Task-Biased Technology Adoption Across Countries

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This paper explores how differences in the adoption of task-biased technologies contribute to GDP gaps across countries. We introduce a country-specific measure of task intensity to quantify the relative importance of tasks within occupations, which can be readily applied in quantitative analysis. Using this measure, we show that as GDP increases, the share of routine work declines while cognitive work increases. Moreover, differences in task content within specific occupations explain more than half of the cross-country differences in routine work. We then develop a production framework where technology is task-specific, and occupations are aggregates of tasks, with which we rationalize both optimal task and occupational demands. We use this model to quantitatively assess the differences in task-biased technology adoption across countries and its implications for GDP gaps. Our main counterfactual exercise shows that closing the dispersion in task productivity adoption reduces the average GDP gap relative to the United States by around 25%.

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1. Introduction

Technology plays a central role in shaping labor allocation. Recently, the leading hypothesis in this context has been task-biased technological change, which claims that technological advancements disproportionately affect certain types of tasks or activities, leading to shifts in the demand for different kinds of labor. More specifically, routinization —the process by which standardized, repetitive tasks are increasingly automated—has been identified as a critical driver of these changes. While much of the literature has focused on the risks faced by certain occupations, there is a growing recognition that technological progress could ultimately alter the nature of work across all occupations. In other words, some jobs may disappear entirely, while others may evolve as technology redefines the tasks performed. Understanding the impact of task-biased technological change is therefore crucial for analyzing broader economic outcomes, such as productivity growth, wage inequality, and the divergence in labor market outcomes across countries. In this context, this paper aims to examine how countries vary in their adoption of task-biased technologies and how these variations contribute to disparities in GDP.

In the first part of the paper, we use data for 35 countries from the Survey of Adult Skills (PIAAC) to develop an occupation and country-specific measure of task intensity, which aims at quantifying the relative importance of tasks across occupations and countries. The key innovation of this measure is that it can be readily used in quantitative analysis. The methodology for constructing the task intensity measure involves a two-step approach. First, we conduct factor analysis to assign task scores to individuals based on the frequency of activities performed in their jobs. This process results in three distinct task categories: Cognitive, Interactive, and Routine. Each category correlates with specific sets of activities, allowing us to effectively capture the nuances of task performance within different occupations. Second, we rescale these scores to derive a quantitative measures of task intensity for each occupation and country, which reflect the relative importance of different tasks within jobs.

Our empirical analysis highlights a key relationship between GDP and task intensity: the share of routine work is decreasing with GDP, a result that aligns with the routine-biased technological change (RBTC) hypothesis. We next show that this pattern emerges through two channels: employment composition —richer countries, on average, have a lower share of employment in occupations intensive in routine tasks—; and within-occupation differences —in richer countries, all occupations are less intensive in routine tasks. A between-within decomposition reveals that the within-occupation channel accounts for more than half of the differences in routine work. This suggests that task-biased technological change not only results in "disappearing jobs", but also changes the nature of work within narrowly defined employment groups.

In the second part of the paper, we develop a production framework in which technology is task-specific. We define tasks as core activities performed at work. In the model, final output is produced by combining occupations, and occupations are different aggregates of a common set of tasks. Our model provides a framework to rationalize how task-specific productivities influence both task and occupational optimal demands. Specifically, we show that when both tasks and occupations are complements in production, an increase in the productivity of a task reduces the demand for that task across all occupations. In turn, it also decreases the labor share of the occupations where that task is relatively more important.

Next, using the production framework, we estimate relative task productivities across countries by leveraging data on wages, employment shares, and task intensities. Task-biased productivities are calibrated using the United States as a benchmark. Our analysis reveals significant cross-country differences in task productivities, particularly in routine tasks relative to cognitive and interactive tasks. These differences are positively correlated with GDP per capita: doubling GDP per capita increases routine task productivity relative to cognitive tasks by 112% and to interactive tasks by 58 %. This pattern reflects the complementarity between tasks and cross-country variations in task intensities.

Finally, through counterfactual exercises, we quantify the impact of eliminating dispersion in task productivities across countries. Equalizing task productivities reduces the average GDP gap relative to the U.S. for poorer countries by 25.6%, raising their GDP from 57% to 68% of U.S. levels. The analysis underscores the negative impact of dispersion in task-specific productivities on GDP, particularly in low-income countries where gaps in task-biased productivity are higher. In turn, the limited impact of equalization stems from differences in employment composition, which mediate the effect of task-biased technologies on aggregate output.

Related literature

Task-biased technological change has been central to understanding labor markets in modern economies. Foundational work by Acemoglu and Autor (2011) argued that automation complements high-skilled tasks and displaces routine ones, a process that leads to job polarization –where low-skill and high-skill occupations grow, but middle-skill, routine-intensive jobs shrink. Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) expanded on this by linking job polarization to the declining cost of automation, off-shoring, and the increasing demand for low-skill services. Graetz and Michaels (2018) found that industrial robots boost productivity but exacerbate wage inequality. More recently, Acemoglu and Restrepo (2019) have built on this framework by distinguishing between the displacement effect of automation, which reduces labor demand for certain tasks, and the reinstatement effect, where new tasks emerge. Relatedly, Caines, Hoffmann, and Kambourov (2016) have explored how task-biased technological change shifts labor towards higher-skill, non-routine roles, where wage growth is concentrated. Together, this body of research emphasizes how task-biased technologies have reshaped labor demand and wage structures, particularly by reducing demand for routine work.

Related research uses quantitative methods to examine how task-biased technological change shapes employment and productivity. Both Bárány and Siegel (2020) and Lee and Shin (2017) use models with task-specific technologies to explain employment shifts across sectors and occupations in the U.S. in the past decades. Similarly, Aum, Lee, and Shin (2018) focus in explaining aggregate productivity trends in the U.S., while Pena and Siegel (2021) focus on the cross-country dimension of this process and estimate routine-biased technologies across countries. Our paper is closely related to this literature as we use a quantitative framework to infer task productivities from the data; however, previous research has has treated tasks and occupations as equivalent, whereas we distinguish tasks as distinct units of production within occupations, which we believe more directly addresses the nature of task-biased technological change.

Finally, empirical research has documented variation in the task content of occupations, both over time (Atalay et al. 2020; Hershbein and Kahn 2018) and across countries (Lo Bello, Sanchez Puerta, and Winkler 2019; Lewandowski et al. 2022; Caunedo, Keller, and Shin 2023), linking these patterns to technological advancements. In particular, both Lewandowski et al. (2022) and Caunedo, Keller, and Shin (2023) also use PIAAC data and show that the prevalence of routine tasks within occupations declines as GDP increases, an empirical fact that we also document in this paper. More recently, De Vera and Garcia-Brazales (2024) also leverage PIAAC data to examine the relationship between routine work and establishment size. Our empirical approach contributes to prior work by constructing a measure of task intensity with clear quantitative interpretation, enabling its application in quantitative analysis.

2. Measuring the task intensity of occupations

In this section, we build a country-specific measure for the task intensity of occupations. The aim of this measure is to quantify the relative importance of tasks within occupations and compare these intensities across countries. We will first describe the data, then the procedure for constructing the measure, and finally, we will characterize the main patterns observed.

2.1. Data

The primary data source for constructing the task intensity of occupations is the Survey of Adult Skills, part of the Programme for the International Assessment of Adult Competencies (PIAAC), a program of the OECD. Data on employment shares come from the International Labour Organization (ILO), while GDP data is sourced from the World Development Indicators (WDI).

The PIAAC survey is an individual-level assessment of the population's skills, including literacy, numeracy, and problem-solving abilities, as well as the application of these skills in both the workplace and other settings. Data was collected in three rounds, spanning from 2011 to 2017. Importantly, the survey includes a comprehensive set of variables that capture what workers do in their jobs and how frequently they perform these activities. We use this set of variables to construct the task intensity measure. Demographic information (such as gender, age, and education level) and work-related characteristics (such as occupation, industry, and income) are also available. Specifically, occupations are observed up to the 2-digit level of the International Standard Classification of Occupations (ISCO-08). Our sample includes only employed individuals with valid occupational data and comprises 149,494 individuals.

In our baseline measure, we define three tasks (Cognitive, Interactive, and Routine) and consider nine occupations (defined at the 1-digit ISCO level). The set of countries for the cross-country analysis is determined by the data available in our primary data source (the PIAAC survey), which covers 35 countries[1]. In Appendix A we present descriptive statistics on the sample.

2.2. A measure for the task intensity of occupations across countries

The procedure for deriving our measure of task intensity consists of two steps.

In the first step, we assign task scores to each individual using factor analysis. Each individual is assigned a score for each task: a higher score means the task is performed with higher frequency, and vice versa. However, these scores do not have a quantitative interpretation. Because of this, in the second step, we rescale these scores and add them to calculate a share of each task in each occupation. We interpret this as a measure of task intensity, reflecting the relative importance of each task within an occupation. This approach allows us to quantitatively measure task inputs, which is a key element of the theoretical framework, and represents a novel aspect of our methodology.

The following paragraphs provide a more detailed description of these two steps.

First step. Assigning task scores to occupations. In this step, we select a broad set of variables from the PIAAC survey that measure the frequency of activities performed at work, for example: 'how often do you read articles at work?'; 'how often do you advise people at

[1] These are: Austria, Belgium, Canada Chile, Czech Republic, Denmark, Ecuador, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Russian Federation, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Turkey, United Kingdom and United States.

work?'. All variables range from 1 to 5 (1 indicating the lowest frequency, 'never', and 5 the highest frequency, 'every day').

Using this set of variables, we perform factor analysis. The advantage of this approach is that it does not predetermine either the set of variables associated with each task or the weights of the variables when computing the scores for each task.

In our baseline measure, we focus on the first three factors, which we label as distinct tasks based on their strong correlation with specific sets of activities. The first task, Cognitive, is associated with activities such as reading (e.g., instructions, news, publications, books, manuals, financial statements), writing (e.g., letters, emails, reports), and solving complex problems. The second task, Interactive, is linked to activities such as sharing work-related information, teaching, advising, planning others' activities, influencing people, negotiating, and solving complex problems. Lastly, the third task, Routine, is characterized by a negative correlation with activities such as determining the sequence of tasks, deciding how to perform work, managing work speed and hours, organizing personal time, and planning one's own activities. Additional details on the full set of variables and two alternative measures used as robustness checks are provided in Appendix B.

After selecting these three factors, we predict scores for the full sample at the individual level. As previously discussed, these scores have only a qualitative interpretation: a higher (or lower) score indicates that the task is performed more (or less) frequently relative to other individuals in the sample.

