Automation, Human Task Innovation, and Labor Share: Unveiling the Role of Elasticity of Substitution[*] [†]

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Abstract

This paper investigates the elements contributing to the decline in labor share, with a specific focus on the roles of 'automation' and 'innovation in human tasks.' We construct a general equilibrium model that separately incorporates both robot and non-robot capital to derive an econometric specification. Based on our regression results, we estimate the elasticity of substitution between labor and non-robot capital to be less than one. Conversely, the elasticity of substitution between tasks is estimated to be one. Together with these estimates, our regression results yield three major findings. First, we identify two distinct channels through which robots affect labor share: automation and the decrease in the price of robots. Both channels are found to negatively impact labor share. Our general equilibrium model predicts that the effect of declining robot prices will intensify as robots become more prevalent. Second, we are the first to empirically evaluate the impact of human task innovation on labor share by constructing a novel index for new human tasks. Our accounting analysis suggests that the positive influence of human task innovation outweighs the adverse effects of automation. Lastly, by utilizing estimates of the elasticity of substitution between labor and non-robot capital, as well as between tasks, we elucidate the mechanisms through which factor prices affect the labor share. Specifically, we find that both the negative effect of automation and the positive effect of human task innovation are amplified through the aggregated task price channel.

JEL D24, D33, E24, E25, J23, O33, O57.

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[†]Replication data and code and the most recent version of paper: https://github.com/jayjeo/public/tree/main/Laborshare

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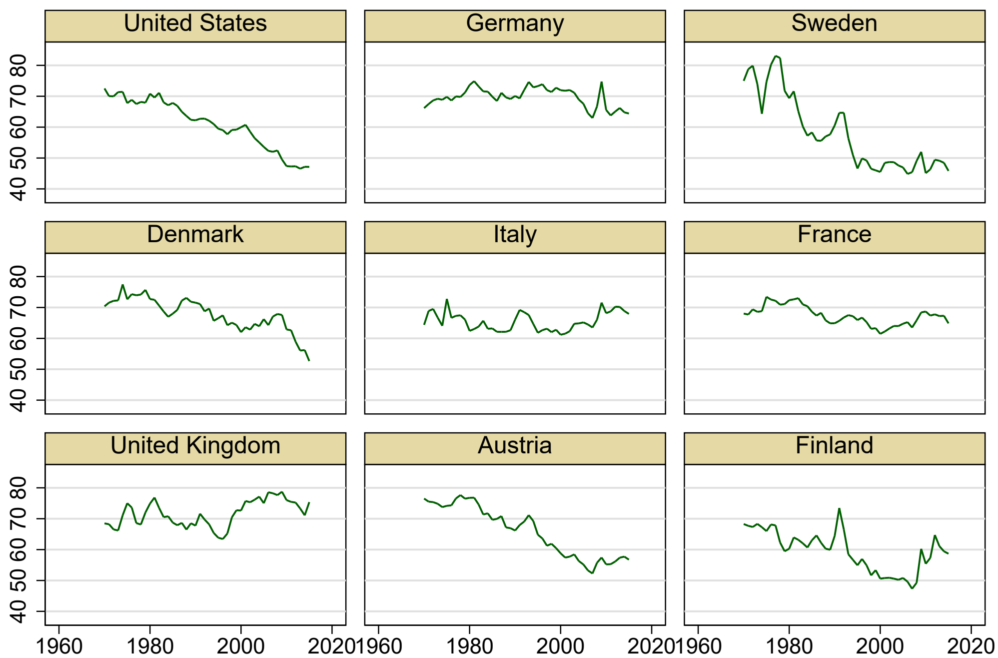
1 Introduction

Karabarbounis and Neiman (2014) and Autor et al. (2020) have noted that the global labor share has followed a declining trend since the early 1980s, with an average decrease of about five percentage points. Figure 1, based on data compiled by Gutiérrez and Piton (2020), compares the labor shares in the manufacturing sector between the USA and the eight EU nations that we studied. While the USA, Sweden, Denmark, and Austria have witnessed significant declines, other countries report comparatively slight decreases. This discrepancy indicates that global labor share trends exhibit considerable heterogeneity, further underscoring our aim to investigate variations across countries and sectors to better understand this decline.[1]

Figure 1: Labor shares



Although the precise cause of this decline is still a topic of debate, advancements in automation emerge as a possible key driver. The urgency of addressing the diminishing labor share intensifies with the accelerated growth in automation and artificial intelligence technologies. For instance, Boston Dynamics has unveiled Atlas, a humanoid robot with impressive speed and capabilities.[2] The recent debut of Chat-GPT

[1]In this context, our study aligns with Graetz and Michaels (2018), which assesses seventeen EU countries, although their focus is predominantly on productivity growth rather than the decrease in labor share.

