. On the one hand, Bárány and Siegel (2018) document a close connection between the evolution of occupational employment and structural change for the US economy over the past six decades. On the other hand, Goos et al. (2014), Duernecker and Herrendorf

at the sectoral level too, albeit only for a sub-sample of countries as we need further information on real value-added by sector. By large, the sectoral results are aligned with the aggregate patterns. Indeed, we find that the biases in occupation technologies in the goods sector and in the service sector are qualitatively the same, and thus as documented in our aggregate analysis. However, we find that in services, contrary to in goods and the aggregate economy, the technology augmenting routine labour compared to the capital-augmenting technology declines with development.

In the next section we describe our data sources and document patterns of occupational employment and wages in the cross-section of countries. Section 3 introduces our model framework and implements the development accounting exercise through which we identify occupation-specific technologies. In Section 4 we study the implications of technical differences for the dispersion of GDP per hour worked across countries by running a series of counterfactuals. Section 5 conducts the accounting exercise at the sectoral level and Section 6 shows robustness of our main results to alternative reparametrizations and accounting for workers' 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, for our analysis we need more disaggregated information as we want to distinguish between different occupational labour inputs at the aggregate and sectoral level. The development accounting exercise also requires data on relative occupational average wages within a country and sector as well as macro data on real GDP and sectoral real value added. We therefore have to combine multiple sources of micro and macro data. Our final dataset includes 92 countries. 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

(2022), Lee and Shin (2017), and Bárány and Siegel (2020) show task-biased technical change can have implications for labour reallocations, not only across occupations, but also across sectors.

[3]For some countries we have information on hourly wages by occupation, for others only on earnings. When we infer countries' technologies in the model-based accounting exercise, what we need to use is the ratio of occupational wages within the country. When we cannot construct relative occupational wages, we use relative occupational earnings instead, implicitly assuming that these two ratios are identical.

occupation, for at least one year for 113 countries from 1970 to 2020.[4] These variables are the key for conducting our development accounting exercise differentiating technologies by occupation. As we also conduct our accounting exercise at the sectoral level, 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.

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 et al. (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

[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.

[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)".

match our definition of persons engaged.[6] 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.[7] 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.[8] Appendix A gives further details on 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.[9] 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 depending on their task-content in the United States into routine and non-routine.[10] 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. Table 1 lists the resulting classification of occupations into these three groups. When we analyse the data we alternatively focus on routine vs. non-routine occupations or on the categorization into routine, manual, and abstract occupations. To conduct our cross-country analysis with labour differentiated by occupation, we collapse the dataset according to year, country and occupation.

For the 113 countries with complete information on persons engaged, hourly wages or

[6]Our construction of average wages/earnings reflect the number of hours worked in each occupation.

[7]The ILOSTAT and OWW datasets do not provide information on occupational wages/earnings and weekly hours worked for persons engaged, that is why we use the information available for employees. In the case of the relative occupational wages-earnings, this procedure implicitly assumes that the ratios for persons engaged and employees are the same. With respect to the weekly hours worked, we are in practice assuming that the shares of the total occupational worked hours are the same for employees and persons engaged.

[8]Specifically, we use 5% State Sample 1990 and the ACS of 2005 and 2014. For the classification of occupations, we used the "harmonized occupation coding scheme based on the Census Bureau's 2010 ACS occupation classification scheme" available in IPUMS USA. In its most aggregated groups, this classification can be roughly matched with the ISCO 1 digit and with our grouping of occupations presented in Table 1.

[9]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.

[10]While Autor and Dorn (2013) exclude agricultural occupations from their analysis of U.S. labour markets, we assign these to the group of routine occupations. We want to keep workers in these jobs in our development accounting analysis since (i) they contribute to GDP and (ii) for many less developed economies the agricultural employment share is not as small as it is for the U.S.

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: The abstract and manual occupations jointly give the set of all non-routine occupations. Note that in the 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).

earnings and weekly hours worked, we collect macro data from the Penn World Tables (PWT) version 10.0 provided by Feenstra et al. (2015), the World Development Indicators of the World Bank (2021), and from ILOSTAT on GDP, GDP per worker, capital stock, the labour share in GDP and other relevant variables. We will use these macro variables when conducting our development accounting exercise which tries to identify how GDP differences across countries can arise due to differences in technologies and in production factors, capital and the various occupational labour inputs. For GDP we use the output-side real GDP at chained PPPs (in mil. 2017US$) from the PWT, as constant PPP allows us to make cross-country and cross-time comparisons. Our variable for capital stock comes from the PWT version 10.0, which measures the capital stock at constant local currency units and at current PPP (in mil. 2017US$); thus, we use the GDP deflator between the output-side real GDP at current PPPs and the output-side real GDP at chained PPPs to convert the capital stock from current PPP 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 two (four) broad sectors shown in Appendix Table A1.[11] Second, for the sectoral analysis of Section 5, we differentiate

[11]Each dataset has a specific classification scheme for industries, we therefore focus on broader sectors

between goods and services sectors. The goods sector can be broken into agriculture and industry sectors, this is relevant as for some developing countries agriculture represents a high share of the valued added and employment. The services sector is split into high skilled and low skilled services, based on the skills or educational composition of labour in each industry, which is a standard in the recent structural transformation literature (Buera and Kaboski (2012), Duernecker et al. (2017), Bárány and Siegel (2021)).

For the sectoral data we use the World Input-Output Database (WIOD) by Timmer et al. (2015) and World KLEMS[12] to obtain data on sectoral nominal gross value added, sectoral nominal capital stock, sectoral labour share and sectoral number of total hours worked by persons engaged. To deflate sectoral gross value added and the capital stock, we use the GGDC Productivity Level Database (benchmark 2005) by Inklaar and Timmer (2014) to obtain the sectoral PPP for 2005. The PPPs' sectoral breakdown matches with our goods and services industry-grouping. The fact that we only have access to the sectoral PPPs for the goods and services sectors and only for one year (2005) restricts the analysis of occupation-specific technology levels by sector to 31 countries.[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. 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 82.30 (83.81) percent of observations corresponding to 2015 (1995) or more recent years.[14] [15]

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

only, which we can construct consistently across the different datasets by assigning them to one of our broad sector classifications

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

[13]However, with the amount of data collected, it is possible to estimate the relative sectoral-occupational technologies for other countries and years. We can do this because the model expressions for the sectoral-occupational technologies do not include the absolute real values of sectoral gross value added and capital stock.

[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).

[15]If we focus our attention on the sectoral level, we have a total of 73 countries, of which 52 belong to the "1990s" sample, 55 to the "2005" sample (as mentioned, we include a sample for "2005" in order to obtain the absolute labour augmenting technologies at the sectoral level using sectoral PPP data from the GGDC Productivity Level Database) and 60 to the "2010s" sample. In the "2010s" sample 90 percent of observations correspond to 2014 or more recent years.

aggregate and occupational data, whereas the sectoral dataset contains 70 countries. Finally, we conduct an exercise to detect outliers and exclude them from the analysis.[16] 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, we are able to estimate the absolute labour augmenting technologies for 31 countries (all for the "2005") and the relative technologies for 41 countries (25 for the "1990s", 36 for the "2005" and 35 for the "2010s"). 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.

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 and economic development. We show how the employment and income share of labour in routine occupations and how the relative wages of routine workers vary with real GDP per hour worked in the cross-section of countries. Figure 1 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] 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 U.S. since the 1950s).

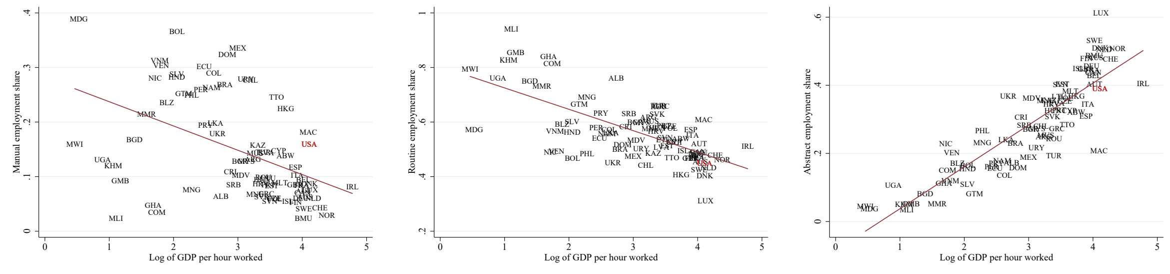
In Table 2 (columns two to four) we show how the annual average percentage point change of the employment shares per occupation vary across the cross-country distribution of the GDP per hour worked. Countries at the top of the income distribution have experienced, on average, a faster annual decrease in the routine employment share compared with the bottom quartile. This suggest the existence of a process of substitution

[16]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).

[17]We can compute in our data also the correlation between the employment shares in terms of occupations and in terms of skills. In the 1990s, the correlation between abstract and skilled labour shares was 0.71, whereas the correlation between routine and unskilled was 0.36 (37 countries included). For the 2010s, these correlations are 0.80 and 0.20, 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 cannot fully capture the full dynamics associated with technical change biased against routine workers.

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

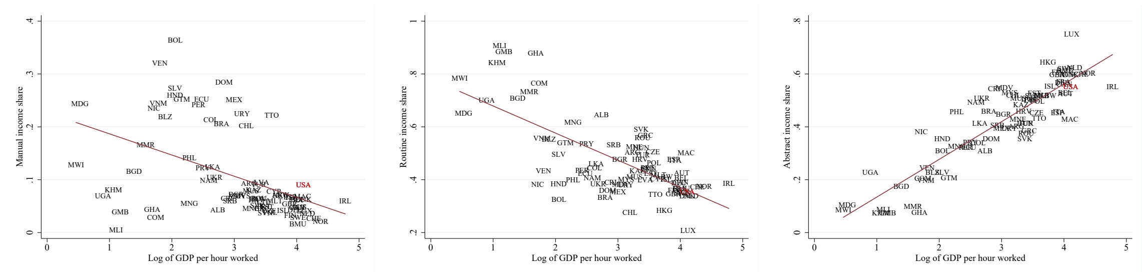


(a) Manual share (b) Routine share (c) Abstract share

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 2 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.

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



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

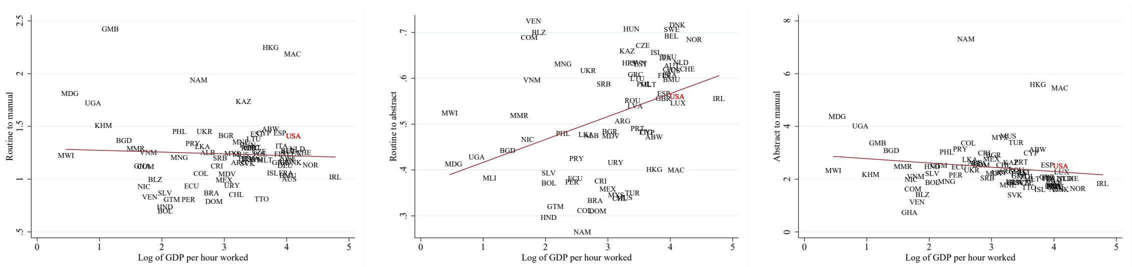
Notes: This figure plots the three occupational groups' occupational income share against log of real GDP per hour worked based on the cross-section of countries in the 2010s. In this figure the 2010s sample contains 81 countries.

[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.

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 3 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 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 (Appendix Figure A1 and Figure A2 present additional information on the employment structure). 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.

Figure 3: 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.

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	0.16
2	-0.14	-0.24	0.38	-0.11	-0.43	0.54	-0.43	0.00
3	0.05	-0.31	0.26	-0.05	-0.45	0.50	0.82	-0.47
4	-0.01	-0.31	0.32	-0.06	-0.45	0.51	0.35	-0.53

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.