Table 1 shows the average scores when individuals are grouped by occupation at the 1-digit ISCO level, while Table 2 presents examples of high-scoring and low-scoring occupations for each task at the more detailed 2-digit ISCO level. Occupations that score high in non-routine cognitive tasks include managers and professionals, while the lowest scores are given to skilled agricultural workers and those in elementary occupations. For non-routine interactive tasks, the highest scores are also associated with managers and professionals, whereas clerical and elementary occupations receive the lowest scores. Finally, the occupations with higher scores in routine tasks are operators and assemblers, while managers receive the lowest average scores in routine tasks.

Second step: Towards a quantitative interpretation of task scores. In this second step, we rescale the factor scores and sum them to calculate a measure of task shares by occupation.

First, we rescale the factor scores to the range $[0, 1]$. This means that individuals with the lowest scores for a given task will be assigned a rescaled score of zero, which can be interpreted as not performing the task at all. Conversely, those with rescaled scores close to one are individuals who perform the task very frequently.

Second, we aggregate the rescaled scores at the individual level to obtain the 'share' that each task represents in their job, which we refer to as 'task intensity'. In this way,

TABLE 1. Average factor scores by task and occupation

ISCO Code	Description	Cognitive	Interactive	Routine
1	Managers	0.73	0.86	-0.51
2	Professionals	0.69	0.56	-0.20
3	Technicians and assoc. professionals	0.49	0.34	-0.14
4	Clerical support	0.38	-0.10	0.00
5	Service and sales	-0.34	-0.06	0.11
6	Skilled agric., forestry and fishery	-0.84	-0.58	-0.21
7	Craft and related trades	-0.48	-0.23	0.11
8	Operators and assemblers	-0.60	-0.57	0.52
9	Elementary occupations	-0.92	-0.75	0.32

TABLE 2. Highest-scoring and lowest-scoring occupations by task (2-digit ISCO-08)

	Highest Scores	Lowest Scores
Cognitive	ICT Professionals; Business and administration professionals	Cleaners and helpers; Subsistence farmers, fishers, hunters
Interactive	Teaching professionals; Hospitality, retail and other services managers	General and keyboard clerks; Refuse workers, other elementary workers
Routine	Stationary plant and machine operators; Assemblers	Chief executives, senior officials and legislators; Administrative and commercial managers

this method uses information on task frequency to quantify the relative importance of different tasks within a job. Finally, we group the shares by occupation and by country[2]. The advantage and innovation of this approach is that it provides a measure for task intensities that we can use in quantitative analysis. Furthermore, this method allows us to compare task intensities both across occupations and across countries.

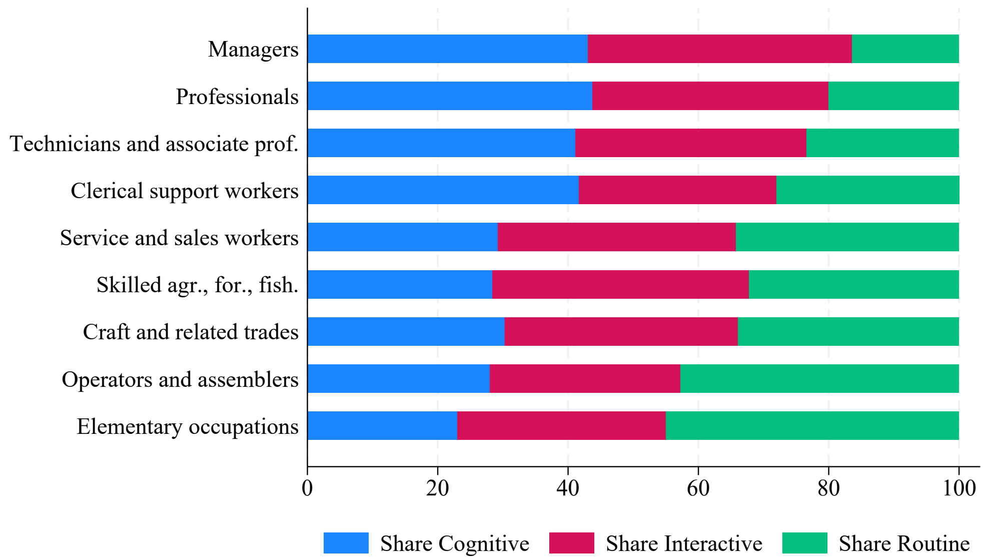
2.3. Main empirical patterns

Figure 1 displays the task intensity across occupations for the case of the United States. According to our measure, the share of the Cognitive task ranges from 23% for elementary occupations to around 45% for managers and professionals. The Interactive task ranges from 30% for operators and assemblers to 41% for managers. Finally, the Routine task ranges from around 20% to more than 40% for operators, assemblers and elementary

[2]To clarify this method and its interpretation, consider two simple examples. First, imagine a worker with a high rescaled score of one for all three tasks. This indicates that the worker performs all tasks with equal high frequency. By summing the scores and normalizing to obtain shares, the worker is assigned an equal share of 0.33 for each task, reflecting their equal importance within the job.

Now consider a second example where the worker has a rescaled score of zero for cognitive and interactive tasks, but a moderate score of 0.5 for routine tasks. This reflects very low frequency of cognitive and interactive tasks, with routine tasks being performed more often. In this case, the method assigns shares of 0 to cognitive and interactive tasks, and a share of one to the routine task, accurately capturing its relative predominance.

FIGURE 1. Task intensities by occupation. United States.

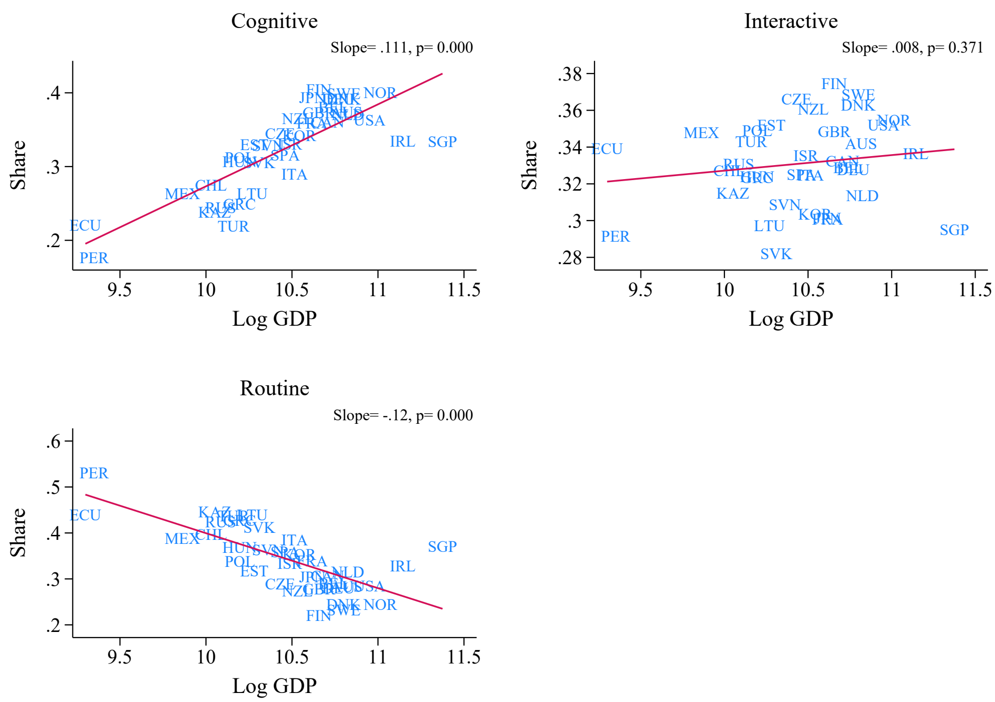


occupations.

In turn, Figure 2 shows the average task intensities by country, revealing a key pattern: as GDP increases, the share of routine work declines, while the importance of cognitive work rises. According to our estimation, the share of total routine work in a country ranges from approximately 50% in relatively poorer countries to around 25% in richer countries. A 10% increase in GDP is associated with a decrease of 1.2 p.p. in the share of routine tasks. Conversely, the share of cognitive work increases with GDP, ranging from about 20% to 40%, and a 10% increase in GDP is associated with an increase of 1.1 p.p. in the share of cognitive tasks. Lastly, there is no clear trend for interactive tasks across different levels of GDP. Overall, the pattern shown in Figure 2 suggests an almost one-to-one trade-off between the cognitive and the routine tasks. In Appendix B, we show that this main pattern is consistent with alternative measures for task intensity.

These findings align with the routine-biased technological change (RBTC) literaturem which typically attributes the decline in routine work to shifts in occupational structures: as GDP increases, the demand for occupations intensive in routine tasks decreases. However, in Figure 3 we show that the share of routine work *within occupations* also declines with GDP. In other words, as GDP grows, the content of work becomes less routine-biased, even within the same occupation. The figure highlights a significant and negative association between routine task intensity and GDP across all occupations. The same pattern is observed even when examining more detailed occupations, defined at the 2-digit level of ISCO-08, meaning within-occupation differences still persist even when examining narrower occupation groups. We present these results in Appendix B, where we also

FIGURE 2. Average task intensities across countries



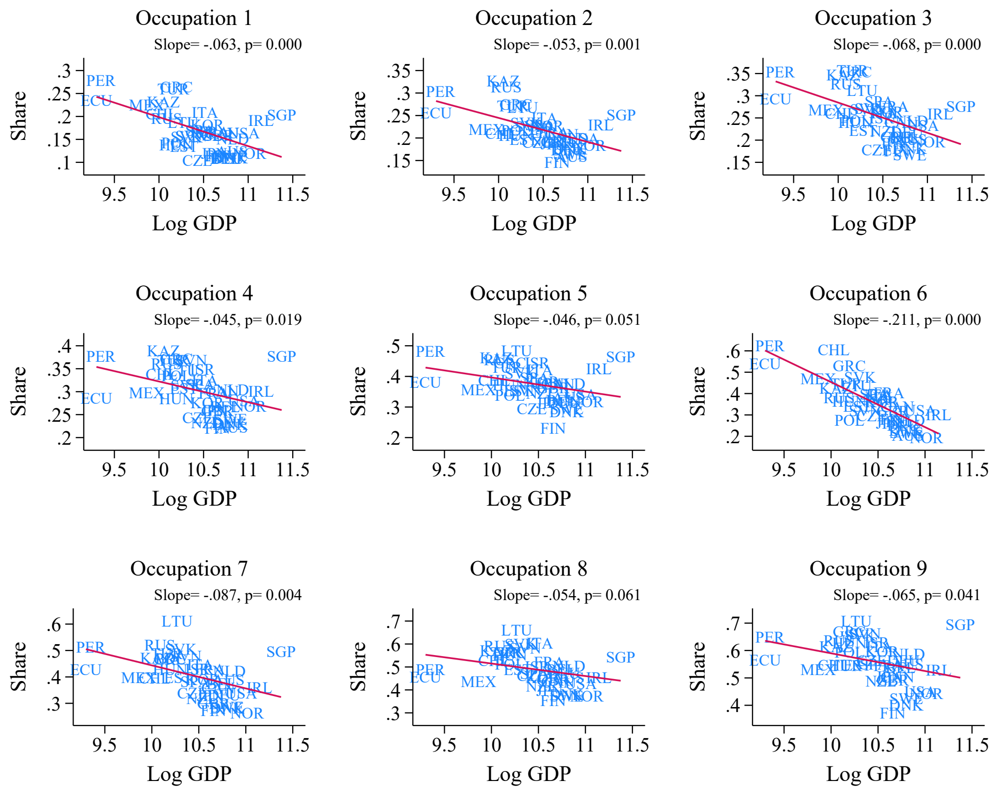
explore the variation of cognitive and interactive tasks across GDP within occupations.