[2]https://youtu.be/-e1_QhJ1EhQ

4, which astoundingly achieved a 10% ranking in the United States bar exam, further underscores the rapid evolution of AI systems.[3]

The influence of automation on labor share remains a prominent topic in active research. Several studies such as those by Acemoglu and Restrepo (2020), Acemoglu et al. (2020), Dauth et al. (2021), and Martinez (2018) suggest that automation reduces labor share. In contrast, findings from research like De Vries et al. (2020) and Gregory et al. (2016) propose that automation amplifies labor share. Moreover, studies by Humlum (2019) and Hubmer and Restrepo (2021) explore the diverse impacts of automation on various population groups and industry sectors.

Yet, another factor potentially promoting labor share is the 'innovation in human tasks' —innovative tasks beyond the capabilities of robots. Autor (2015) contends that the sustained relevance of human labor in the future will largely depend on the pace at which 'innovation in human tasks' outstrips the advancement of automation. Despite its significance, the effect of innovation in human tasks on labor share is still relatively underexplored. Our primary objective is to assess the impacts of the interaction between the rise of automation and the innovation in human tasks on the labor share.

Automation and innovation in human tasks are not the only factors contributing to changes in labor share. In literature, many other reasons have been meticulously examined, especially using causality techniques. However, fewer studies attempt to measure multiple reasons within a unified framework (Bergholt et al., 2022).[4] Grossman and Oberfield (2022) highlighted the importance of utilizing general equilibrium analysis, stating: "Many authors present different sides of the same coin ... Even if the various mechanisms are all active, it becomes difficult to gauge what part of the effect estimated in one study has already been accounted for elsewhere." To address this challenge, we adopt a general equilibrium model, an approach that represents a contribution to the existing literature. The study most akin to ours is that of Acemoglu and Restrepo (2022). They too utilize a general equilibrium model, though their main focus is on wage inequality rather than the decline in labor share.

Our analysis incorporates five potential determinants within our general equilibrium model: automation, innovation in human tasks, capital price, robot price, and wages.[5] Our model predicts that automation will adversely affect the labor share. Our

[3] https://youtu.be/EunbKbPV2C0

[4] Bergholt et al. (2022) points out that "while a large literature has discussed each of these four explanations in isolation, an empirical analysis including all of them in the context of the same model is lacking. Our aim is to fill this gap."

[5] In this context, the research by Bergholt et al. (2022) closely aligns with our study. They examine rising markups, increased worker bargaining power, a declining investment price, and escalating automation as factors contributing to the falling labor share. Although their methodology, which employs time series techniques (Structural VAR with sign restrictions) and focuses exclusively on the USA, differs from ours, their findings are in line with our results. They identify automation as a principal driver of the reduction in labor share. Interestingly, they conclude that a declining capital price does not

regression results corroborate this prediction. Our most significant contribution lies in the empirical examination of the impact of innovation in human tasks on labor share. To the best of our knowledge, we are the first to empirically investigate this relationship. Our findings indicate that innovation in human tasks serves as an effective counterbalance to the negative effects of automation on labor share. This is particularly the case in the USA, where the advent of new tasks holds substantial importance.

We estimate that the elasticity of substitution *between labor and non-robot capital* is less than one, while the elasticity of substitution *between tasks* is estimated to be one. Based on these estimates, we clarify the mechanisms by which the prices of factors — labor, robots, and non-robot capital— influence labor share. Specifically, we observe that both the negative effect of automation and the positive effect of innovation in human tasks are amplified through the aggregated task price channel: First, automation and innovation in human tasks alter the composition of tasks performed by robots and those performed by labor. Second, this change in composition affects the aggregate task price. Finally, the change in the aggregate task price, in turn, affects labor share through substitution among labor, robots, and non-robot capital.

Meanwhile, our estimation of the elasticities also allows us to make coherent predictions about the directional impact of three prices on labor share —non-robot capital price, robot price, and wages— based solidly on our general equilibrium model. First, the model anticipates a positive association between labor price and labor share. Second, the model predicts a negative association between the price of non-robot capital and labor share. The underlying intuition stems from the gross complementarity between labor and non-robot capital. Specifically, when wages rise, employment levels do not decrease proportionally, leading to an increase in labor share. Similarly, a decline in the price of non-robot capital results in an increase in labor share. Third, the model predicts a positive but insignificant association between robot price and labor share — when robot price declines, the labor share would slightly decrease. The insignificance is attributable to the low current estimate of the share of robot cost among the total costs, which includes robot cost and labor cost. These directional trends and magnitudes of labor price, non-robot capital price, and robot price are confirmed by our regression results.

Our results enrich the existing literature by emphasizing the importance of the elasticity of substitution *between labor and capital*, which has also been highlighted by recent studies like those of Martinez (2018), Oberfield and Raval (2021), and Zhang (2023). Our work resonates with studies like Glover and Short (2020), which also report the elasticity below one and stress the importance of bias correction when estimating this. To address omitted variable bias, we regress factors such as automation, innovation in human tasks, wages, robot prices, and capital prices on labor share, indicating the significance of automation and innovation in human tasks. Our findings

contribute to the decrease in labor share.

are consistent with Glover and Short (2020).