3 Analysis with an Aggregate Production Function

Similar to Bárány and Siegel (2021) we make assumptions about the degree of substitutability or complementarity between different forms of occupational labour by imposing a structure on the production function. Assuming perfect competition in labour markets, we then derive profit maximising firms' optimality conditions which equate an occupation's wage rate to its marginal product which in turn is a function of production inputs. We invert these optimality conditions to back out for each country factor-augmenting productivity terms from observables. In particular, we make use of data on the occupational labour input shares and mean wages by occupation to infer –conditional on a value of the elasticity of substitution– relative technologies of occupational labour inputs within a country. In specifications with capital as further production factor, the amount of capital per hour worked together with the share of capital in total value-added pins down the relative technology of capital compared to the labour technologies. Given the observed factor inputs and the relative technologies of each country, we solve for the technology levels such that the countries' implied real GDP per hour worked matches the one in the data.[19] The method of inferred factor-augmenting technology is in essence the

[19]Note, these occupation-specific technologies are different to occupations' marginal products or wages. An occupation's marginal product does not depend on an occupation's technology alone, but also on the other occupations' technologies and the occupational employment structure. Given the observables our model allows to infer the occupation-specific technologies. In our baseline analysis of this section we draw on a one-sector model to study overall GDP differences as this does not require sectoral data. One concern might be that cross-country differences in the sectoral composition of value-added or in relative sectoral prices might be confounding our results (c.f. foontnote 2). However, in section 5 we show that in the subset of countries for which we have sectoral data, the general patterns of the occupation-biased technology differences across countries also holds at the sectoral level.

approach of Bárány and Siegel (2021), but applied to the cross-country context.[20]

As discussed in the introduction, we infer technology based on the observed equilibrium allocation of workers into occupations (as well as other objects in the data). That this allocation reflects occupational choices does not pose a problem to backing out technologies. However, if occupational choices are affected by technologies, for instance through their effects on wages, this endogeneity matters for the role of technological differences in shaping cross-country differences in GDP. In section 4 we will therefore conduct two types of counterfactuals. In the first one, we will study consequences of eliminating technology differences at given inputs, including the occupational structure. In the second type of experiments, we will allow countries' occupational composition to adjust to changes in technology by endogenising occupational choice.

To explain our approach we start in Section 3.1 with a much simplified production function that distinguishes only between routine and non-routine labour. In Section 3.2 we differentiate further between manual, routine, and abstract occupational labour inputs, and develop our preferred specification that also models capital as production factor in Section 3.3.

3.1 Routine and Non-routine Labour as Distinct Inputs

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[21]

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

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 B the optimality conditions of the representative firm's

[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] Throughout we use CES specifications for our aggregate production function. As noted by Bárány and Siegel (2021), this has some advantages. First, CES functions are relatively simple to calibrate, allowing to capture the nature of occupation-biased technical change with a small set of parameters. Second, CES functions are flexible enough to avoid the need of imposing restrictions on the nature of technical change. Third, this production side approach does not require to make assumptions about the sources of changes in relative wages, and we are not obliged to model labour supply choices and capital accumulation.

profit maximisation problem can be rearranged to give

$$\frac{\mu_{R,i}}{\mu_{N,i}} = \left(\frac{1-\alpha}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{w_{R,i}}{w_{N,i}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{R_i}{N_i}\right)^{\frac{1}{\sigma-1}}, \tag{2}$$

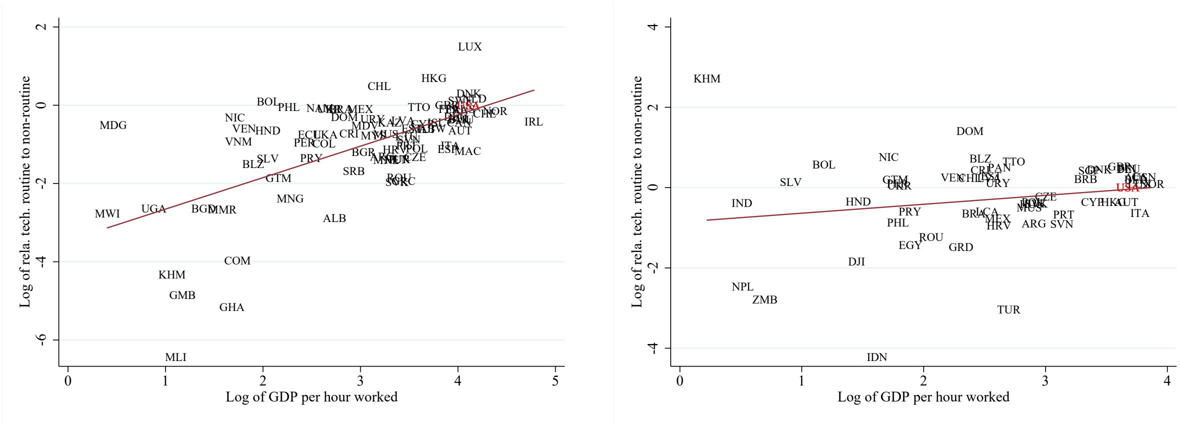
where $w_{R,i}$ and $w_{N,i}$ denote the routine and the non-routine wage rates respectively. This condition informs us about the optimal relative occupational productivities within a country. Equation (2) together with (1) allows us to derive country i's routine technology as

$$\mu_{R,i} = \left(\frac{Y_i^{\frac{\sigma-1}{\sigma}} w_{R,i} R_i^{\frac{1}{\sigma}}}{\alpha(w_{R,i}R_i + w_{N,i}N_i)}\right)^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

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 (2) 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; (3) gives us $\mu_{R,i}$ and $\mu_{N,i}$ follows from (2). 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 4.

While there is some dispersion in the implied relative routine to non-routine technologies, Figure 4a 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 1). Figure 4 also reveals that, while due to data availability the 1990s sample contains a smaller set of countries, the relationship between relative routine to non-routine technologies and GDP per hour worked is also positive in the 90s decade. However, it is worth to note that the slope of the regression line in Figure 4a

Figure 4: Relative routine to non-routine technologies based on (1) 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 (1) 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.

is statistically significant and is approximately 3.6 times higher than the slope in the regression line of Figure 4b (which is not statistically significant), suggesting that the technical bias against routine workers in more developed economies has increased over time.[22]

3.2 Routine, Manual and Abstract Labour as Distinct Inputs

One drawback of the parsimonious specification in the previous subsection is that it lumps all non-routine labour together into one category. Yet, as the task content differs substantially within the non-routine category, in particular with respect to cognitive activities, we now split non-routine into manual and abstract occupations. Following Bárány and Siegel (2021) we allow for the technologies of all three occupational groups to differ and assume for the aggregate production function

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

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. Just like before, Y_i is the real GDP per hour worked and σ the elasticity of substitution

[22]Due to data availability the set of countries included in the 1990s and in the 2010s cross-section differs. However, the increasing routine-bias over time we see also in the balanced panel of 44 countries. Between the 1990s and the 2010s, routine labour augmenting technical change has been the fastest, see Table 5.

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 results hold through when relaxing this assumption.

Assuming perfect competition in labour markets, we can derive (see Appendix B) expressions for relative technologies within a country as

$$\frac{\mu_{M,i}}{\mu_{A,i}} = \left(\frac{1-\alpha-\beta}{\beta}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{w_{M,i}}{w_{A,i}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{M_i}{A_i}\right)^{\frac{1}{\sigma-1}}, \tag{5}$$

$$\frac{\mu_{R,i}}{\mu_{M,i}} = \left(\frac{\beta}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{w_{R,i}}{w_{M,i}}\right)^{\frac{\sigma}{\sigma-1}} \left(\frac{R_i}{M_i}\right)^{\frac{1}{\sigma-1}}, \tag{6}$$

where 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

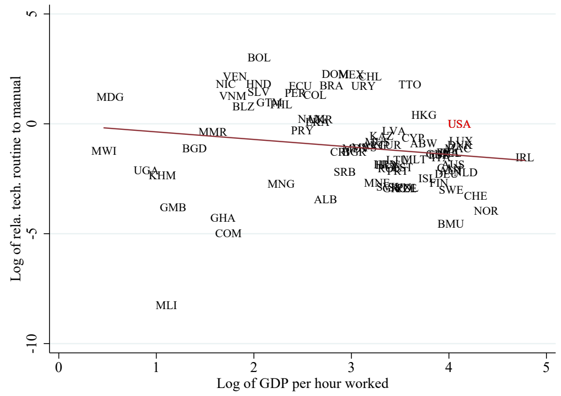
$$\mu_{M,i} = \left(\frac{Y^{\frac{\sigma-1}{\sigma}} w_{M,i} M_i^{\frac{1}{\sigma}}}{\beta(w_{R,i}R_i + w_{M,i}M_i + w_{A,i}A_i)}\right)^{\frac{\sigma}{\sigma-1}}. \tag{7}$$

We set, as in Bárány and Siegel (2021), the substitution elasticity $\sigma = 0.6$, and take again the US as the benchmark economy for which we normalise all factors' technologies to take the same value, i.e. $\mu_{R,benchmark} = \mu_{M,benchmark} = \mu_{A,benchmark}$. We then use equations (5) and (6) to obtain a value for α and β, which given our normalisation capture a combination of the occupational intensities and the relative occupational productivities of the US. However, as already noted before, this normalisation does not drive any of our results as all our results are 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 (5) to (7). This gives us all countries factor-augmenting technologies, $\mu_{R,i}, \mu_{M,i}, \mu_{A,i}$ relative to the US economy.

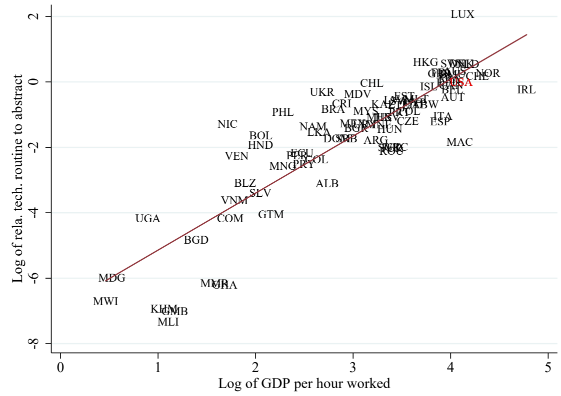
Figure 5 plots the resulting relative technologies against GDP per hour worked in the 2010s and 1990s. The two periods display similar patterns, indicating that the connection between occupation-biased technical change is fairly stable over time.[23] These plots reveal several important insights. First, the relative technologies do vary considerably with economic development as captured by real GDP per hour worked. Second, while

[23] When we estimate the regression lines of the four sub-figures in Figure 5 we find that the slopes for routine to manual technologies vs GPD per hour worked are not extremely different in the 1990s (-0.51) and 2010s (-0.34); however, the slope of the line for routine to abstract technologies in the 2010s is approximately 2.3 times higher compared to the slope in the 1990s.

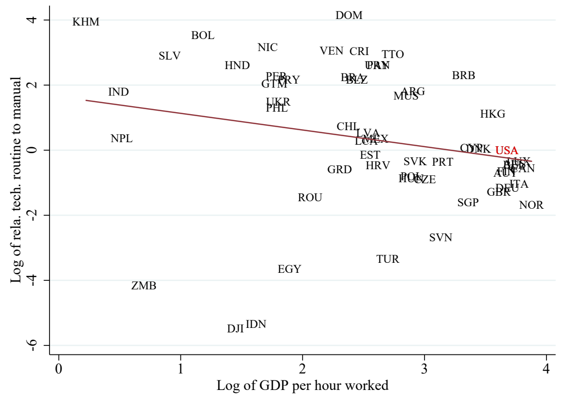
Figure 5: Relative technologies based on (4) vs real GDP per hour worked



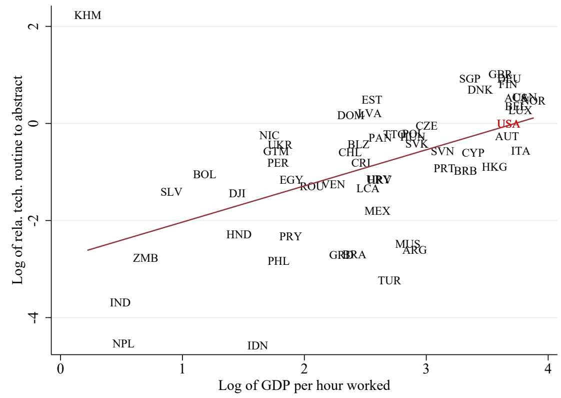
(a) Routine to manual technologies (2010s)



(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 (4) 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.

the technology of routine compared to abstract labour tends to increases with GDP per hour worked, it decreases relative to manual labour's technology. Third, the differential trends of manual and of abstract relative technologies implies that it is important to differentiate between the two occupational groups. Specifying the production function as in (4) is therefore better suited for a development accounting exercises than the one in (1), which pooled manual and abstract labour, and thus their factor-augmenting technologies, together into the non-routine group. Fourth, accounting for these three occupational groups gives new insights beyond what has been established in the literature that differentiate between unskilled and skilled labour. While there might be a strong connection between the share of college-educated workers and the abstract employment share, our results highlight differential technology trends between manual and routine labour, which a model with only two inputs, such as two skill groups, would not be able to identify.