Overall, these findings suggest that RBTC has potentially a 'double effect': it not only shifts the occupational structure towards less-routine occupations, but also reduces the relative importance of routine work across all occupations. To assess the relative contribution of these two channels in explaining differences in overall task intensity across countries, we perform a decomposition analysis, using the United States' task intensities and occupational shares as a reference.

Let τ^c_{jk} denote the task intensity of task k in occupation j in country c, and let e^c_j represent the employment share of occupation j in country c. The difference between average task intensities between country c and the United States can be decomposed into three components: the within effect, which captures differences in task intensities within occupations; the between effect, which captures differences in occupational shares; and the cross-effect, which accounts for the correlation between task intensities and occupational shares:

$$\sum_j (\tau^c_{jk} e^c_{jk} - \tau^{US}_{jk} e^{US}_{jk}) = \underbrace{\sum_j (\tau^c_{jk} - \tau^{US}_{jk}) e^{US}_{jk}}_{\text{Within effect}} + \underbrace{\sum_j \tau^{US}_{jk} (e^c_{jk} - e^{US}_{jk})}_{\text{Between effect}} + \underbrace{\sum_j (\tau^c_{jk} - \tau^{US}_{jk})(e^c_{jk} - e^{US}_{jk})}_{\text{Cross-effect}}$$

FIGURE 3. Routine task intensity by occupation, across countries



Note: Occupational codes (1-digit level) are as follows: (1) Managers; (2) Professionals; (3) Technicians and Associated Professionals; (4) Clerical Support Workers; (5) Service and Sales Workers; (6) Agricultural, Forestry and Fishery Workers; (7) Craft and Related Trades Workers; (8) Operators and Assemblers; (9) Elementary Occupations.

Table 3 shows the results of this decomposition for the three tasks. On average, the share of cognitive work in the sample countries is 4.8 p.p. lower than in the U.S., while the share of interactive work is 2.6 p.p. lower. Conversely, routine work is on average 7.3 p.p. higher than in the U.S. Notably, for all tasks, the variation in task shares within occupations (the within effect) plays the most significant role in explaining these differences. In particular, 57% of the cross-country differences in routine work can be attributed to variations in task content within occupations.[3]

[3] Using a different measure, Caunedo, Keller, and Shin (2023) perform a similar decomposition and also find that the within effect is stronger than the between effect for most of the tasks they consider.

TABLE 3. Average task intensity differences and within-between decomposition

	Mean difference (p.p.)	Contribution		
		Between	Within	Interaction
Cognitive	-4.8	0.43	0.51	0.07
Interactive	-2.6	0.15	0.69	0.16
Routine	7.3	0.33	0.57	0.10

Note: The first column displays the average difference in task intensity between countries in our sample and the U.S. The last three columns show the relative contribution of each component of the decomposition.

3. Model

In this section we introduce a production framework that can rationalize the observed differences in task intensities across countries. Eventually, we will use the model to quantitatively assess the differences in task-biased technology adoption across countries and its implications for GDP gaps.

In the model, final output is produced by combining occupations. Occupations, in turn, are aggregates of tasks, which we define as key activities performed at work. In this way, tasks are the primary units of production and are combined in different ways across occupations. Crucially, the set of tasks is common to all occupations, and technology is task-specific.

3.1. Setup

We start by defining final output and occupational output.

Final output Y is produced by combining J occupations. Let H_j denote the occupational output of occupation j and assume a CES production function with elasticity of substitution σ. The production function is given by:

$$Y = \left[\sum_j \gamma_j^{\frac{1}{\sigma}} H_j^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where γ_j are CES weights of different j occupations, such that $\sum_j \gamma_j = 1$. In particular, if $\sigma > 1$, occupations are substitutes in production and if $\sigma < 1$, occupations are complements.

In turn, occupational output H_j is a CES composite of K tasks, with elasticity of substitution η, expressed as:

$$H_j = \left[\sum_k \alpha_{jk}^{\frac{1}{\eta}} (A_k \cdot T_{jk})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{2}$$

Similarly, if $\eta > 1$, tasks are substitutes in production, and complements if $\eta < 1$. In this equation, T_{jk} represents the quantity of task k in occupation j, while the term A_k denotes the task-specific technology, which does not vary across occupations. In this way, changes in A_k have an impact in all occupations, with their impact mediated by the importance of task k within each occupation. Finally, α_{jk} denotes the CES weights such that $\sum_k \alpha_{jk} = 1$.

To define the task input T_{jk}, let N_j denote employment in occupation j. Then:

$$T_{jk} = \tau_{jk} \cdot N_j \tag{3}$$

where τ_{jk} is the intensity of task k in occupation j, such that $\sum_k \tau_{jk} = 1$. [4]

3.2. Optimal occupation and task demand

We now derive the expressions for the optimal labor demand for occupation j and the optimal demand for task k within each occupation j. For clarity, we present the maximization problems separately.

Optimal demand for occupations. To determine the optimal quantity of labor demand for occupation j, assume firms take prices as given and solve the following profit maximization problem:

$$\max_{H_j} \quad p \cdot Y - \sum_j w_j \cdot H_j \qquad\qquad s.t. : Y = \Big[\sum_j \gamma_j^{\frac{1}{\sigma}} H_j^{\frac{\sigma-1}{\sigma}} \Big]^{\frac{\sigma}{\sigma-1}}$$

where p is the price of the final good and w_j is the wage of occupation j.

The first order condition of this problem yields the demand for occupation j:

$$H_j = \left[\frac{p \cdot \gamma_j}{w_j} \right]^{\sigma} \cdot Y \tag{4}$$

where the price of the final good p is determined as the ideal price index:

$$p = \left[\sum_j \gamma_j \cdot w_j^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \tag{5}$$

From equation 4, the optimal allocation between occupational outputs of two occupations j and l satisfies:

[4]Notice that occupational output in equation 2 can be rewritten in per worker terms as:

$$h_j = \Big[\sum_k \alpha_{jk}^{\frac{1}{\eta}} (A_k \cdot \tau_{jk})^{\frac{\eta-1}{\eta}} \Big]^{\frac{\eta}{\eta-1}}$$

$$\frac{H_j}{H_l} = \frac{\gamma_j}{\gamma_l} \cdot \left(\frac{w_l}{w_j}\right)^{\sigma} \tag{6}$$

which is a function of the relative wages, the relative weights and the elasticity of substitution σ.

Optimal task demand. Next, to derive the optimal demand for task k in occupation j, assume that firms take prices as given and solve the following maximization problem:

$$\begin{aligned} \max_{T_{jk}} \quad & H_j \\ \text{s.t.} \quad & H_j = \left[\sum_k \alpha_{jk}^{\frac{1}{\eta}} (A_k \cdot T_{jk})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \\ & \sum_k T_{jk} = N_j. \end{aligned}$$

Intuitively, in this problem, we are solving for the optimal task demand at the occupation level, as if the firm could freely allocate a unit of labor across the set of tasks or, in other words, as if the firm could demand tasks directly. This assumption can rationalize different task allocations within occupations.

For task inputs to be chosen optimally, the equalization of marginal products of tasks must hold. That is, the marginal products between any two tasks k and l within the same occupation must be equal:

$$MPT_{jk} = MPT_{jl} \quad \forall \quad k, l \in K$$

This condition implies that the optimal task allocation of tasks k and l satisfies:

$$\frac{T_{jk}}{T_{jl}} = \frac{\alpha_{jk}}{\alpha_{jl}} \left(\frac{A_k}{A_l}\right)^{\eta-1} \tag{7}$$

In this way, the relative task demand within an occupation is determined by the relative task productivities, the relative weights and the elasticity of substitution η.

3.3. Equilibrium characterization

The equilibrium is characterized by the first order conditions of the optimization problems and the labor market clearing condition, that simply states $N_j = \bar{N}_j$, where $\bar{N}_j$ is labor supply in occupation j, which we consider fixed and exogenous.

From equation 7 and the condition $\sum_k \tau_{jk} = 1$, we can derive closed-form solutions for task inputs T_{jk}:

$$T_{jk} = \overline{N_j} \frac{\alpha_{jk} {A_k}^{\eta-1}}{\sum_k \alpha_{jk} (A_k)^{\eta-1}} \tag{8}$$

Next, plugging the expression for the optimal task input into the equation for occupational output, we obtain an expression for the occupational bundle H_j:

$$H_j = \overline{N_j} V_j \quad \text{where} \quad V_j = \left(\sum_k \alpha_{jk} A_k^{\eta-1} \right)^{\frac{1}{\eta-1}} \tag{9}$$

Finally, aggregate output can be expressed as:

$$Y = Z \left(\sum_j \gamma_j^{\frac{1}{\sigma}} (V_j \overline{N_j})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{10}$$

and, given the labor market clearing condition, the equilibrium wage for occupation j is given by:

$$w_j = Y^{\frac{1}{\sigma}} \gamma_j^{\frac{1}{\sigma}} (V_j \bar{N}_j)^{-\frac{1}{\sigma}} \tag{11}$$

3.4. Discussion and implications

Two important implications arise from the equilibrium characterization of the model, which we discuss below. In Appendix C we provide the necessary derivations.

PROPOSITION 1. *The effect of task productivity A_k on task demand T_{jk} depends on the elasticity of substitution η. In particular, if tasks are complements ($\eta < 1$), an increase in the productivity of task k decreases the demand for task k, within all occupations j:*

$$\frac{\partial T_{jk}}{\partial A_k} < 0 \quad \textit{if} \quad \eta < 1 \quad \forall j \tag{12}$$

PROPOSITION 2. *The effect of task productivity A_k on occupation demand depends on the elasticity of substitution σ. In particular, if occupations are complements ($\sigma < 1$), an increase in the relative productivity of occupation j with respect to occupation l reduces the relative income* *share of occupation j. Formally, we have:*

$$\frac{\partial\left(\frac{w_j H_j}{w_l H_l}\right)}{\partial\left(\frac{V_j}{V_l}\right)} < 0 \quad \textit{if} \quad \sigma < 1.$$

Together, these propositions provide a framework to rationalize how task-specific productivities influence both task and occupational optimal demands. In particular, if both tasks and occupations are complements in production, an increase in the productivity of task k reduces the demand for task k in all occupations. In turn, it reduces the labor share of the occupations in which task k is relatively more important.