3.2.1 Routine, Manual and Abstract Labour and Capital as Inputs

The simple production function in (4) 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 would be to assume a Cobb-Douglas production function in capital and a CES labour aggregator of the following form:

$$Y_i = K_i^{\gamma}\left(\left(\alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}} + \beta(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha-\beta)(\mu_{A,i}A_i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}\right)^{1-\gamma}. \quad (8)$$

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 (5) and (6), which pin down relative technologies within a country, continue to hold. Accounting for capital in the neutral way assumed in (8) affects only the level we infer for a country's technology, which is now given by

$$\mu_{M,i} = \left(\frac{Y^{\frac{1}{1-\gamma}\frac{\sigma-1}{\sigma}} w_{M,i} M_i^{\frac{1}{\sigma}}}{\beta K_i^{\frac{\gamma}{1-\gamma}\frac{\sigma-1}{\sigma}}(w_{R,i}R_i + w_{M,i}M_i + w_{A,i}A_i)}\right)^{\frac{\sigma}{\sigma-1}}. \quad (9)$$

But since (5) and (6) 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 3 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.[24] As one would expect, the ranking of GDP per hour worked, which of course is a measure of the productivity of an economy's average 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 5 percent above the cross-country average, the bottom 25 percent have abstract technologies that are 6 percent above the world average. This dispersion is much smaller

[24] 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 3 with the results provided by the nested CES specification we present in section 3.3.

Table 3: Cross-country comparison of occupation-augmenting technologies in 2010s based on (8)

Quartile of GDP p.w.	GDP p.w. rel. to world	Technology relative to world avg.		
		Manual	Routine	Abstract
1	0.33	0.03	0.31	1.06
2	0.74	0.19	0.55	1.04
3	1.14	0.62	0.98	0.84
4	1.82	3.22	2.21	1.05

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 (8) 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.

than the spread in GDP per hour worked in this cross-section. In contrast, differences in manual technologies across GDP per hour worked quartiles are much more pronounced, 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.

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

In the previous sections when we include capital as an additional input in our aggregate production function we use a Cobb-Douglass structure in capital, assuming efficiency neutrality in the way this input is used in the production process. We can relax this assumption by using a nested CES production function to rule out efficiency neutrality in capital. We adopt the structure of the nested formulation used by Bárány and Siegel (2021), allowing for factor-augmenting technology for capital.[25] Our nested CES specification has the following structure:

$$Y_i = \left(\phi\left[\alpha(\mu_{R,i}R_i)^{\frac{\sigma-1}{\sigma}} + \beta(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha-\beta) \times (\mu_{A,i}A_i)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}\frac{\eta-1}{\eta}} + (1-\phi)(\mu_{K,i}K_i)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \tag{10}$$

where $\mu_{K,i}$ is the factor-augmenting technology for capital in country i. In this formulation the most inner nesting is the combination of effective routine, abstract and manual

[25] 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 vary across the occupational labour inputs.

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. Using the production function (10) we can back out the countries' technologies from observables conditional on $\sigma < 1$ and $\eta < 1$ with the following expression (see Appendix B for derivations):

$$\frac{\mu_{K,i}}{\mu_{R,i}} = \left(\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{1}{\eta-1}} \frac{r_i}{w_{R,i}} \left(\frac{\phi}{1-\phi}\right)^{\frac{\eta}{\eta-1}} \alpha^{\frac{\sigma}{\sigma-1}} \left(\frac{1}{\theta_{R,i}}\right)^{\frac{\eta-\sigma}{(\sigma-1)(\eta-1)}} \tag{11}$$

$$\frac{\mu_{R,i}}{\mu_{A,i}} = \left(\frac{\theta_{R,i}}{\theta_{A,i}}\right)^{\frac{1}{\sigma-1}} \frac{w_{R,i}}{w_{A,i}} \left(\frac{1-\alpha-\beta}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \tag{12}$$

$$\frac{\mu_{R,i}}{\mu_{M,i}} = \left(\frac{\theta_{R,i}}{\theta_{M,i}}\right)^{\frac{1}{\sigma-1}} \left(\frac{\beta}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \frac{w_{R,i}}{w_{M,i}} \tag{13}$$

$$\mu_{K,i} = \frac{Y_i}{K_i(1-\phi)^{\frac{\eta}{\eta-1}} \left(\frac{(1-\Theta_{K,i})}{\Theta_{K,i}} + 1\right)^{\frac{\eta}{\eta-1}}}, \tag{14}$$

where $\Theta_{K,i} = \frac{r_i K_i}{Y_i}$ is the non-labour share in GDP of country i, r_i is the rental price of capital[26] in country i and $\theta_{o,i}$ the share of labour income going to occupation $o \in \{R, M, A\}$. We take the US as the benchmark economy to normalise all factors's technologies and define $\mu_{R,benchmark} = \mu_{M,benchmark} = \mu_{A,benchmark} = \mu_{F,benchmark}$. This helps us to obtain α, β and ϕ, using equations (11), (12) and (13). When using the data to infer technologies here, we take –as in the other specifications– the US as the benchmark economy and set the elasticity parameters to $\sigma = 0.60$ and $\eta = 0.84$ (all factors are considered to be gross complements), which are the values Bárány and Siegel (2021) use in their calibration against US data. Figure 6 plots the relative routine labour augmenting technologies for the 2010s and 1990s.

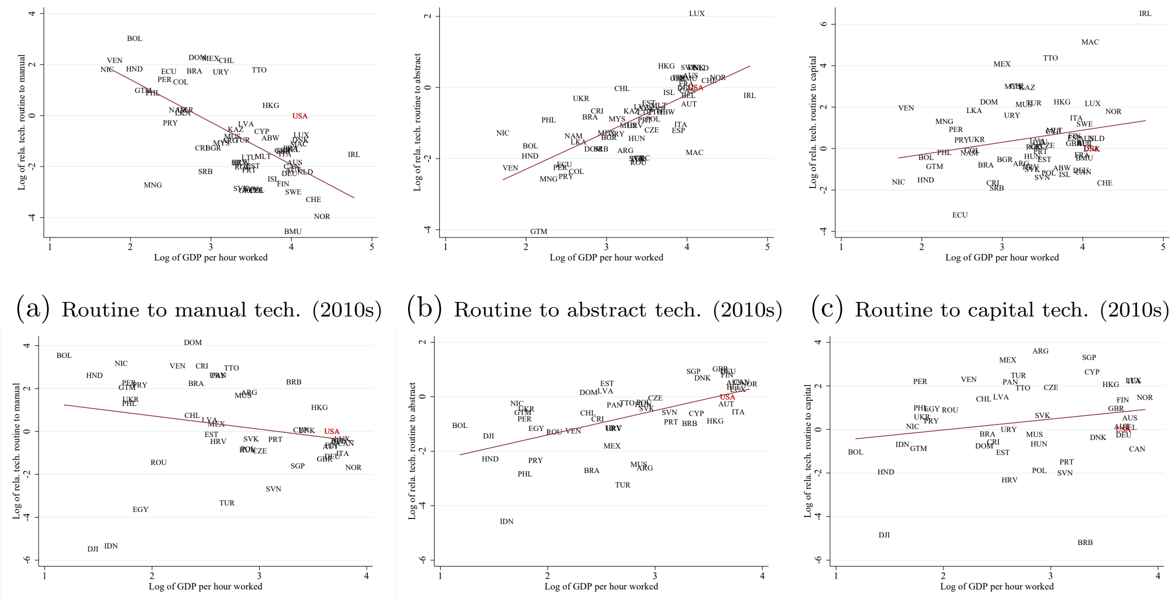
The relative technologies of routine to manual and abstract occupations display the same patterns documented before for both samples. This is not a surprise, as the occupational labour inputs are aggregated using the same symmetric structure as in equation (4). However, that technology becomes more routine-biased compared to capital in both samples, is a conclusion beyond what was possible to infer with the aggregate production function (8).[27] Equation (10) is our preferred specification as it incorporates all

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

[27] When we estimate the regression lines of the six sub-figures in Figure 6 we find that, while the slopes for the lines for routine to abstract and capital technologies are rather similar between the 1990s and the 2010s, the slope for routine to manual technologies in the 2010s is approximately 5 times higher than the corresponding slope in the 1990s.

mechanisms we want to account for, yet is parsimonious enough as it only requires the calibration of two elasticity parameters.

Figure 6: Relative technologies based on (10) 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 (10) 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 the technologies in the 2010s across countries by reporting the ratios of the quartile average of a technology relative to the world average for each occupation-specific technology.[28] The results in Table 4 resemble those obtained in Table 3. The dispersion in manual labour augmenting technologies is higher than the one observed in the GDP per hour worked and the other factor augmenting technologies. Routine workers in countries at the top of the income distribution use on average 11 times better technology than routine workers in countries located in the bottom 25 percent. An interesting result is that allowing for non-neutrality in the efficiency of capital increases the dispersion in routine and abstract labour augmenting technologies. Finally, capital augmenting technology is the least dispersed factor augmenting technology in the 2010s cross-section.

To some degree, the patterns in the occupation-specific technologies that we document here echo those for sectoral labour productivity or TFP differences across countries. It is well known that with development the share of the agricultural sector declines and

[28] In Table A4 we present a cross-country comparison of the occupational employment structure and by quartiles of occupation augmenting technologies.

Table 4: 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	0.06	0.22	0.66	0.84
2	0.74	0.25	0.66	0.86	0.62
3	1.14	0.43	0.76	0.57	1.00
4	1.82	3.33	2.42	1.94	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 (10) with $\sigma = 0.60$ and $\eta = 0.84$. In this figure 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.

the one of services increases (e.g. Herrendorf et al. (2014)) and that amongst broad economic sectors the cross-country productivity gaps are largest in agriculture (e.g. Caselli (2005), Duarte and Restuccia (2010)). Given how occupational employment shares vary with development in Figure 1, it might seem that our findings for the dispersions of occupational technologies pick up these known sectoral facts, in particular if one associates routine occupations with manufacturing and abstract occupations with service sector jobs. However, our results are not just reflecting these sectoral differences for two reasons. First, the classification of workers into occupations is not due to sectors and there is no one-to-one mapping from one to the other. Second, the patterns of the occupation-bias in technology are also discernible within economic sectors, as we show in Section 5 for the set of countries where we have sectoral data.

Finally, we extend the cross-country comparison of occupation-specific technologies to an over-time comparison. For the sub-sample of 43 countries for which we can compute technologies in the 1990s and in the 2010s we present the results in Table 5, where for each country and technology we compute the geometric rate of growth. While countries at the top of the income distribution have experienced a higher rate of growth for manual and routine labour augmenting technologies, all countries report a negative growth in capital augmenting technologies. Our results indicate that more developed countries have experienced faster routine-biased technical change than less developed countries, with the fastest changes in the third quartile of GDP per hour worked.

Table 5: 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	4.41	5.27	-0.62	-1.49	2.87
3	6.12	6.05	1.52	-2.17	2.73
4	4.36	4.95	0.13	-1.87	1.69

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 (10) 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.

4 Implications of technical differences for cross-country dispersion in GDP per hour worked

To understand the role the identified technologies play in shaping cross-country productivity differences, we conduct a series of counterfactual exercises based on our baseline results of Section 3.3. In a first set of experiments, we evaluate in partial equilibrium what the cross-country distribution would have looked like if all countries had an input's frontier technology, at given inputs. To do this we assign, one by one, to each technology the highest value we found in our analysis across all countries in the 2010s. In a second set of experiments we allow for the occupational employment shares to adjust in response to technologies. To do this, we utilize an equilibrium model where occupational choice and occupational labour demands respond endogenously to changes in technologies.