4. Quantitative Analysis

In this section, we describe how we take the model to the data and quantify relative task productivities across countries. The estimation strategy involves fixing certain parameters and calibrating others to align the model with the observed data. The following sections detail the steps involved in the quantitative analysis and evaluate the fit of the model.

4.1. Functional forms and data

To conduct our quantitative exercise, we extend the production function introduced in the previous section. Following Hall and Jones (1999), we represent total output using a Cobb-Douglas production function that aggregates capital and labor:

$$Y = ZK^{\omega}H^{1-\omega}$$

where ω denotes the constant returns-to-scale parameter, K represents the total stock of physical capital, and Z indicates total factor productivity (TFP).

Aggregate data for GDP, average hours worked, and the physical capital stock are obtained from the Penn World Tables. In addition, we define a set of $j = 9$ occupations, categorized according to the 1-digit ISCO-08 classification, and a set of $k = 3$ tasks: Cognitive, Interactive, and Routine. Data on task intensities and wages are sourced from the PIAAC microdata, which also determines the countries included in the estimation. Task intensities are measured as described in Section 2, while wages are expressed in PPP-adjusted hourly terms. Employment shares are derived from ILO data.

4.2. Calibration strategy

In this section, we detail the steps for the calibration. A summary of the parameters, their sources, and the estimation procedure is presented in Table 4.

First, we define the parameters of our model that are externally calibrated. Based on previous literature, we set the constant returns to scale parameter $\omega = 0.33$ (Hall and Jones 1999) and the elasticity of substitution across occupations $\sigma = 0.815$ (Aum, Lee, and Shin 2018).

Next, we define the United States as a benchmark country, from which we compute a set of key parameters. First, we fix task productivities in the United States to be equal across tasks (i.e., $A_k = 1\, \forall k$), and compute the task weights α_{jk} from the first-order condition for tasks derived in the production framework (Equation 7). We also infer the occupation weights γ_j from Equations 6 and 9, using data on wages and employment in the U.S. The parameters α_{jk} and γ_j are assumed to be country-invariant, and its estimated values are reported in Table 5.

With these parameters, we compute task-biased productivities for every other country. For any country c, task-biased productivities are computed as a weighted average of the first-order conditions expressed in Equation 7:

$$\frac{A_{k,c}}{A_{1,c}} = \sum_j \frac{\overline{N_{j,c}}}{\overline{N_c}} \left(\frac{T_{jk,c}}{T_{j1,c}} \frac{\alpha_{j1}}{\alpha_{jk}} \right)^{\frac{1}{\eta-1}}$$

We identify all task-biased productivities assuming they average to 1, i.e., $\overline{A_{k,c}} = 1$. This identifiying assumption is consistent with the fact that the average A_k in the US is equal to 1. Consequently, this assumption makes sure that differences in the task-biased productivities across countries are not influenced by a *level* effect, which is captured by the country-specific TFP parameter Z_c. Notice that this also affects, the interpretation of potential differences in task-biased productivities across countries: our approach allows to compare differences in relative task productivities across countries, while it does not allow to compare the level of task-biased productivities. With these values, we compute $V_{j,c}$ and hence $H_{j,c}$.

Finally, using data on capital and GDP, we compute the TFP residual $\tilde{Z}_c$ for every country as follows:

$$\tilde{Z}_c = \log \frac{Y_c}{L_c} - \frac{\omega}{1-\omega} \log \left(\frac{K_c}{Y_c} \right) - \log \frac{H_c}{L_c}$$

where $\tilde{Z}_c = Z_c^{\frac{\omega}{1-\omega}}$. The final step involves iteratively adjusting the elasticity parameter η to minimize the difference between the model-predicted employment shares and the observed data:

$$\min_{\eta} \|\theta_{jc}^{\text{MODEL}} - \theta_{jc}^{\text{DATA}}\|$$

where $\theta_{jc}^{\text{MODEL}}$ and $\theta_{jc}^{\text{DATA}}$ represent the occupation income shares predicted by the model and observed in the data, respectively.

TABLE 4. Summary of calibrated parameters

Parameter	Description	Value	Source/Target
Country-invariant parameters			
ω	Constant returns to scale parameter	0.33	Hall and Jones (1999)
σ	Occupation elasticity	0.815	Aum, Lee, and Shin (2018)
η	Task elasticity	0.725	Occupation income share
α_{jk}	Occupation-task weights		US task intensities
γ_j	Occupation weights		US income share
Country-variant parameters			
$A_{k,c}$	Task productivity		Task intensities
Z_c	TFP		GDP per capita

Note: In the top panel we report parameters that are invariant for all countries. While the values for the return to scale parameter ω and the elasticity of substitution between occupation are picked from the literature, the rest are obtained by method of moments. In the bottom panel we include parameters that are country specific.

TABLE 5. Occupation-task weights α_{jk} and occupation weights γ_j

Occupation	Cognitive	Routine	Interactive	Occupation weights
Managers	0.431	0.164	0.405	0.146
Professionals	0.437	0.200	0.363	0.292
Technicians and associate prof.	0.412	0.234	0.355	0.160
Clerical support workers	0.417	0.280	0.303	0.079
Service and sales workers	0.292	0.342	0.365	0.123
Skilled agr., for., fish.	0.284	0.322	0.394	0.003
Craft and related trades	0.303	0.339	0.358	0.084
Operators and assemblers	0.280	0.427	0.292	0.050
Elementary occupations	0.230	0.450	0.320	0.063

Note: The table reports the value for occupation-task weights α_{jk} and γ_j used for the calibration exercise. The values are obtained from the US, by assuming that the task productivities are constant (i.e $A_k^{US} = 1$). The parameters γ_j in the fourth column are obtained using the wage equation and the employment share for the US.

4.3. Estimated task productivities and model fit

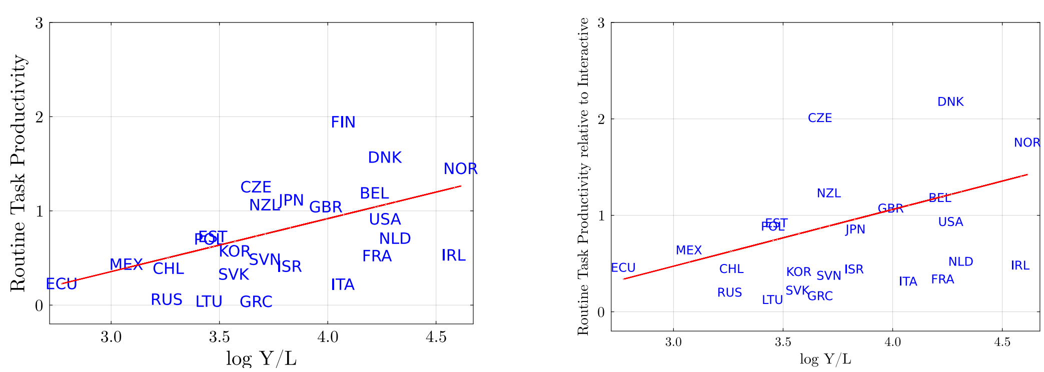
Figure 4 shows the estimated relative task productivities across countries. Panel 4A shows the routine task productivity relative to the cognitive task productivity, while Panel 4B plots the routine task productivity relative to the interactive task productivity. Both plots show a positive relation, meaning that the relative productivity of the routine task is increasing with GDP per capita. Moreover, the relation is stronger for the routine task productivity relative to cognitive: doubling GDP per capita is associated with an increase in routine task productivity relative to cognitive of 112% (Panel A), and with an increase in routinetask relative to interactive of 58% (Panel B). This is the result of complementarity between tasks and of the cross-country pattern observed in the data with respect to task intensities.

Figure 4 illustrates the estimated relative task productivities across countries. Panel 4A displays the routine task productivity relative to cognitive task productivity, while Panel 4B plots routine task productivity relative to interactive task productivity.

Both panels reveal a positive relationship, indicating that the relative productivity of routine tasks increases with GDP per capita. This trend is more pronounced for routine tasks relative to cognitive tasks, with a doubling of GDP per capita associated with a 112% increase in routine task productivity relative to cognitive (Panel A). For routine tasks relative to interactive tasks, the same GDP increase results in a 58% rise in relative productivity (Panel B). This relationship is the result of complementarity between tasks and the observed cross-country pattern in task intensities, documented in the empirical section.

FIGURE 4. Relative tasks productivity and GDP per worker

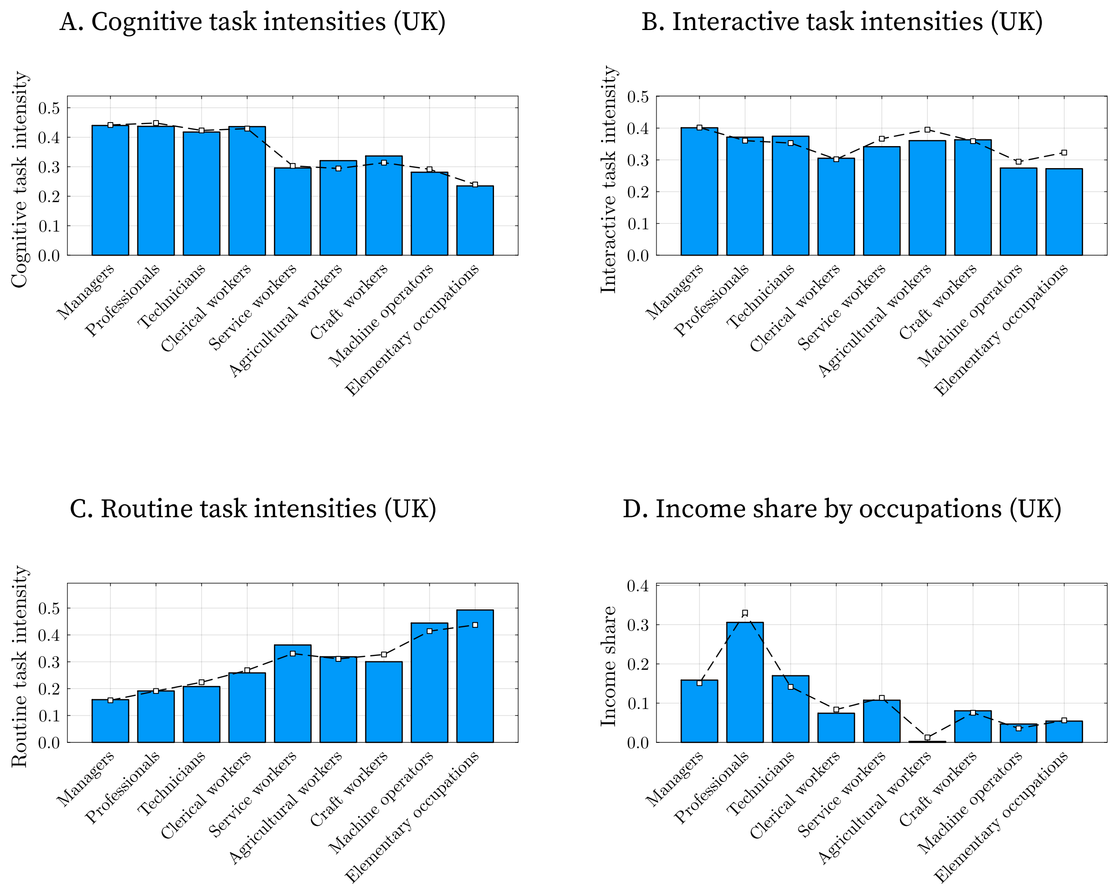
A. Routine Task Productivity relative to Cognitive B. Routine Task Productivity relative to Interactive



Note: Panel A shows the relationship between the routine task productivity relative to the cognitive task productivity. The red line indicates a linear fit betwee the relative productivity and the (log)GDP per worker. The estimated slope is 1.12(t-stat: 1.91). Panel B shows the relationship between the routine task productivity relative to the interactive task productivity and (log) GDP per worker. The estimated slope for the linear fit is 0.58 (t-stat: 1.71).