4.1 Implications of technology differences at given inputs

In this exercise, we assign to each technology the highest value we found in our analysis across all countries in the 2010s and we leave the other technologies and all inputs at their actual values. We then compute in each simulation and in the data the implied ratio of GDP per hour worked at the 90th percentile to the 10th percentile, as well as the 90-to-50 and the 50-to-10 percentile ratio. Table 6 shows the results.

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 of GDP per hour worked, the effect would have been relatively modest (a reduction by 6.4 percent), considering that this technology has

Table 6: Data and Counterfactual Inequality in Partial Equilibrium of GDP per hour worked in the 2010s

Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology				
		Manual	Routine	Abstract	Capital	All
90-10 Ratio	6.22	5.82	5.39	8.65	5.45	4.06
90-50 Ratio	1.95	1.89	1.67	2.56	1.88	1.62
50-10 Ratio	3.19	3.08	3.23	3.37	2.90	2.51

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 (10) 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.

the highest dispersion across the income distribution (as shown in Table 4). A somewhat larger effect would occur if all economies had access to the best routine technology (13.3 percent), even though the dispersion in routine technologies is smaller than the one of manual (see Table 4). 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 1), 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 in 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.

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. This would reduce per hour worked income differences by about 35 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 technologies reduces inequality by more in the bottom of the distribution (by about 21 percent) than in the top (by about 17 percent). On the contrary, eliminating differences in routine technologies only, compacts the distribution of GDP per hour worked more at the top (by about 14 percent) than at the bottom. Yet these numbers are considerably smaller than what the literature has found when not differentiating labour by occupation.[29] The reason we find smaller gains

[29] In Figures A3 and A4, and Tables A5 and A6 we show that these results are qualitatively the same when we use information solely coming from persons engaged or male workers.

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. Note, in computing these counterfactuals we kept countries' occupational employment shares constant. 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

In our previous counterfactual exercises we have kept countries' occupational employment shares constant. However, one would expect that the process of convergence in technologies goes hand-in-hand with changes in the occupational employment structure. To evaluate the full effect that technology has on cross-country differences in GDP, we should take into account how the various technologies through their impact on the occupational labour demands impact wages and the employment structure. To do this, we adapt the model of Bárány and Siegel (2020) to the cross-country context. 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 C. 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 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 8).

In this model with endogenous occupational employment structure, we then re-run our counterfactual exercises. Table 7 reports the resulting inequality measures and Table 8 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.

By large our conclusions are unchanged but several things are worth to point out. We continue to see that assigning the best abstract technology to all countries increases

Table 7: Data and Counterfactual Inequality of GDP per hour worked in the 2010s under Endogenous Occupational Labour Shares

Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 Ratio	6.22	4.90	5.52	9.57	5.45	3.66
90-50 Ratio	1.95	1.87	1.59	2.56	1.88	1.56
50-10 Ratio	3.19	2.63	3.48	3.74	2.90	2.34

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 C. 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.

cross-country income disparities. However, this effect here is even larger than in partial equilibrium with constant occupational shares, since equalising only the technology of abstract occupations, but keeping all other technologies constant, widens the cross-country differences in the occupational employment structure (see Table 8). In terms of assigning only the best manual or the best routine occupational technology to all countries, there is one very noticeable difference to the previous results. In general equilibrium manual augmenting technologies account for most of the observed GDP per hour worked differences across countries (measured by the 90-10 ratio of GDP per hour worked), while in partial equilibrium routine technologies were the most equalising. However, routine augmenting technologies still have the highest equalising effect in the 90-50 ratio. In our last experiment we eliminate all technology differences across countries. When we assign all the best input-specific technologies to all countries the dispersion of the GDP per hour worked is compressed the most. In terms of the 90-10 ratio, the per hour worked income differences are reduced by approximately 41 percent (compared to 35 percent in partial equilibrium, see Table 6). While the 90-50 ratio changes under endogenous occupational composition 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.

Table 8 presents how the occupational labour shares change in each of the counterfactual scenarios. When we assign one occupation's best technology to all countries, there is a reduction in the labour share of that occupation across the income distribution. However, note that the labour share ordering in the occupation that is being substituted remains preserved across the distribution of countries. When we assign all occupations' best technologies at once to all countries, there is an assimilation of the occupational employment structure across the income distribution, towards the employment structure of countries located at the top quartiles of the GDP per hour worked. Precisely, this assimilation process is the main driver behind the higher reduction in inequality of GDP per hour worked differences in general equilibrium in comparison to partial equilibrium.

Table 8: 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	0.31	0.31	0.30	0.61	0.08	0.05	0.66	0.29	0.14	0.57	0.30
2	0.15	0.57	0.28	0.22	0.34	0.45	0.19	0.68	0.13	0.04	0.63	0.33	0.11	0.56	0.33
3	0.10	0.53	0.36	0.15	0.28	0.57	0.15	0.70	0.15	0.03	0.57	0.40	0.10	0.53	0.37
4	0.08	0.47	0.46	0.10	0.26	0.63	0.12	0.67	0.20	0.03	0.49	0.48	0.09	0.51	0.40

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 C. 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.

5 Sectoral Analysis

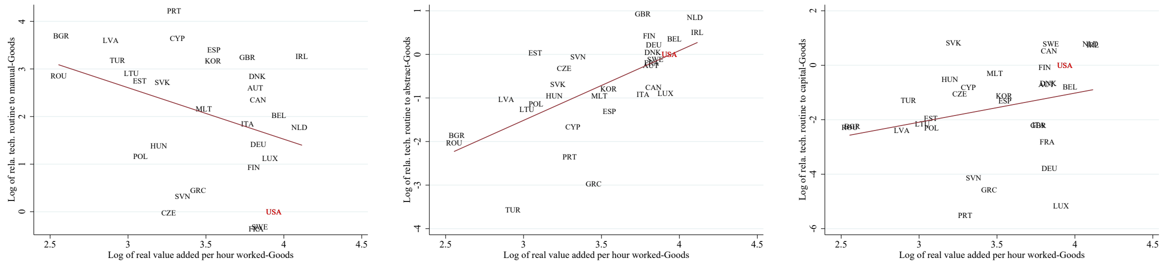
With the aim to see whether the results presented in previous sections stem from cross-country differences in sectoral composition and to study the nexus between biased technical change, employment structure, and structural transformation, we conduct our analysis at the sectoral level. To implement this, we use our benchmark equation (10) and our sectoral-occupational data already described in Section 2.1. We have collected data for the goods sector and for the services sector that allows us to compute the absolute and relative factor augmenting technologies in these two sectors. We focus our attention on the year 2005, as it allows us to compute the absolute and relative technologies with the same cross sectional sample and data.

In Figure 7 we plot the inferred sectoral factor-augmenting relative technologies against the sectoral value added per hour worked at current PPPs (2005 US$). While the results are based on a reduced sample of 31 countries,[30] the patterns 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. That is, our results on the occupation bias in technology that we documented based on the aggregate production function and in the much larger sample of countries are upheld also within the sectors

[30] All countries in this sample, with the exemption of Korea, are included in our 2010s sample.

we consider here. Yet, for the services sector the labour augmenting technology of routine occupations compared to capital technology decreases with average sectoral labour productivity, which differs from the aggregate pattern.

Figure 7: Sectoral relative technologies based on (10) vs sectoral real value added per hour worked for 2005



(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 (10) with $\sigma = 0.60$ and $\eta = 0.84$ against log sectoral real value added per hour worked in the 2005 for the goods and services sectors. In this figure the 2005 sample contains 31, where the sub-sample contains only the countries for which we have sectoral 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 can compute relative factor augmenting technologies, but not conduct our accounting exercise as sectoral PPP data to deflate value-added and the capital stock are not available. Most technology patterns seen in the two sector classification of Figure 7 are discernible in the finer four sector classification of Appendix Figure A5 too. 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 industry sub-sector: 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 industry sub-sector, 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 and sub-sectoral composition across goods and services.

Table 9: Sectoral Data and Counterfactual Inequality of GDP per hour worked in 2005

Goods- Counterfactual: Best Technology						
	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 Ratio	5.68	5.32	4.11	6.42	8.28	2.28
90-50 Ratio	1.92	1.80	1.37	2.12	2.84	1.39
50-10 Ratio	2.96	2.96	3.00	3.03	2.92	1.63
Services- Counterfactual: Best Technology						
	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 Ratio	2.02	2.04	2.47	2.83	2.92	1.62
90-50 Ratio	1.34	1.32	1.31	1.47	1.78	1.19
50-10 Ratio	1.50	1.55	1.88	1.92	1.64	1.36

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 (10) with $\sigma = 0.60$ and $\eta = 0.84$. In this table the 2005 sample contains 31 countries, where the sub-sample contain only the countries for which we have sectoral data.

We replicate our counterfactual exercise of Section 4 to evaluate how the cross-country sectoral income distribution would have looked like if all countries had access to the best factor augmenting technology. Assigning the sector specific technology frontier of routine occupations to all countries in the goods sector and leaving the other technologies and all inputs at their actual values would have the most equalising effect. However, in the services sector assigning the best routine technology would increase the cross-country sectoral dispersion of output per hour worked between the 90th and the 10th percentiles. In fact, we observe that all 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-50 ratio in manual and routine abstract 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.[31] 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.

6 Robustness Checks and Extensions

To check for the robustness of our results, we conduct a series robustness checks and extensions. Firstly, we calibrate our preferred specification of the aggregate production function under a different set of substitution elasticities to see if our conclusions are sensitive to different parametrisation. Secondly, we take into account cross-country differences in human capital and include efficiency units of labour into our calibration. Finally, we use a different specification of the nested CES function and compare the results against our preferred specification of the aggregate production function.

6.1 Alternative and heterogeneous substitution elasticities

Our results using the benchmark equation (10) are based on a parametrisation with two set of elasticities: $\sigma = 0.60$ and $\eta = 0.84$. We also explore the impact of changing the values of these elasticities. To implement this we follow the "one-deviation principle" and change the values of the elasticities one by one, leaving everything else constant. These changes will impact 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. The alternative values we choose for the elasticities are guided by the literature, where the vast majority of studies allowing for productivity shifters have found values below one, both for the substitution elasticity between occupations (e.g. Goos et al. (2014), Lee and Shin (2017), Aum et al. (2018)) and for the one between capital and labour (e.g. Lawrence (2015), Herrendorf et al. (2015), Oberfield and Raval (2021)). Like Bárány and Siegel (2021) we use 0.70 and 0.50 as the alternative values for σ, while for η the alternative elasticities are 0.75 and 0.65. Table 10 shows the correlation between the 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

[31]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.

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.

We also explore how the results shown in our counterfactual analysis of the inequality of GDP per hour worked change with different parametrisation of the elasticities of substitution (see Appendix Table A7). First, we analyse the results when the values of σ change to 0.70 and 0.50. Routine and manual technologies continue to be the most alone equalising labour augmenting technologies in both scenarios. Also, we observe that when σ takes the value of 0.50 there is a decrease in the dispersion effect of assigning the best abstract labour augmenting technology. Second, we analyse the changes in our results when η takes the values of 0.75 and 0.65. When the elasticity of substitution between occupations and capital is below 0.84 the equalising effect of routine and abstract labour augmenting technologies increases. Overall, our conclusions are robust to the change in the elasticity of substitution between labour inputs and between labour inputs and capital.

Table 10: Correlation between factor augmenting technologies based on (10) 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: $\sigma = 0.60$ & $\eta = 0.84$	-0.65	0.00	0.70	0.00	0.23	0.07
Alternative: $\sigma = 0.70$	-0.65	0.00	0.69	0.00	0.25	0.05
Alternative: $\sigma = 0.50$	-0.65	0.00	0.72	0.00	0.22	0.08
Alternative: $\eta = 0.75$	-0.65	0.00	0.70	0.00	0.52	0.00
Alternative: $\eta = 0.65$	-0.65	0.00	0.70	0.00	0.72	0.00

Notes: This table presents the relative technologies inferred based on the aggregate production function (10) 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.

6.2 Nested CES with efficiency units of labour

In our baseline equation (10) we are implicitly assuming that workers in all countries have the same efficiency level, as labour inputs are represented by the share of hours worked per occupation. Not taking into account cross-country differences in human capital might obscure the role of routine biased technical change in explaining differences in productivity between countries. In order to assess the role of human capital, we adopt the approach of Bárány and Siegel (2021) and augment the model for efficiency units of labour by fitting a Mincer log wage regression. We adopt two strategies. In the first one we run a Mincer wage regression (equation (15)) for each country with all the required information available. 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 et al. (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

$$\log(w_j) = \beta_0 + \beta' X_j + \epsilon_j, \tag{15}$$

where X_j is a vector of worker js' characteristics, which includes years of schooling s_j, a second order polynomial for potential work experience e_j interacted with a dummy for college education (15 years or more of education) *college* and a gender dummy $female$.[32]

To ensure comparability of the Mincerian returns across countries, we use a similar definition for years of schooling based on the International Standard Classification of Education (ISCED). In addition, we deflate the nominal wages/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. After running regression (15) in each country, we predict the workers' efficiency units using formula (16). Finally, we obtain the averages per occupation and country. 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 (16)

$$\begin{aligned} e_j = \exp(\hat{\beta}_1\, s_j + \hat{\beta}_2\, female_j + &\hat{\beta}_3\, e_j + \hat{\beta}_4\, e_j^2 \\ &+ \hat{\beta}_5\, college_j + \hat{\beta}_6\, college_j * e_j + \hat{\beta}_7\, college_j \times e_j^2). \end{aligned} \tag{16}$$

Table 11 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

[32] We define potential work experience as $e_j = age_j - s_j - 6$.

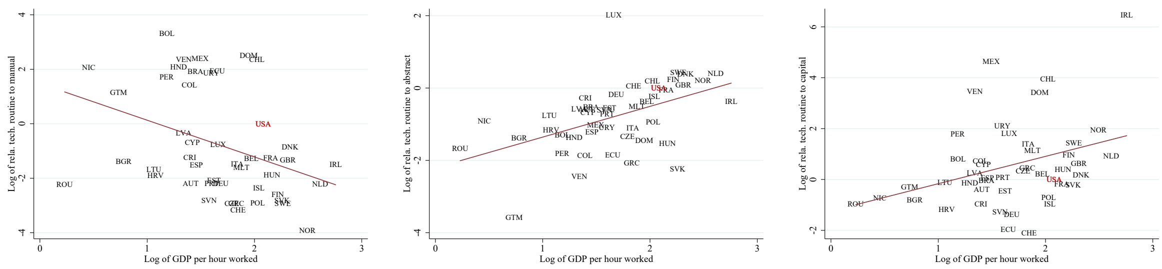
amount of labour that the firm optimally chooses to $oe_i = o_i * \bar{e}_{o,i}$, where $o \in \{R, M, A\}$. Thus, we can obtain an estimate of the occupational efficiency wages per hour in country i as $\hat{w}_{o,i} = \frac{\bar{w}_{o,i}}{\bar{e}_{o,i}}$.

Table 11: Data on average efficiency units of labour by occupation in the 2010s

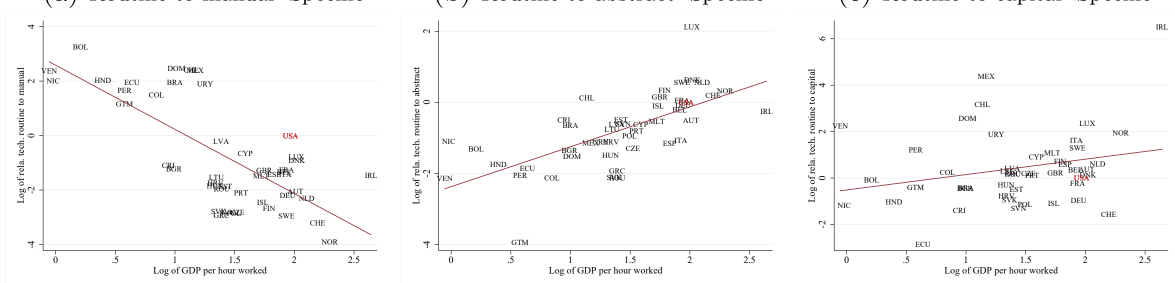
Quartile of GDP p.h.w	Capital p.h.w	Country-specific Mincer regression			Benchmark country Mincer regression		
		Manual	Routine	Abstract	Manual	Routine	Abstract
1	50.16	2.79	2.64	5.41	5.52	5.28	9.09
2	162.68	5.67	6.94	11.21	6.27	6.7	9.61
3	234.33	5.55	6.33	8.37	6.22	6.86	9.41
4	331.24	6.48	7.23	9.19	5.94	6.78	9.63
USA	214.26	5.77	6.63	9.44	6.38	7.47	10.54

Notes: This table reports by quartile of real GDP per hour worked the average efficiency units of labour by occupation predicted from (16) based on estimating (15) in each country (columns 3 to 5) and on estimating (15) 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 8: Relative technologies with efficiency units of labour based on (10) vs real GDP per hour worked in the 2010s



(a) Routine to manual- Specific (b) Routine to abstract- Specific (c) Routine to capital- 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 (10) 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 sub-samples 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 this information we proceed to re-calibrate equation (10) and obtain the factor augmenting technologies for the 2010s (see Figure 8). In the first panel of Figure 8 the efficiency units of labour are obtained from country-specific Mincer regressions, while in the second panel the efficiency units are obtained using the US as the benchmark country to run the Mincer regression. Figure 8 contains a smaller set of countries compared to our baseline scenario (see Figure 6), as we only include countries in which we can compute the efficiency units of labour using our two strategies. While we have a smaller set of countries, the patterns displayed by the two panels of this figure are qualitatively and quantitatively similar to the ones observed in our baseline scenario.

Table 12: Data and Counterfactual Inequality of GDP per hour worked with efficiency units of labour in the 2010s

Country-specific Mincer regression						
Range of GDP	Actual	Counterfactual: Best Technology				
per hour worked	Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	3.48	3.48	3.52	4.82	5.21	3.28
90-50 ratio	1.92	1.83	1.80	2.13	2.67	1.41
50-10 ratio	1.81	1.90	1.96	2.26	1.95	2.33
Benchmark country Mincer regression						
Range of GDP	Actual	Counterfactual: Best Technology				
per hour worked	Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	4.24	3.74	4.51	7.71	4.13	3.38
90-50 ratio	1.80	1.83	1.56	2.21	1.51	1.43
50-10 ratio	2.35	2.04	2.89	3.50	2.73	2.36

Notes: 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 aggregate production function (10) with $\sigma = 0.60$ and $\eta = 0.84$ with efficiency units of labour. The top panel reports results based on country-specific Mincer returns in the construction of labour efficiency units. The bottom panel's results are obtained using the US as the benchmark country in the construction of the Mincer coefficients. 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 as well as age and years of schooling by occupation.

We also compute the counterfactual scenarios shown in Section 4 (see Table 12). For this smaller sample, both panels show that there is less dispersion of the output per hour worked, however, our main conclusions remain unchanged, as in both panels manual and routine labour augmenting technologies have the most equalising effect when we vary one technology at a time. Quantitatively, the equalising role of capital augmenting technology differences is somewhat reduced when we account for efficiency units of labour.

6.3 Different nested CES specification

As a robustness test to our baseline specification (10), we also explore a different structure of the nested CES production function. This new 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 asssume here for the aggregate production function

$$Y_i = \Bigg(\alpha(\mu_{M,i}M_i)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\Big[\beta(\mu_{A,i}A_i)^{\frac{\gamma-1}{\gamma}} + (1-\beta) \times \left(\phi(\mu_{R,i}R_i)^{\frac{\eta-1}{\eta}} + (1-\phi)(\mu_{K,i}K_i)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta(\gamma-1)}{(\eta-1)\gamma}}\Big]^{\frac{\gamma(\sigma-1)}{(\gamma-1)\sigma}}\Bigg)^{\frac{\sigma}{\sigma-1}} \tag{17}$$

where in the most inner nesting routine labour and effective capital are nested together and considered to be gross substitutes, i.e. $\eta > 1$. This gives a routine-task aggregate that is then combined with effective 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 effective manual labour under a substitution elasticity σ to produce final output.[33]

Under the production function (17), a country's technologies can be backed out from observables (again conditional on parameterizing the substitution elasticities) according to the following equations (see Appendix B for derivations):

$$\frac{\mu_{K,i}}{\mu_{R,i}} = \frac{r_i}{w_{R,i}}\left(\frac{\phi}{1-\phi}\right)^{\frac{\eta}{\eta-1}}\left(\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{1}{\eta-1}} \tag{18}$$

$$\frac{\mu_{A,i}}{\mu_{R,i}} = \left(\frac{\theta_{A,i}}{\theta_{R,i}}\right)^{\frac{1}{\gamma-1}}\left(\frac{1-\beta}{\beta}\right)^{\frac{\gamma}{\gamma-1}}\left(\frac{w_{A,i}}{w_{R,i}}\right)\phi^{\frac{\eta}{\eta-1}}\left(1+\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{R,i}}\right)^{\frac{\gamma-\eta}{(\eta-1)(\gamma-1)}} \tag{19}$$

$$\frac{\mu_{M,i}}{\mu_{A,i}} = \left(\frac{\theta_{M,i}}{\theta_{A,i}}\right)^{\frac{1}{\sigma-1}}\left(\frac{w_{M,i}}{w_{A,i}}\right)\left(\frac{1-\alpha}{\alpha}\right)^{\frac{\sigma}{\sigma-1}}\beta^{\frac{\gamma}{\gamma-1}}\left(1+\frac{\theta_{R,i}}{\theta_{A,i}}+\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{A,i}}\right)^{\frac{\sigma-\gamma}{(\gamma-1)(\sigma-1)}} \tag{20}$$

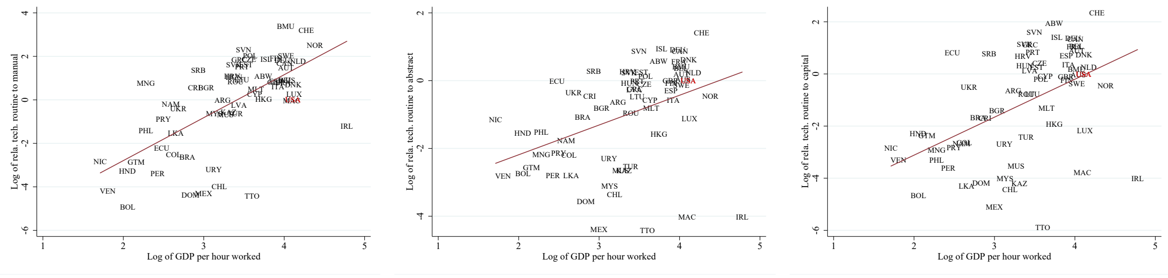
$$\mu_{M,i} = \frac{Y_i}{\alpha^{\frac{\sigma}{\sigma-1}}M_i\left(1+\left(\frac{\theta_{A,i}}{\theta_{M,i}}\right)\left(1+\frac{\theta_{R,i}}{\theta_{A,i}}+\frac{\Theta_{K,i}}{(1-\Theta_{K,i})\theta_{A,i}}\right)\right)^{\frac{\sigma}{\sigma-1}}}, \tag{21}$$

When using the data to infer technologies here, we take –as in the other specifications–

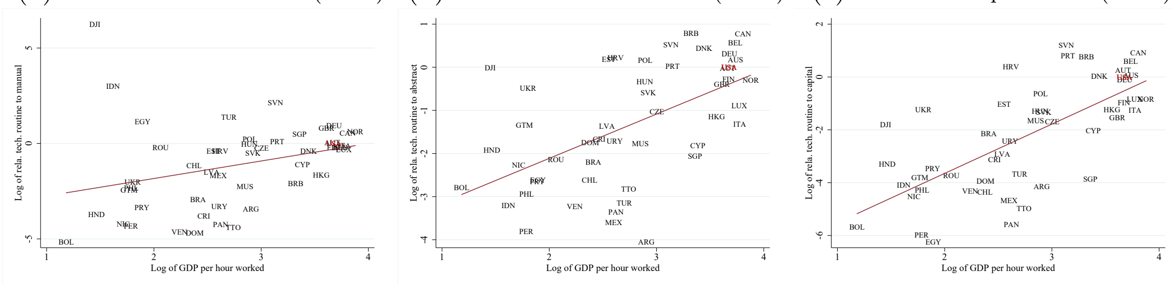
[33]This production structure implies that the effects of capital accumulation on the demand for labour differs across the occupational groups. This in line with Kehrig (2018)'s finding that the degree of substitutability between computer equipment and labour varies across occupations.