Regarding the model fit, Figure A7 compares the task intensities by occupation produced by the model with those in the data for the United Kingdom, together with the income shares by occupation. The model successfully captures the different patterns in task intensities for the three task types, as well as the income shares by occupation observed in the data. This is true not only for country similar to the U.S., but also for less

FIGURE 5. Task intensities and income share by occupations in the UK



Note: Panel A shows the comparison between the cognitive task intensities for each occupation in the United Kingdom observed in the data and those reproduced by the model. Similarly, Panels B and C show the comparison between interactive and routine task intensities in the data and in the model. Finally, Panel D shows the difference between the occupation income shares produced by the model and those observed in the data.

developed countries[5].

5. Counterfactual exercises and main results

In this section, we perform a series of counterfactual exercises to assess the implications of task-biased technology adoption for GDP gaps.

Our main counterfactual exercise consists on assessing the effect of closing dispersion in task-biased technologies across countries on the GDP gaps. Recall that in the calibration we set task-productivities in the United States to 1 ($A_k^{US} = 1$), which by default implies no

[5]In Appendix D we report a similar figure for Chile, a country among those with the lowest income in our sample.

TABLE 6. The impact of dispersion in task-biased technologies on GDP per capita

	All countries		GDP below US	
	Y/L (*Data*)	$\tilde{Y/L}$ ($A_k = 1$)	Y/L (*Data - Below US*)	$\tilde{Y/L}$ ($A_k = 1$)
p90	1.03	1.24	0.84	1.01
p75	0.95	1.01	0.67	0.83
p50	0.57	0.76	0.55	0.61
p25	0.45	0.53	0.44	0.49
p10	0.37	0.41	0.36	0.38
mean	0.69	0.8	0.57	0.68

Note: The table shows the distributions of GDP gaps relative to the US in the data and as a result of the counterfactual exercise. The first two colums show GDP gaps for all countries in the sample, while the last two columns focus on the average GDP gaps for countries that are relatively poorer than the US.

dispersion of task productivities in this country. This counterfactual exercise then consists in setting $A_k = 1$ in all countries, thus assuming the same relative task productivities that in the U.S. Importantly, this disregards the productivity *level*, which is captured by the country-specific TFP and is held constant during the countrerfactual exercise.

Table 6 shows the distributions of GDP gaps relative to the US in the data and as a result of the counterfactual exercise. The first two colums show GDP gaps for all countries in the sample, while the last two columns focus on the average GDP gaps for countries that are relatively poorer than the US.

In particular, when considering those countries that are relatively poorer than the US, the average GDP per capita of countries is 57% of that of the US. Closing the dispersion in task producivities increases this number to 68%. In other words, an average GDP gap of 43% is reduced to 32%, meaning that task productivity dispersion explains around 25.6% of the GDP gap. [6]

While we find higher variance in task-biased productivities in low-income countries, eliminating dispersion has a moderate effect on the GDP of countries at the very bottom of the distribution: the limited impact stems from differences in employment composition across countries, which can affect the extent to which task-biased productivity changes negatively influence aggregate output.

[6]The dispersion in task-specific productivity affects GDP negatively. In fact, one can apply a second-order Taylor expansion to the the term V_j to obtain:

$$V_j = \bar{A_k} + (\eta - 2)\frac{Var_\alpha(A_k)}{2\bar{A_k}}$$

Notice that, when the elasticity of substitution between tasks is lower than 1 (i.e. tasks are complements), an increase in the variance of task-biased productivities A_k reduces the whole term V_j and therefore it negatively affects aggregate output.

6. Conclusion

In this paper, we propose a novel measure of task intensity that provides a quantitative interpretation of the relative importance of cognitive, interactive, and routine tasks within jobs and across countries. Our empirical analysis reveals that as countries grow richer, the share of routine work decreases, both driven by employment composition and by changes in the content of work within occupations.

We next put forward a theoretical framework that rationalizes differences in task intensities across countries. The key elements of this framework are considering occupations as aggregates of a common set of tasks, and defining task-specific technologies. By taking the model to the data, we quantify relative task productivities across countries and show that the relative productivity of routine tasks increases with GDP.

Finally, through counterfactual exercises, we illustrate how varying the level and composition of task-biased technology adoption impact GDP gaps across countries. In particular, we show that by eliminating the dispersion in task-biased productivities the average gap with respect to the United States reduces of around 25%.

We believe these findings highlight several promising directions for future research, offering opportunities to deepen our understanding of the underlying mechanisms and to explore their implications in other contexts.

In our framework the impact of technological change in our model shapes the task-content of each occupation. Allowing for changes in the occupational structure can give insight on the impact of task-biased technological change not only, on task intensities within an occupation, but also on the occupational structure of the economy. Furthermore, worker skills can potentially matter in understanding task-biased technology adoption: in fact, by learning and accumulating human capital, they can make easier the adoption of task-biased technologies.

By introducing sectors in our framework, task-biased technological adoption can be linked to the process of structural change observed along the development path: advances in routine biased technologies can disproportionately increase the productivity in the manufacturing jobs and it can therefore trigger the reallocation of workers towards other occupations and sectors.

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Appendix A. PIAAC data availability and summary statistics

A.1. List of countries and sample size

Table A1 presents the list of countries, the data collection period, and the sample size for each country. The data collection period spans from 2011 to 2017, corresponding to different rounds of the PIAAC survey. The total sample size is 230,691 individuals.

A.2. Demographic descriptive statistics

Table A2 presents basic demographic statistics by country, including gender composition, age, and education levels. The baseline sample includes only employed individuals with valid occupational data and comprises 149,494 individuals.

TABLE A1. Survey of Adult Skills. Data collection period and sample size, by country

Country	Period	Sample size
Austria	2011-2012	5,130
Belgium	2011-2012	5,463
Canada	2011-2012	26,683
Chile	2014-2015	5,212
Czech Republic	2011-2012	6,102
Denmark	2011-2012	7,328
Ecuador	2017	5,702
Estonia	2011-2012	7,632
Finland	2011-2012	5,464
France	2011-2012	6,993
Germany	2011-2012	5,465
Greece	2014-2015	4,925
Hungary	2017	6,149
Ireland	2011-2012	5,983
Israel	2014-2015	5,538
Italy	2011-2012	4,621
Japan	2011-2012	5,278
Kazakhstan	2017	6,050
Korea	2011-2012	6,667
Lithuania	2014-2015	5,093
Mexico	2017	6,306
Netherlands	2011-2012	5,170
New Zealand	2014-2015	6,177
Norway	2011-2012	5,128
Peru	2017	7,289
Poland	2011-2012	9,366
Russian Federation	2011-2012	3,892
Singapore	2014-2015	5,468
Slovak Republic	2011-2012	5,723
Slovenia	2014-2015	5,331
Spain	2011-2012	6,055
Sweden	2011-2012	4,469
Turkey	2014-2015	5,277
United Kingdom	2011-2012	8,892
United States	2011-2012, 2017	8,670
Total		230,691

Note: Data for Belgium correspond to Flanders region. Data for the United Kingdom corresponds to England and Northern Ireland.

TABLE A2. Survey of Adult Skills. Demographic characteristics by country. Employed individuals

Country	Females (%)	Age (mean)	Education (% more than HS)	Sample size
Austria	47.9	-	-	3,647
Belgium	46.5	41.7	47.3	3,301
Canada	47.2	-	64.8	19,111
Chile	44.0	39.9	30.2	3,539
Czech Republic	44.6	40.7	24.4	3,610
Denmark	47.7	41.0	41.4	5,275
Ecuador	40.0	38.0	30.9	3,314
Estonia	51.4	40.5	50.1	5,313
Finland	49.8	41.9	49.0	3,846
France	48.0	41.1	33.9	4,438
Germany	46.3	-	41.2	3,995
Greece	40.8	41.1	41.7	2,361
Hungary	46.6	-	45.1	4,207
Ireland	48.3	39.4	59.8	3,626
Israel	48.7	39.0	50.4	3,458
Italy	39.7	41.2	18.0	2,810
Japan	42.2	42.3	47.8	3,832
Kazakhstan	43.9	38.7	53.8	3,585
Korea	41.0	41.6	41.3	4,342
Lithuania	50.8	41.0	57.2	3,175
Mexico	39.2	37.2	17.4	3,834
Netherlands	46.2	40.1	35.2	3,890
New Zealand	48.6	-	58.6	4,467
Norway	49.2	40.1	49.0	3,491
Peru	42.6	37.0	23.1	5,199
Poland	44.6	39.4	40.6	5,024
Russian Federation	47.3	39.5	81.7	2,165
Singapore	46.3	-	65.0	3,872
Slovak Republic	44.7	40.5	26.4	3,276
Slovenia	45.4	41.4	32.1	2,953
Spain	45.7	41.1	41.1	3,312
Sweden	47.7	42.0	41.7	3,302
Turkey	21.7	35.5	20.9	2,154
United Kingdom	46.5	40.1	42.5	5,783
United States	47.8	-	52.1	5,987
Total	45.7	40.1	45.2	149,494

Note: Data for Belgium corresponds to Flanders region. Data for the United Kingdom corresponds to England and Northern Ireland.

Appendix B. Task intensity: baseline and alternative measures

In this section, we present details on the construction of the task intensity measure and show that the main patterns remain consistent across alternative measures.