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 9 plots the inferred relative technologies in the 2010s and the 1990s cross-sections of countries.

Figure 9: Relative technologies based on (17) 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 (17) 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.

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 in both samples. The patterns in technology of routine compared to abstract labour are qualitatively the same as in our baseline, whereas the relationship between 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 9, 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 $\sigma > 1$.[34] In contrast, the pattern of relative routine to abstract technologies is qualitatively the same in Figures 6 and 9 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 (17) both inputs are considered to be gross substitutes. This is due to the structure of the aggregate production function, in which several bundles of inputs are aggregated together with different elasticities of substitution. In fact, 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 the countries' average income per hour worked. Hence, overall the results derived from the nested specification (17) are in line with what we found under our preferred specification (8).

When we evaluate the implications of technical differences for cross-country dispersion in average labour productivity based on the nested production function (17), we draw virtually the same conclusions as under our baseline specification. In Table 13 we show measures of GDP per hour worked dispersion implied by eliminating differences in factor-augmenting technologies across countries. These numbers are similar to the ones in Table 6, even more so when focusing on the model implied dispersion relative to the dispersion in the data. In this specification the routine technology is the one that compresses the most the distribution of the GDP per hour worked among all factor augmenting technologies. The distribution is equalized even more when countries are assigned the best possible technology for each production factor, just as in Table 6. Overall we see that the results are robust across alternative specifications of the (aggregate) production function.

Table 13: 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	6.22	5.18	3.85	6.51	4.56	2.65
90-50 ratio	1.95	1.82	1.54	1.98	1.69	1.43
50-10 ratio	3.19	2.84	2.49	3.28	2.69	1.86

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 (17) 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.

[34] 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.

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 31 countries with data also at the sector-occupation level.

We establish a series of new facts of economic development. We document that the employment share of routine and manual occupations decreases with the increase of the GDP per hour worked, whereas the share of abstract occupations has a positive relationship with average productivity. We further show that in more developed countries the routine labour share has decreased more rapidly than in less developed countries, while the share of abstract occupations exhibits the opposite pattern.

Drawing on our model framework with the three occupational labour inputs for a development accounting exercise, we demonstrate that while the technology of routine occupations tends to increase with the GDP per hour worked compared to abstract occupations, it decreases with respect to manual occupations. We further document that with development technology becomes more routine-biased compared to capital. Analysing the dispersion of technologies across the GDP per hour worked distribution, we find that the dispersion of manual augmenting technologies is higher than the one observed in the other factor augmenting technologies, with capital-augmenting technologies being the less disperse. Our results suggest that the productivity of routine workers in the top quartile of countries, which tend to have low routine employment shares, is about 11 times higher than in the bottom quartile of countries ranked by GDP per hour worked. Interestingly, we see that countries in the upper half of the distribution have experienced a faster growth of routine-augmenting technologies between the 1990s and the 2010s. These results are complementary to Rossi (2022) who documents that highly educated workers are relatively more productive in rich countries. While his finding is 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 technologies would impact GDP differences. We find that eliminating manual or routine technology differences would have comparable equalising effects. However, for the technology of abstract occupations we find that if all countries were assigned the frontier technology the dispersion of GDP per hour worked would increase. This is due to international differences in the occupational employment structure, with more developed countries having a higher share of abstract occupations. When we eliminate all cross-country differences in technologies by assigning the frontier values for each occupation and for capital, we find the most compressing effect: per hour worked income differences would be reduced by about 35 percent. When we allow for countries' employment structure to adjust to technology in our model with endogenous occupational choice, this effect becomes even stronger, approximately 41 percent.

Our results, which are robust to various alternative specifications and parametrisations, highlight the nuanced nature of economic development. There are many well-known differences between the technology used in rich and in poor countries. What we newly demonstrate is that there are also occupation-biases in the technology differences. Our paper highlights that not only occupation-biased technical change and the occupational employment structure vary systematically with development, but also that level differences in occupation-specific technologies matter for cross-country GDP differences.

References

Aum, S., Lee, S. Y. T., and Shin, Y. (2018). Computerizing industries and routinizing jobs: Explaining trends in aggregate productivity. *Journal of Monetary Economics*, 97(C):1–21.

Autor, D. H. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5):1553–97.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *The American Economic Review*, 96(2):189–194.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Bárány, Z. L. and Siegel, C. (2018). Job Polarization and Structural Change. *American Economic Journal: Macroeconomics*, 10(1):57–89.

Bárány, Z. L. and Siegel, C. (2020). Biased Technological Change and Employment Reallocation. *Labour Economics*, 67(1):101930.

Bárány, Z. L. and Siegel, C. (2021). Engines of Sectoral Labor Productivity Growth. *Review of Economic Dynamics*, 39(1):304–343.

Buera, F. J. and Kaboski, J. P. (2012). The Rise of the Service Economy. *American Economic Review*, 102(6):2540–69.

Buera, F. J., Kaboski, J. P., Rogerson, R., and Vizcaino, J. I. (2021). Skill-Biased Structural Change. *The Review of Economic Studies*. rdab035.

Caselli, F. (2005). Accounting for Cross-Country Income Differences. In Aghion, P. and Durlauf, S. N., editors, *Handbook of Economic Growth*, volume 1, chapter 9, pages 679 – 741. Elsevier.

Caselli, F. (2016). *Technology Differences over Space and Time*. Princeton University Press.

Caselli, F. and Ciccone, A. (2013). The contribution of schooling in development accounting: Results from a nonparametric upper bound. *Journal of Development Economics*, 104(C):199–211.

Caselli, F. and Ciccone, A. (2019). The Human Capital Stock: A Generalized Approach: Comment. *American Economic Review*, 109(3):1155–74.

Caselli, F. and Coleman, W. J. (2006). The World Technology Frontier. *American Economic Review*, 96(3):499–522.

Caunedo, J., Keller, E., and Shin, Y. (2021). Technology and the task content of jobs across the development spectrum. Working Paper 28681, National Bureau of Economic Research.

Duarte, M. and Restuccia, D. (2010). The Role of the Structural Transformation in Aggregate Productivity. *The Quarterly Journal of Economics*, 125(1):129–173.

Duernecker, G. and Herrendorf, B. (2022). Structural Transformation of Occupation Employment. *Economica*, n/a(n/a). forthcoming.

Duernecker, G., Herrendorf, B., and Valentinyi, A. (2017). Structural Change within the Service Sector and the Future of Baumol's Disease. Working Paper DP12467, CEPR.

Eurostat (2021a). Labour Force Survey (EU-LFS) microdata 1983-2020. Release 2021, version 1.

Eurostat (2021b). European Union Statistics on Income and Living Conditions (EU-SILC) microdata 2003-2020. Release 2021, release 2, rev 1.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The Next Generation of the Penn World Table. *American Economic Review*, 105(10):3150–3182. available for download at www.ggdc.net/pwt.

Freeman, R. B. and Oostendorp, R. H. (2012). The Occupational Wages around the World (OWW) Database: Update for 1983-2008. Retrieved January 20, 2020.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, 104(8):2509–26.

Hall, R. E. and Jones, C. I. (1999). Why do Some Countries Produce So Much More Output Per Worker than Others? *The Quarterly Journal of Economics*, 114(1):83–116.

Hendricks, L. (2002). How Important Is Human Capital for Development? Evidence from Immigrant Earnings. *American Economic Review*, 92(1):198–219.

Hendricks, L. and Schoellman, T. (2022). Skilled Labor Productivity and Cross-Country Income Differences. *American Economic Journal: Macroeconomics*. forthcoming.

Herrendorf, B., Herrington, C., and Valentinyi, A. (2015). Sectoral Technology and Structural Transformation. *American Economic Journal: Macroeconomics*, 7(4):104–33.

Herrendorf, B., Rogerson, R., and Valentinyi, A. (2014). Growth and Structural Transformation. In *Handbook of Economic Growth*, volume 2, chapter 6, pages 855–941. Elsevier.

Inklaar, R. and Timmer, M. (2014). The relative price of services. *Review of Income and Wealth*, 60(4):727–746.

Inter-American Development Bank (IADB) (2021). Inter-American Development Bank: Harmonized Household Surveys of Latin America and the Caribbean (CMAEH). https://microdatos.iadb.org/node/11. Retrieved October 14, 2021.

International Labour Organization (ILO) (2020). International Labour Organization Statistics (ILOSTAT) [data set]. Retrieved January 20, 2020.

Jones, B. F. (2014). The Human Capital Stock: A Generalized Approach. *American Economic Review*, 104(11):3752–77.

Jäger, K. (2017). EU KLEMS Growth and Productivity Accounts 2017 release - Description of Methodology and General Notes. Open access publications from EU KLEMS and The Conference Board, EU KLEMS and The Conference Board.

Kehrig, M. (2018). Comment on "Computerizing Industries and Routinizing Jobs: Explaining Trends in Aggregate Productivity" by Sangmin Aum, Sang Yoon (Tim) Lee and Yongseok Shin. *Journal of Monetary Economics*, 97:22–28.

Klenow, P. and Rodriguez-Clare, A. (1997). The neoclassical revival in growth economics: Has it gone too far? In *NBER Macroeconomics Annual 1997, Volume 12*, pages 73–114. National Bureau of Economic Research, Inc.

Kunst, D. (2019). Deskilling among manufacturing production workers. Discussion Paper 2019-050/VI, Tinbergen Institute.

Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018). Life Cycle Wage Growth across Countries. *Journal of Political Economy*, 126(2):797–849.

Lawrence, R. Z. (2015). Recent Declines in Labor's Share in US Income: A Preliminary Neoclassical Account. Working Paper 21296, National Bureau of Economic Research.

Lee, S. Y. T. and Shin, Y. (2017). Horizontal and Vertical Polarization: Task-Specific Technological Change in a Multi-Sector Economy. Working Paper 23283, National Bureau of Economic Research.

Manuelli, R. E. and Seshadri, A. (2014). Human Capital and Wealth of Nations. *American Economic Review*, 104(9):2736 – 2762.

Mas, M. and Benages, E. (2020). Knowledge-based Capital in a Set of Latin American Countries: The LA KLEMS-IADB Project. Open access publications from LA KLEMS, LA KLEMS.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25 years. *The Review of Economics and Statistics*, 96(1):60 – 77.

Minnesota Population Center (2020). Integrated Public Use Microdata Series, International. Version 7.2 [dataset].

Montenegro, C. E. and Hirn, M. L. (2009). A new disaggregated set of labor market indicators using standardized household surveys from around the world. World development report background paper, World Bank.

Ngai, L. R. and Pissarides, C. A. (2007). Structural Change in a Multisector Model of Growth. *The American Economic Review*, 97(1):429–443.

Oberfield, E. and Raval, D. (2021). Micro data and macro technology. *Econometrica*, 89(2):703–732.

Reijnders, L. S. and de Vries, G. J. (2018). Technology, offshoring and the rise of non-routine jobs. *Journal of Development Economics*, 135:412–432.

Rossi, F. (2022). The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation. *American Economic Review*, 112(1):235–266.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., and Sobek, M. (2020). Integrated Public Use Microdata Series, International, USA. Version 10.0.

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. *Review of International Economics*, 23(3):575–605. available for download at http://www.wiod.org/home.

Vizcaino, J. I. (2021). Skills, Technologies and Development. Working paper, University of Nottingham.

vom Lehn, C. (2020). Labor market polarization, the decline of routine work, and technological change: A quantitative analysis. *Journal of Monetary Economics*, 110(1):62 – 80.

World Bank (2021). World Development Indicators. Retrieved February 11, 2021.

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.[35]

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

[35] For some countries and years ILOSTAT provides occupational information from two or more different surveys. We select only one survey using the following hierachy: 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 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.[36] 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 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,

[36] 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.