B.1. List of variables from PIAAC survey

Table A3 shows the list of variables from the PIAAC survey used to construct the baseline and alternative measures through factor analysis, which we label 'Alternative 1' and 'Alternative 2'. In all cases, we kept most of the relevant variables in the survey, filtering out only those with insufficient variation across individuals. Table A4 details the number of factors retained for each task intensity measure, describes the main variables that correlate with each factor and the task that we use to label each factor. In both the baseline measure and in Alternative 1 we identify three tasks –'Cognitive', 'Interactive' and 'Routine'–, while in Alternative 2 we also includes a fourth task, 'Manual'. Importantly, all the three measures consistently identify the set of activities that characterize the routine task.

The main differences between the measures are the number of variables included and the number of factors selected during factor analysis. The baseline measure is preferred, as it uses a compact set of variables that allows us to clearly identify three distinct factors that we label 'Cognitive', 'Interactive' and 'Routine.' Under Alternative Measures 1 and 2, in contrast, we use a larger set of variables and select more factors. This expansion occurs because, as more variables are included, some activities become more closely related to specific occupations (for example, numeracy activities). The baseline measure provides a simpler interpretation while encompassing a broad enough range of variables to capture general patterns.

TABLE A3. List of variables to build task measures

Variable name	Variable description	Baseline	Alternative Measure 1	Alternative Measure 2
d_q11a	Work flexibility - Sequence of tasks	✓	✓	✓
d_q11b	Work flexibility - How to do the work	✓	✓	✓
d_q11c	Work flexibility - Speed of work	✓	✓	✓
d_q11d	Work flexibility - Speed of work	✓	✓	✓
f_q02a	Sharing work-related information	✓	✓	✓
f_q02b	Teaching people	✓	✓	✓
f_q02c	Presentations	✓	✓	✓
f_q02d	Selling	✓	✓	✓
f_q02e	Advising people	✓	✓	✓
f_q03a	Planning own activities	✓	✓	✓
f_q03b	Planning others activities	✓	✓	✓
f_q03c	Organising own time	✓	✓	✓
f_q04a	Influencing people	✓	✓	✓
f_q04b	Negotiating with people	✓	✓	✓
f_q05a	Solving simple problems	✓	✓	✓
f_q05b	Solving complex problems	✓	✓	✓
f_q06b	Working physically for long	✓	✓	✓
f_q06c	Using hands or fingers			✓
g_q01a	Reading directions or instructions	✓	✓	✓
g_q01b	Reading letters memos or mails	✓	✓	✓
g_q01c	Reading newspapers or magazines	✓	✓	✓
g_q01d	Reading professional journals or publications	✓	✓	✓
g_q01e	Reading books	✓	✓	✓
g_q01f	Reading manuals or reference materials	✓	✓	✓
g_q01g	Reading financial statements	✓	✓	✓
g_q01h	Reading diagrams maps or schematics	✓	✓	✓
g_q02a	Writing letters memos or mails	✓	✓	✓
g_q02c	Writing reports	✓	✓	✓
g_q02d	Filling in forms	✓	✓	✓
g_q03b	Calculating costs or budgets		✓	✓
g_q03c	Using or calculating fractions or percentages		✓	✓
g_q03d	Using a calculator		✓	✓
g_q03f	Preparing charts graphs or tables		✓	✓
g_q03g	Using simple algebra or formulas		✓	✓

Note: All variables measure the frequency with which an activity is performed at work and range from 1 to 5 as follows: 'Never', 'Less than once a month', 'Less than once a week', 'At least once a week', 'Every day'. The questions on work flexibility have a different wording, as follows: 'Not at all', 'Very little', 'To some extent', 'To a high extent', 'To a very high extent'.

TABLE A4. Factor analysis for baseline and alternative measures

	Baseline	Alternative Measure 1	Alternative Measure 2	Label (task)
Factor 1	Reading, writing	Reading, writing, doing calculations	Reading, writing	Cognitive
Factor 2	Teaching, advising, negotiating, influencing people	Teaching, advising, negotiating, influencing people	Teaching, advising, influencing people	Interactive
Factor 3	Work flexibility, planning, organising	Work flexibility, planning, organising	Work flexibility, planning, organising	Routine
Factor 4		Reading financial statements, calculating costs/budgets	Reading financial statements, calculating costs/budgets	Cognitive
Factor 5			Read diagrams, prepare charts, using algebra	Cognitive
Factor 6			Reading (news, journals, books)	Cognitive
Factor 7			Working physically, using hands/fingers, read instructions	Manual

Note: In the cases in which more than one factor identifies the same task we use the mean of factor scores to compute the score for that task.

B.2. Comparison across task intensity measures

In this section, we demonstrate that the two alternative measures exhibit patterns consistent with those shown in Figures 2 and 3 in the main text. Specifically, these patterns include a declining share of routine work as GDP increases and an opposite trend for cognitive work.

Alternative Measure 1

Figure A1 shows the average task intensities across countries based on Alternative Measure 1, as described above. The figure shows that the share of cognitive work increases with GDP, the share of routine work decreases with GDP, and the share of interactive work does not vary with GDP. While the strength of the relationship appears somewhat weaker with this alternative measure, the qualitative patterns are identical to those observed with the baseline measure.

FIGURE A1. Average task intensities across countries. Alternative Measure 1

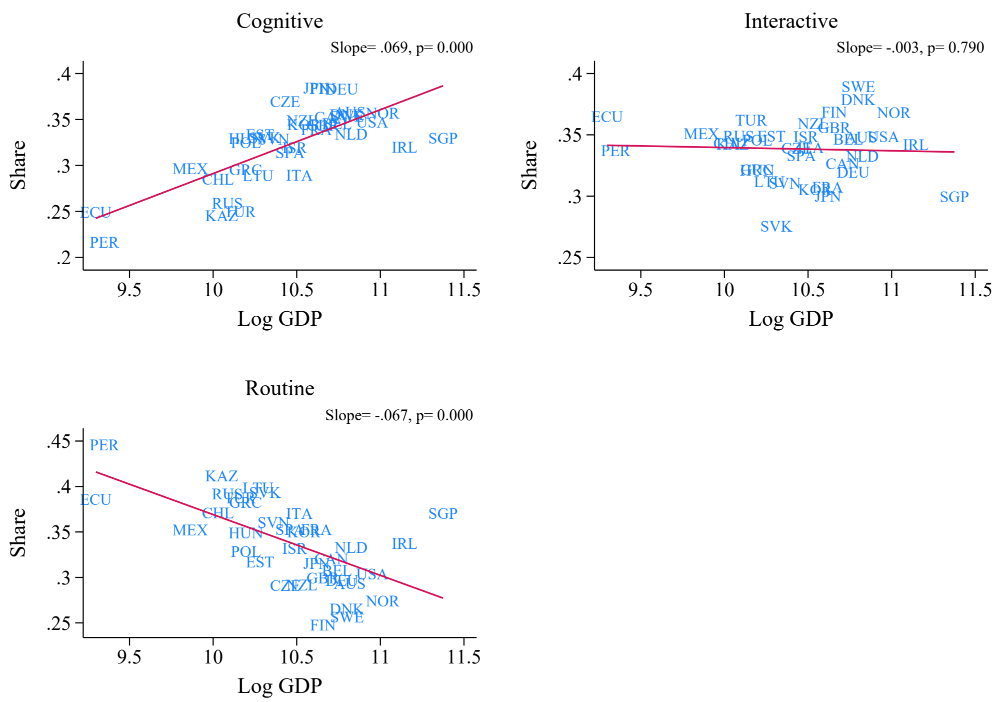


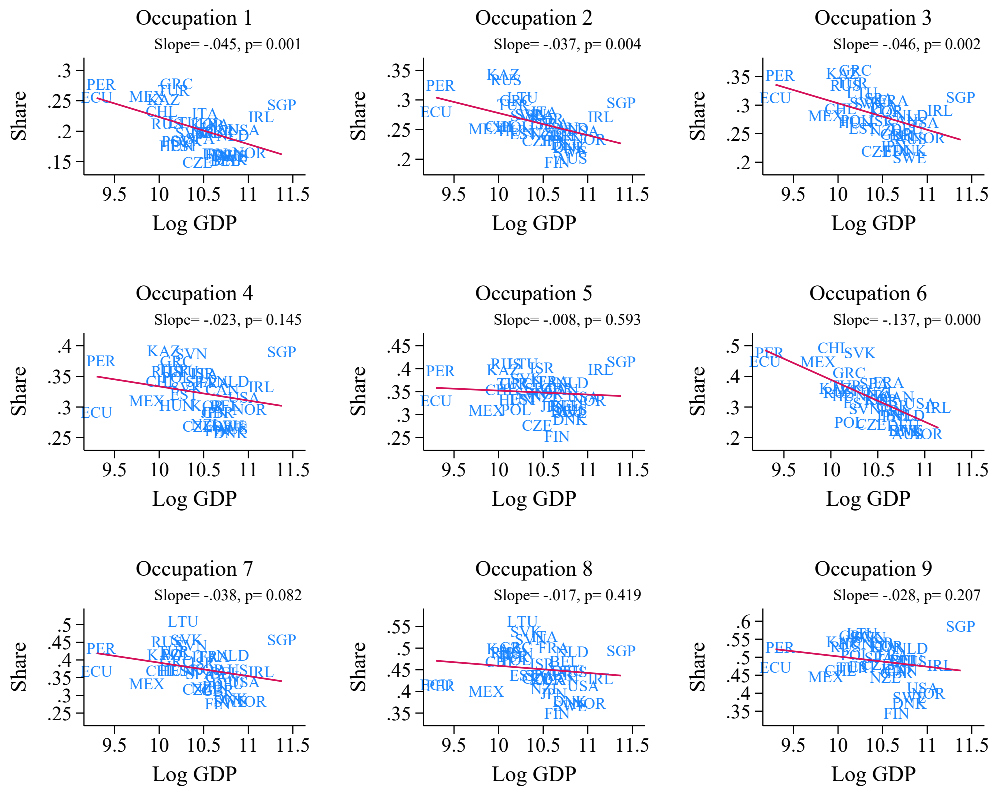
Figure A2 shows the routine task intensity by occupation across countries. The relationship between routine task intensity and GDP is also negative for all occupations, although for some occupations the relation is not statistically significant. This pattern is consistent with the findings discussed in the main text.

Alternative Measure 2

Figure A3 shows the average task intensities across countries based on Alternative Measure 2, as described above. As in the previous cases, the figure demonstrates that the share of cognitive work increases with GDP, the share of routine work decreases with GDP, and the share of interactive work remains largely unaffected by GDP. The relationship between these variables is weaker compared to the baseline measure. Additionally, Alternative Measure 2 shows that including a fourth task category, 'manual', does not alter this pattern, as the task intensity of manual work does not vary significantly with GDP.

Figure A4 shows the routine task intensity by occupation across countries using Alternative Measure 2. The relationship between routine task intensity and GDP mirrors that of Alternative Measure 1: it is negative overall, though not statistically significant for some occupations. The overall pattern is consistent with the findings discussed in the main text.

FIGURE A2. Routine task intensity by occupation, across countries. Alternative Measure 1



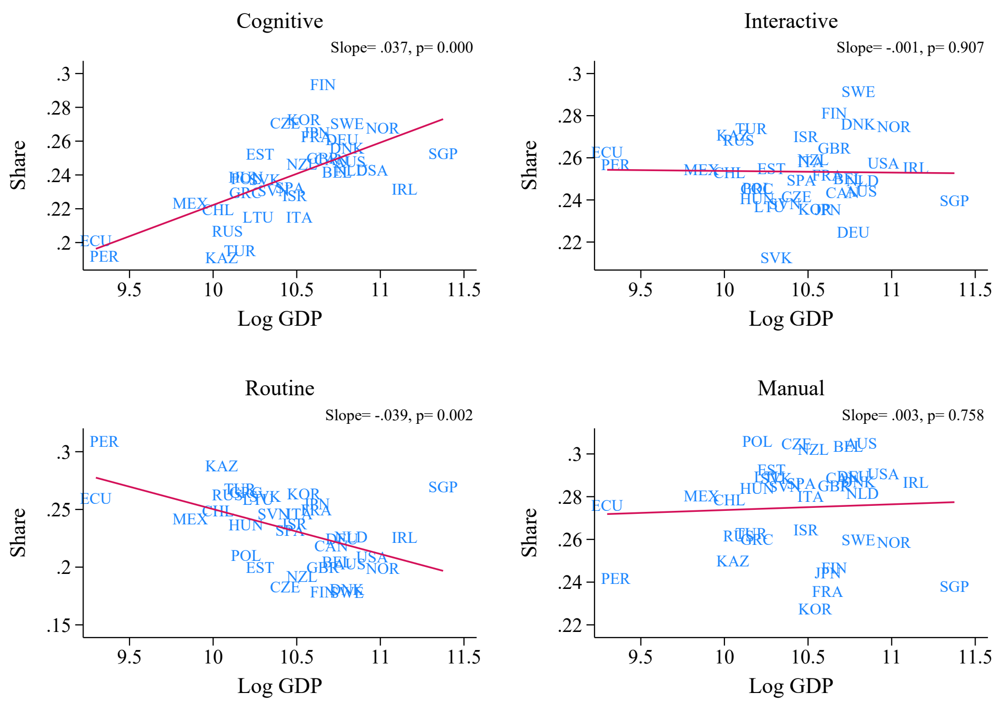
Note: Occupational codes (1-digit level) are as follows: (1) Managers; (2) Professionals; (3) Technicians and Associated Professionals; (4) Clerical Support Workers; (5) Service and Sales Workers; (6) Agricultural, Forestry and Fishery Workers; (7) Craft and Related Trades Workers; (8) Operators and Assemblers; (9) Elementary Occupations.

B.3. Further results on the baseline measure

In this section, we present additional results based on the baseline measure for task intensity. First, Figure A5 illustrates how cognitive task intensity varies across countries and occupations. Consistent with the pattern observed for routine tasks, the figure shows that the positive association between cognitive task intensity and GDP holds within each occupation. Similarly, Figure A6 displays this relation for the interactive task. In this case, there is no clear pattern across occupations, and, in general, the relationship between the share of interactive tasks and GDP is not statistically significant, even when examining within-occupation task composition.

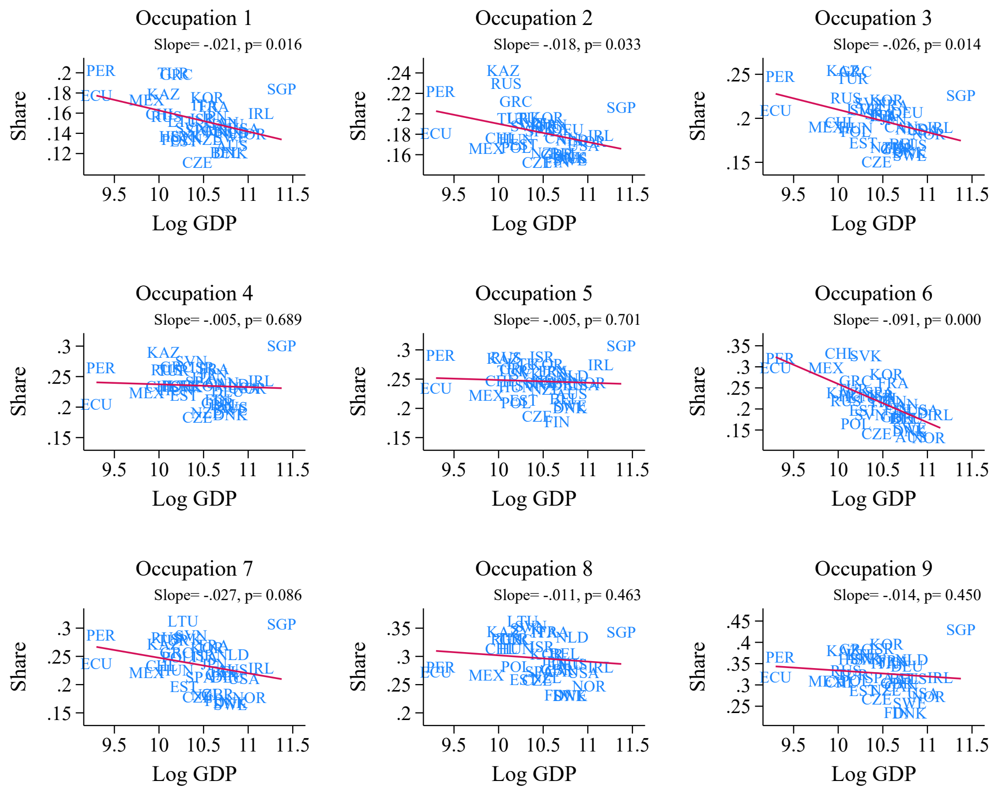
Finally, Table A5 presents the results of regressing task intensity for occupations at the 2-digit level against GDP. The results show a significant positive coefficient for cognitive tasks and a significant negative coefficient for routine tasks. These findings are

FIGURE A3. Average task intensities across countries. Alternative Measure 2



consistent with the main analysis and highlight that the observed patterns persist even when examining narrower occupation groups.

FIGURE A4. Routine task intensity by occupation, across countries. Alternative Measure 2



Note: Occupational codes (1-digit level) are as follows: (1) Managers; (2) Professionals; (3) Technicians and Associated Professionals; (4) Clerical Support Workers; (5) Service and Sales Workers; (6) Agricultural, Forestry and Fishery Workers; (7) Craft and Related Trades Workers; (8) Operators and Assemblers; (9) Elementary Occupations.

Appendix C. Model

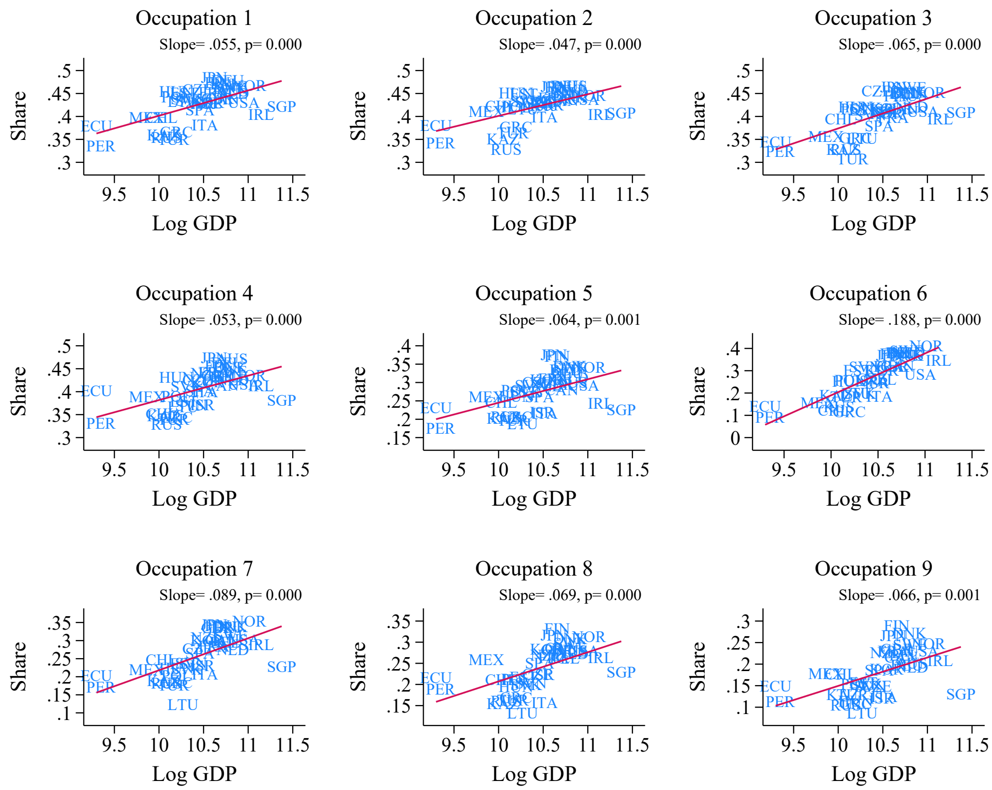
Proof of proposition 1

In this section, we provide a formal proof of the relationship between T_{jk} and A_k. Recall the expression for T_{jk} is given by:

(A1)
$$T_{jk} = \frac{\bar{N}_j \alpha_{jk} A_k^{\eta-1}}{\sum_k \alpha_{jk} A_k^{\eta-1}}$$

First, divide the expression by $\bar{N}_j$ and recall $\frac{T_{jk}}{\bar{N}_j} = \tau_{jk}$, which represents the task intensity of task k in occupation j. From here, take the logaritm of τ_{jk} to get:

FIGURE A5. Cognitive task intensity by occupation, across countries. Baseline measure