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 KLMES and GGDC Productivity Level Database

For the sectoral macro data we use the WIOD by Timmer et al. (2015), the World KLEMS and the GGDC Productivity Level Database by Inklaar and Timmer (2014). 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 use World KLEMS to complement the data for the countries and years not available in the WIOD. Both databases are in nominal values of LCU, then, in order to estimate the absolute labour augmenting technologies at the sectoral level, we use the GGDC Productivity Level Database, which contains information on the PPP at the industry level. This information is available for 42 countries and only for the service and good sectors and for the year 2005.[37]

[37]The goods sector includes: Agriculture, forestry & fishing; Mining & quarrying; Food, beverage & tobacco; Textile products; Leather & footwear; Wood products; Paper, printing & publishing; Coke & refined petroleum; Chemical products; Rubber & plastics; Non-metallic mineral products; Basic & fabricated metal; Machinery; Electrical & optical equipment; Transport Equipment; Other manufacturing; Utilities; Construction. The service sector includes: Motor vehicle & fuel trade; Wholesale trade; Retail trade; Hotels & restaurants; Land transport; Water transport; Air transport; Transport services; Post &

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 comnunications • 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
Goods	Agriculture	• Forestry and logging • Fishing and aquaculture	• Agriculture, forestry and fishing
	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
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
	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

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

telecommunications; Financial services; Real estate; Business services; Government; Education; Health; Other services; Households with employed persons.

Country	Year	Persons engaged	Wages-earnings	Weekly hours worked	Age	Schooling	Output	Persons engaged (overall economy)	Capital stock	Labour share
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
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

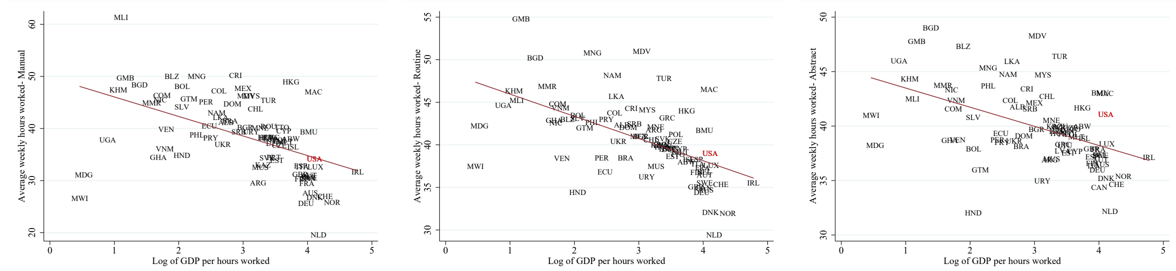
Country	Year	Persons engaged	Wages-earnings	Weekly hours worked	Age	Schooling	Gross value added	Persons engaged (overall economy)	Capital stock	Labour share	PPP (US$ 2005)
AUT	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
AUT	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
AUT	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
BEL	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
BEL	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
BGR	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
BGR	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
BRA	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	WIOD	WIOD	WIOD	WIOD	N.D.
BRA	2014	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	WIOD	WIOD	WIOD	WIOD	N.D.
CAN	1991	IPUMS-I	IPUMS-I	IPUMS-I	IPUMS-I	N.D.	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
CAN	2005	IPUMS-I	OWW	IPUMS-I	IPUMS-I	N.D.	WIOD	WIOD	WIOD	WIOD	GGDC
CHE	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
CHL	1990	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
CHL	2015	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
CRI	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
CRI	2005	CMAEH	OWW	OWW	N.D.	N.D.	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
CRI	2016	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
CYP	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	WIOD	KLEMS	N.D.
CYP	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
CYP	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
CZE	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.

Country	Year	Persons engaged	Wages-earnings	Weekly hours worked	Age	Schooling	Gross value added	Persons engaged (overall economy)	Capital stock	Labour share	PPP (US$ 2005)
CZE	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
CZE	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
DEU	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
DEU	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
DEU	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
DNK	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
DNK	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
DNK	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
DOM	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
DOM	2005	ILOSTAT	CMAEH	CMAEH	N.D.	N.D.	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
DOM	2016	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
ESP	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
ESP	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
EST	1997	EULFS	OWW	EULFS	EULFS	N.D.	KLEMS	KLEMS	WIOD	KLEMS	N.D.
EST	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
EST	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
FIN	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
FIN	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
FIN	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
FRA	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
FRA	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
GBR	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
GBR	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
GBR	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
GRC	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
GRC	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
HND	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
HND	2005	ILOSTAT	CMAEH	CMAEH	N.D.	N.D.	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
HND	2016	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
HRV	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
HUN	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	N.D.	N.D.
HUN	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
HUN	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
IDN	1995	IPUMS-I	IPUMS-I	IPUMS-I	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
IRL	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
IRL	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
ITA	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
ITA	2005	EULFS	OWW	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
ITA	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
KOR	2005	ILOSTAT	OWW	OWW	N.D.	N.D.	WIOD	WIOD	WIOD	WIOD	GGDC
LTU	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	WIOD	KLEMS	N.D.
LTU	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
LTU	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
LUX	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
LUX	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
LUX	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
LVA	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	WIOD	WIOD	WIOD	N.D.
LVA	2005	EULFS	OWW	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
LVA	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
MLT	2005	EUSILC	EUSILC	EUSILC	N.D.	N.D.	WIOD	WIOD	WIOD	WIOD	GGDC
NLD	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
NLD	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
NOR	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
NOR	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
PER	1999	CMAEH	CMAEH	CMAEH	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
PER	2005	I2D2	I2D2	I2D2	N.D.	N.D.	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
PER	2014	I2D2	I2D2	I2D2	CMAEH	CMAEH	KLEMS	KLEMS	KLEMS	KLEMS	N.D.
POL	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
POL	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
PRT	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	WIOD	KLEMS	N.D.
PRT	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
PRT	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
ROU	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	WIOD	KLEMS	N.D.
ROU	2005	EULFS	OWW	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
ROU	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
SVK	1999	EULFS	OWW	EULFS	EULFS	EULFS	KLEMS	KLEMS	WIOD	KLEMS	N.D.
SVK	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
SVK	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
SVN	1997	EULFS	OWW	EULFS	EULFS	N.D.	KLEMS	KLEMS	WIOD	KLEMS	N.D.
SVN	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
SWE	2005	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	GGDC
SWE	2014	EULFS	EUSILC	EULFS	EULFS	EULFS	WIOD	WIOD	WIOD	WIOD	N.D.
TUR	2005	ILOSTAT	OWW	OWW	N.D.	N.D.	WIOD	WIOD	WIOD	WIOD	GGDC
USA	2005	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	WIOD	WIOD	WIOD	WIOD	GGDC
USA	2014	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	IPUMS-U	WIOD	WIOD	WIOD	WIOD	N.D.

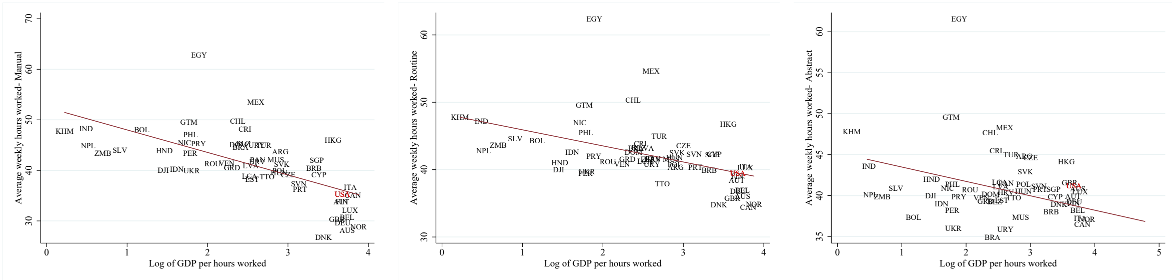
Note: N.D.= No data. IPUMS-I = IPUMS International. IPUMS-U = IPUMS USA. Gross value added = Gross value added at current basic prices (in mill, of LCU). Capital stock = Nominal capital stock (in mill. of LCU).

A.2 Additional Figures and Tables

Figure A1: Occupational average weekly hours worked vs log of GDP per hour worked



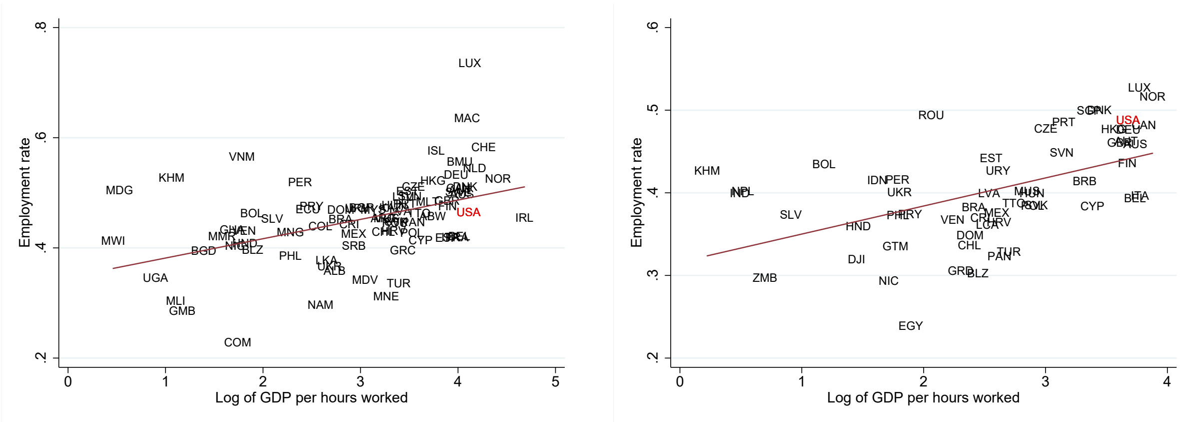
(a) Manual (2010s) (b) Routine (2010s) (c) Abstract (2010s)



(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 A2: Relative occupational employment rates vs real GDP per worker



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

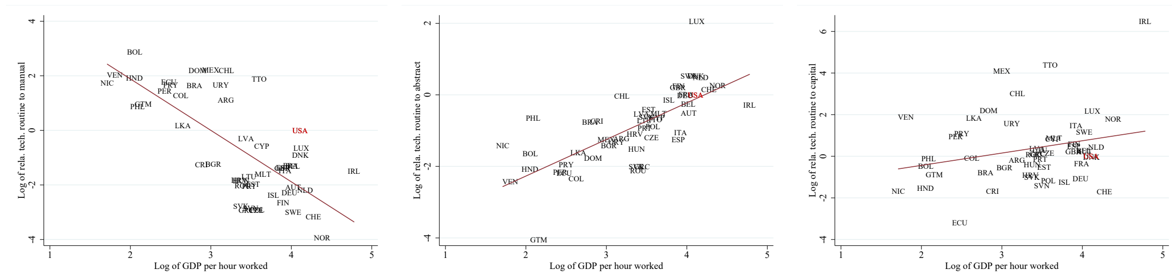
Note: This figure plots the employment rates against log GDP per worker in the cross-section of countries in the 2010s and the 1990s. In this figure the 2010s sample contains 81 countries and the 1990s 57 countries.

Table A4: Cross-country comparison of occupational employment structure vs quartiles of occupation augmenting technologies - in 2010s

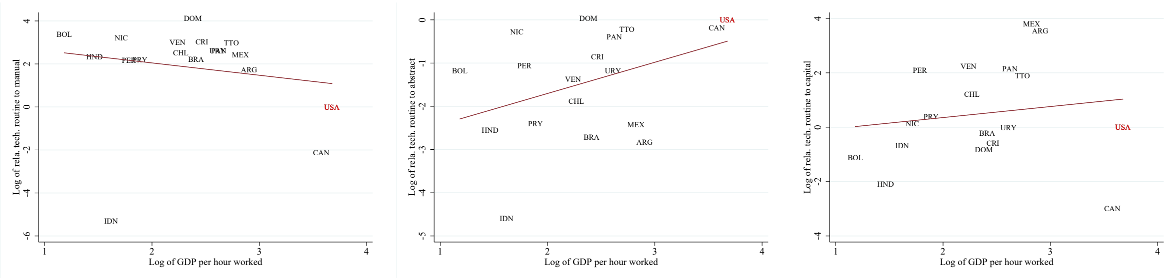
Quart. of tech.	Quartiles of $\mu_{M,i}$			Quartiles of $\mu_{R,i}$			Quartiles of $\mu_{A,i}$			Quartiles of $\mu_{K,i}$		
	M	R	A	M	R	A	M	R	A	M	R	A
1	0.27	0.53	0.20	0.16	0.57	0.27	0.11	0.49	0.40	0.20	0.54	0.26
2	0.15	0.53	0.31	0.17	0.56	0.28	0.12	0.50	0.38	0.16	0.56	0.28
3	0.09	0.55	0.37	0.10	0.49	0.41	0.15	0.55	0.30	0.13	0.51	0.35
4	0.08	0.51	0.42	0.17	0.50	0.34	0.21	0.57	0.23	0.09	0.51	0.40

Note: This table reports by quartile of specific factor augmenting technology (2010s) the average occupational labour share. This is based on the the aggregate production function (10) 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.