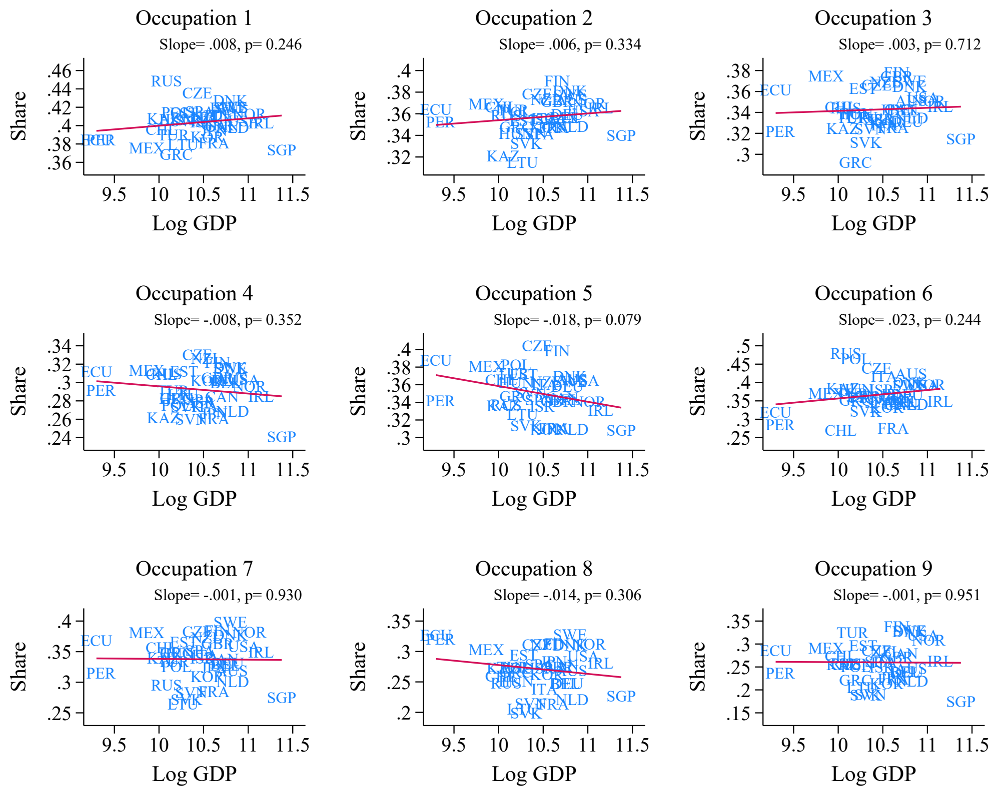
Note: Occupational codes (1-digit level) are as follows: (1) Managers; (2) Professionals; (3) Technicians and Associated Professionals; (4) Clerical Support Workers; (5) Service and Sales Workers; (6) Agricultural, Forestry and Fishery Workers; (7) Craft and Related Trades Workers; (8) Operators and Assemblers; (9) Elementary Occupations.

(A2)
$$\log \tau_{jk} = \log\left(\alpha_{jk} A_k^{\eta-1}\right) - \log\left(\sum_k \alpha_{jk} A_k^{\eta-1}\right)$$

Next, take the partial derivative of τ_{jk} with respect to A_k to obtain:

(A3)
$$\frac{\partial \log \tau_{jk}}{\partial A_k} = \frac{\alpha_{jk} A_k^{\eta-2}}{\alpha_{jk} A_k^{\eta-1}}(\eta-1) - \frac{\alpha_{jk} A_k^{\eta-2}}{\left(\sum_k \alpha_{jk} A_k^{\eta-1}\right)}(\eta-1)$$

FIGURE A6. Interactive task intensity by occupation, across countries. Baseline measure



Note: Occupational codes (1-digit level) are as follows: (1) Managers; (2) Professionals; (3) Technicians and Associated Professionals; (4) Clerical Support Workers; (5) Service and Sales Workers; (6) Agricultural, Forestry and Fishery Workers; (7) Craft and Related Trades Workers; (8) Operators and Assemblers; (9) Elementary Occupations.

Simplifying the expression:

(A4)
$$\frac{\partial \log \tau_{jk}}{\partial A_k} = \frac{(\eta - 1)}{A_k} \left(\frac{\sum_{m \neq k} \alpha_{jm} A_m^{\eta-1}}{\sum_k \alpha_{jk} A_k^{\eta-1}} \right)$$

Clearly, the sign of the derivative depends only on η: if $\eta > 1$, the derivative is positive; if $\eta < 1$, the derivative is negative.

Proof of proposition ??

In this section, we show a formal proof of the relationship between occupational output H_j and task productivity A_k:

TABLE A5. Regression results for within occupation (2-digit ISCO) task intensities

	(1) Cognitive Task Intensity	(2) Interactive Task Intensity	(3) Routine Task Intensity
Intercept	-0.711***	0.275***	1.436***
	[0.064]	[0.034]	[0.085]
Log GDP	0.099***	0.006	-0.105***
	[0.006]	[0.003]	[0.008]
Observations	1,203	1,203	1,203
R2	0.179	0.002	0.122

Note: Column (1) presents the coefficients from a regression of cognitive task intensity by occupation (2-digit level) and country on GDP. Columns (2) and (3) present the coefficients for interactive and routine task intensities, respectively.

Recall the expression for occupation output, given by

$$H_j = \bar{N}_j V_j \tag{A5}$$

where

$$V_j = \left(\sum_k \alpha_{jk} A_k^{\eta - 1} \right)^{\frac{1}{\eta - 1}} \tag{A6}$$

Since $\bar{N}_j$ is fixed, H_j is increasing in A_k only if V_j is increasing in A_k.

Next, we take the logarithm of V_j and compute its partial derivative with respect to A_k. We show that this derivative is always positive, implying that V_j is increasing in A_k:

$$\log V_j = \frac{1}{\eta - 1} \log \left(\sum_k \alpha_{jk} A_k^{\eta - 1} \right) \tag{A7}$$

$$\frac{\partial \log V_j}{\partial A_k} = \left(\frac{\alpha_{jk} A_k^{\eta - 2}}{\sum_k \alpha_{jk} A_k^{\eta - 1}} \right) > 0 \tag{A8}$$

Proof of proposition 2

Defining the labor income share of occupation j as $w_j H_j$ and using equations 9 and 11, the relative labor share between occupations j and l is given by:

$$\frac{w_j H_j}{w_l H_l} = \left(\frac{\bar{N}_j}{\bar{N}_l} \right)^{\frac{\sigma - 1}{\sigma}} \left(\frac{\bar{V}_j}{\bar{V}_l} \right)^{\frac{\sigma - 1}{\sigma}} \left(\frac{\gamma_j}{\gamma_l} \right)^{\frac{1}{\sigma}} \tag{A9}$$

Taking the derivative with respect to the relative occupational productivity $\frac{V_j}{V_l}$, we have

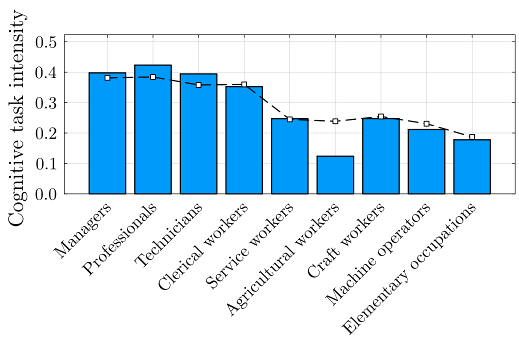
$$\frac{\partial\left(\frac{w_j H_j}{w_l H_l}\right)}{\partial\left(\frac{V_j}{V_l}\right)} = \left(\frac{\bar{N}_j}{\bar{N}_l}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\gamma_j}{\gamma_l}\right)^{\frac{1}{\sigma}} (\sigma - 1) \left(\frac{V_j}{V_l}\right)^{\frac{-1}{\sigma}} \tag{A10}$$

Clearly, the sign of the derivative depends on the magnittude of σ: if $\sigma > 1$, the derivative is positive; if $\sigma < 1$, the derivative is negative.

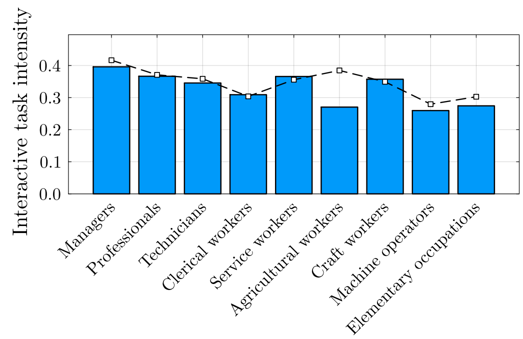
Appendix D. Model fit

FIGURE A7. Task intensities and income share by occupations in the UK

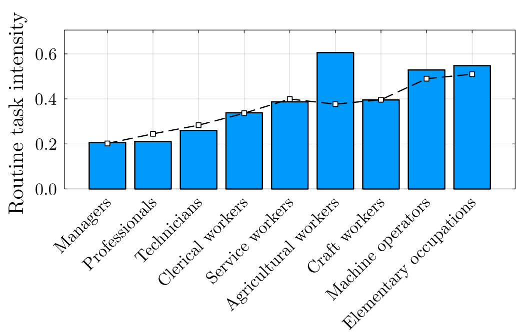
A. Cognitive task intensities (CHL)



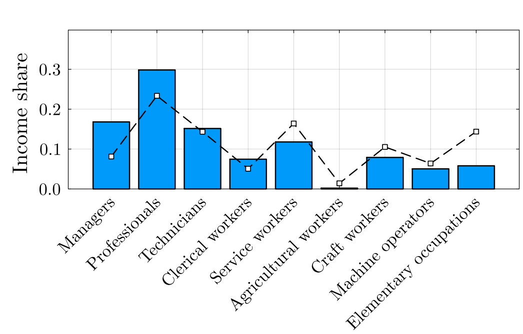
B. Interactive task intensities (CHL)



C. Routine task intensities (CHL)



D. Income share by occupations (CHL)



Note: Panel A shows the comparison between the cognitive task intensities for each occupation in Chile observed in the data and those reproduced by the model. Similarly, Panels B and C show the comparison between interactive and routine task intensities in the data and in the model. Finally, Panel D shows the difference between the occupation income shares produced by the model and those observed in the data.

Appendix E. Results of counterfactual exercise by country

Table A6 reports the result of the counterfactual exercise separately for every country in the sample.

TABLE A6. The effect of dispersion in task-biased productivities on GDP

Country	Y/L *(Data)*	Y/L *Model* ($A_k = 1$)
USA	1.000	1.000
BEL	0.952	1.025
CHL	0.367	0.390
CZE	0.550	0.601
DNK	1.000	1.217
ECU	0.224	0.290
EST	0.452	0.457
FIN	0.823	1.251
FRA	0.964	1.008
GRC	0.550	1.008
IRL	1.373	1.382
ISR	0.643	0.679
ITA	0.824	1.006
JPN	0.644	0.758
KOR	0.500	0.506
LTU	0.443	0.767
MEX	0.303	0.331
NLD	1.046	1.067
NZL	0.574	0.587
NOR	1.418	1.646
POL	0.444	0.450
RUS	0.364	0.628
SVK	0.497	0.535
SVN	0.572	0.583
GBR	0.760	0.777

Note: The table compares GDP observed in the data with the measure of GDP obtained after eliminating the dispersion in task-biased productivities. The reported GDP in both columns is relative to the GDP in the United States