Figure A3: Relative technologies based on (10) 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)

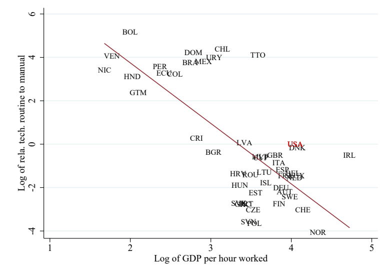
Note: This figure plots the relative technologies inferred based on the aggregate production function (10) with $\sigma = 0.60$ and $\eta = 0.84$ against log GDP per hour worked. In this plot we use non-adjusted hourly wages and the information on employment shares, hourly wages and weekly hours worked 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 A5: Data and Counterfactual Inequality of GDP per hour worked in the 2010s using information exclusively for persons engaged

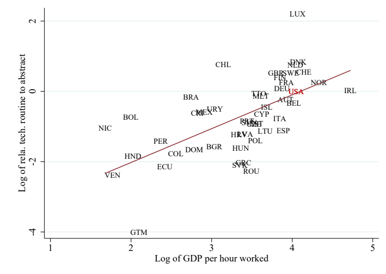
Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 ratio	7.05	6.10	5.85	9.56	5.39	4.17
90-50 ratio	1.90	1.92	1.66	2.29	1.72	1.62
50-10 ratio	3.71	3.17	3.52	4.18	3.13	2.57

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 (10) 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.

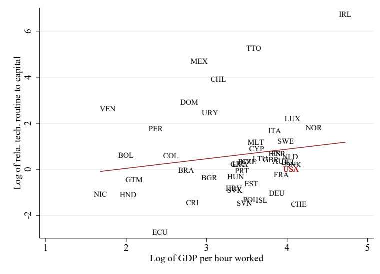
Figure A4: Relative technologies based on (10) vs real GDP per hour worked using information exclusevely for males



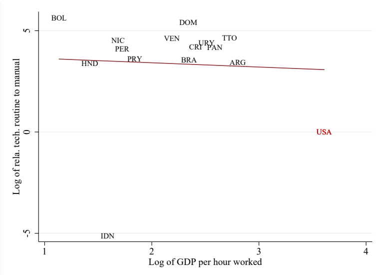
(a) Routine to manual tech. (2010s)



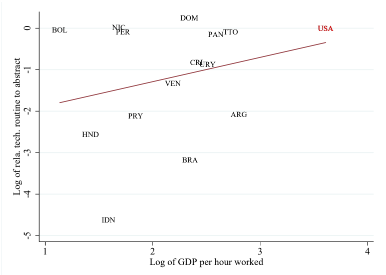
(b) Routine to abstract tech. (2010s)



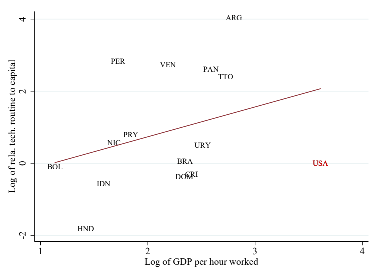
(c) Routine to capital tech. (2010s)



(d) Routine to manual tech. (1990s)



(e) Routine to abstract tech. (1990s)



(f) Routine to capital tech. (1990s)

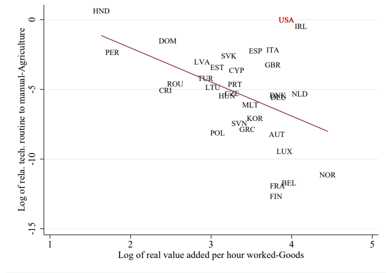
Notes: This figure plots the relative technologies inferred based on the aggregate production function (10) with $\sigma = 0.60$ and $\eta = 0.84$ against log GDP per hour worked. In this plot the information on employment shares, hourly wages and weekly hours worked comes entirely from males. In this 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 A6: Data and Counterfactual Inequality of GDP per hour worked in the 2010s using information exclusively for males

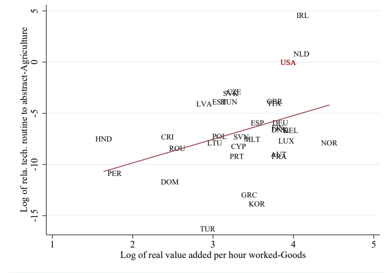
Range of GDP per hour worked	Actual Data	Counterfactual: Best Technology Manual	Routine	Abstract	Capital	All
90-10 ratio	7.17	5.15	6.44	11.91	6.41	4.37
90-50 ratio	1.72	1.77	1.41	2.26	1.93	1.43
50-10 ratio	4.17	2.91	4.55	5.27	3.33	3.05

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 (10) 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.

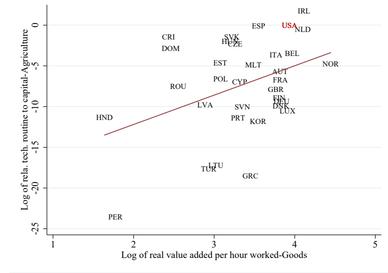
Figure A5: Sectoral relative technologies based on (10) vs sectoral real value added per hour worked for 2005



(a) Agriculture: Routine to manual tech.

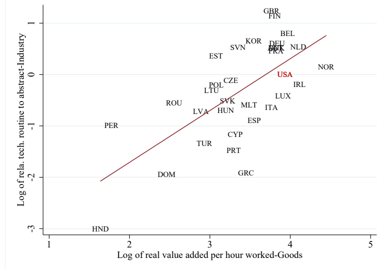


(b) Agriculture: Routine to abstract tech.

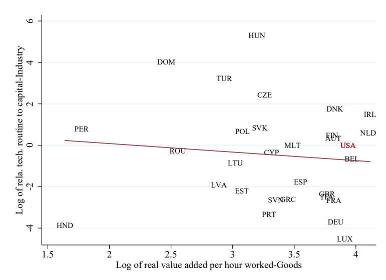


(c) Agriculture: Routine to capital tech.

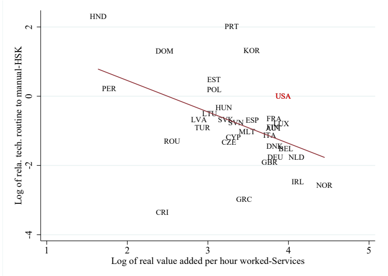
(d) Industry: Routine to manual tech.



(e) Industry: Routine to abstract tech.

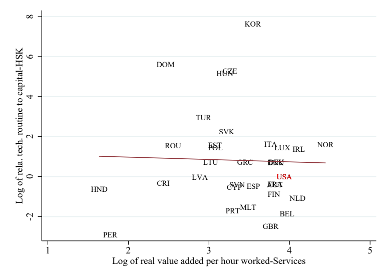


(f) Industry: Routine to capital tech.

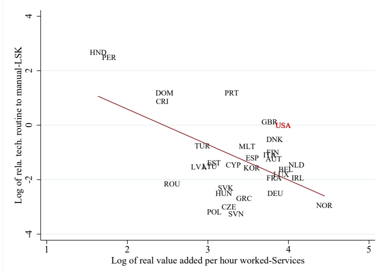


(g) HSK: Routine to manual tech.

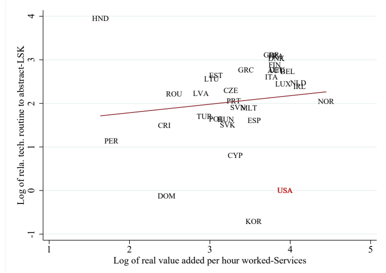
(h) HSK: Routine to abstract tech.



(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 (10) with $\sigma = 0.60$ and $\eta = 0.84$ against the log of goods sector's real value added per hour worked in the 2005 for agriculture and industry, and the the log of services sector's real value added per hour worked in the 2005 for high-skilled services (HSK) and low-skilled services (LSK). In this figure the 2005 sample contains 33 countries. The sub-sample contains only the countries for which we have sectoral data.

Table A7: 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	6.22	5.82	5.39	8.65	5.45	4.06
90-50 ratio	1.95	1.89	1.67	2.56	1.88	1.62
50-10 ratio	3.19	3.08	3.23	3.37	2.90	2.51
Alternative: $\sigma = 0.70$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.22	5.02	5.33	10.16	5.45	4.05
90-50 ratio	1.95	1.88	1.56	2.63	1.88	1.62
50-10 ratio	3.19	2.68	3.42	3.86	2.90	2.50
Alternative: $\sigma = 0.50$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.22	5.99	5.43	7.36	5.45	4.12
90-50 ratio	1.95	1.92	1.73	2.35	1.88	1.62
50-10 ratio	3.19	3.12	3.14	3.13	2.90	2.55
Alternative: $\eta = 0.75$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.22	5.81	5.20	8.07	4.45	4.51
90-50 ratio	1.95	1.89	1.66	2.46	1.60	1.67
50-10 ratio	3.19	3.08	3.14	3.29	2.78	2.70
Alternative: $\eta = 0.65$- Counterfactual: Best Technology						
ratio	Actual Data	Manual	Routine	Abstract	Capital	All
90-10 ratio	6.22	5.81	5.11	7.51	5.17	4.96
90-50 ratio	1.95	1.89	1.64	2.36	1.79	1.71
50-10 ratio	3.19	3.08	3.12	3.18	2.89	2.89

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 (10) 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 Derivations

CES aggregator in routine and in non-routine labour (Section 3.1)

Under the aggregate production function 1, 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 1. 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 (2) in the main text.

Symmetric CES aggregator in routine, manual, abstract labour (Section 3.2)
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 4. The first order conditions for routine, abstract, and manual occupational labour demands are:

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

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

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

which can be can rearranged to give equations 5 and 6 in the main text.

Routine, Manual and Abstract Labour and Capital as Inputs in a Nested CES Specification (Section 3.3)

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

where Y_i is production function specified in 10. 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 12 and 13 in the main text. The process to obtain equations 11 and 14 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 11 in the main text. Finally, plugging the optimum relative input of routine labour to capital and LA in equation 10 allows us to obtain equation14 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 17. 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 18 in the main text. The process to obtain equations 19 to 21 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 $\Theta_{K,i} = \frac{r_iK_i}{Y_i}$, 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:

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

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 19 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:

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

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 20 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 17 allows us to obtain equation 21 in the main text.

C 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 heterogenous workers that optimally select their occupation. In this economy firms operate under perfect competition and wages are such that clear the markets.

Production. The production function of this one-sector economy is represented by our benchmark equation (10). We take the output of this economy as given and then the problem of the representative firm is reduced to minimise the cost choosing occupational labour inputs in a competitive setting.[38] This allows us to endogenise 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 10)[39] and the optimal relative labour demands presented in Appendix B.[40]

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

Households –occupational choice. Following Bárány and Siegel (2020), in this economy we assume the existence of a unit measure of workers that face an idiosyncratic and country-specific cost when selecting one occupation. [41] 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 an occupation if:

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

[38] 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.

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

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

[41] 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.

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 $ln\left(\frac{w_{O,i}}{w_{Q,i}}\right) \geq \tilde{\xi}^j_{Q,i} - \tilde{\xi}^j_{O,i}$, then the occupational cost differences in country i are given by: $\tilde{\xi}^j_{1,i} = \tilde{\xi}^j_{A,i} - \tilde{\xi}^j_{R,i}$ 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:[42]

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

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

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

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.[43] With this set-up, we then calibrate the two means of this distribution (μ_1 and μ_2) and the two elements of the main diagonal in the variance-covariance matrix (σ^2_1 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.

[42] 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).

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

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	-1.31	4.17	-0.25	1.52
3	-0.78	2.15	0.06	1.11
4	-0.49	1.74	0.27	0.92

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.