In contrast, our findings do not support the hypothesis of Karabarbounis and Neiman (2014), who claim that falling capital prices account for half of the recent labor share decline. For their argument to hold, the elasticity would have to be greater than one (gross substitute). Likewise, Piketty and Zucman (2014) suggests potential for gross substitutability, a position we do not support.

Looking forward, as automation becomes increasingly prevalent, both our model and empirical data suggest that the elasticity of substitution *between labor and non-robot capital* will move closer to one. This indicates that the influence of the labor price channel on increasing labor share is likely to diminish in the future.

In the following section, we present our general equilibrium model, while Section 3 details the datasets we used. Section 4 conducts the regression analysis, and Section 5 performs various accountings to ascertain which mechanism predominantly explains labor share decline across different countries and industries. Finally, Section 6 provides our concluding remarks.

2 Model

Acemoglu and Restrepo (2018) have offered a formal model that outlines how labor share is influenced by 'automation' and 'innovation in human tasks.' We have refined our model based on their static version. Our key contribution is the distinction we make between robots and other capital equipment, a distinction their model does not delineate. Acemoglu and Restrepo (2020) found that advancements in robotics negatively impact wages and employment. Conversely, they discovered that other forms of capital positively impact these variables. This distinction emphasizes that 'robots' and 'capital' can carry different implications for labor demand.

We adhere to the definition of a robot as specified by ISO standard 8373:2012, which describes it as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes."[6] The International Federation of Robotics (IFR) also strictly adheres to this definition (Müller, 2022). We source our robot data from the IFR.

In Figure 2, Panel (a) depicts a robot. However, Panel (b) is not robot because this milling machine does not come with any type of hook-up to have it run automatically. Therefore, it is neither reprogrammable nor automatically controlled. Additionally, it cannot be considered multipurpose, as it is designed solely for milling. Also, it does

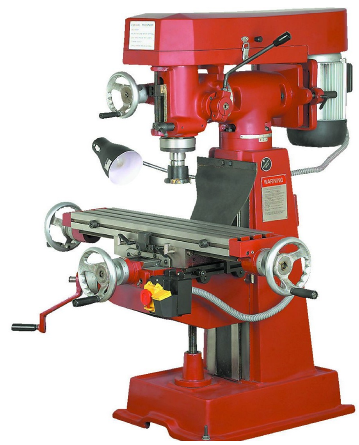
[6] Acemoglu and Restrepo (2020) also defines robots in a manner consistent with this description: "fully autonomous machines that do not need a human operator and can be programmed to perform several manual tasks … This definition excludes other types of equipment."

[7] Vertical milling machine by harborfreight

Figure 2: Examples of Robot

(a) Robot

(b) Not robot[7]



not operate on three or more axes. This example underscores the narrow definition of a robot.

We define ‘automation’ as the enhancement of robots’ capabilities, which allows them to perform tasks that were previously unachievable. Meanwhile, we define ‘innovation in human tasks’ as new tasks that human-workers are expected to perform because those are beyond the capabilities of robots. For instance, according to ONET, the job description for Urban and Regional Planners (SOC 19-3051) expanded from 19 responsibilities in 2019 to include tasks related to statistics and data management. Previously, their responsibilities included: (1) holding public meetings with officials and scientists, (2) advising planning officials on project feasibility and cost-effectiveness, and (3) mediating community disputes. One year later, their scope of tasks widened to incorporate: (1) preparing reports using statistics, (2) developing and maintaining maps and databases, and (3) researching, compiling, analyzing, and organizing information. This serves as a prototypical example of innovation in human tasks, illustrating that individuals aspiring to become Urban and Regional Planners must now acquire skills in data handling and statistics.

Our model holds advantages over existing literature, such as Berg et al. (2018) and DeCanio (2016), which also introduced robots as a separate factor from traditional capital. Firstly, our model comprehensively incorporates factors affecting labor share, most importantly automation and innovation in human tasks, in addition to factor prices. This allows us to quantitatively analyze the extent to which each factor affects labor share across different sectors and countries. Secondly, our model delivers in-depth interpretations regarding the substitutability between labor, capital, and robots. From the regression equations derived from the task-based model, we gain unique insights into the degree of substitutability among factors, as well as the tasks conducted by either labor or robots.

2.1 Environment

2.1.1 Firms

In the model, firms face monopolistic competition, which allows them to generate positive profits. For simplicity, we assume that the production function is the same for all firms[8]. Also, for brevity, we omit the time subscript.

Each firm utilizes a continuum of tasks, indexed between $N-1$ and N, in addition to capital, for production. As in Acemoglu and Restrepo (2018), N increases over time due to innovation in human tasks, which can only be conducted by labor. Additionally, there is an index I that falls between $N-1$ and N. I is related to the possibility of automation and thus increases along with improvements in automation technology. Specifically, tasks below I in firm i can technically be conducted by either labor or robots, while tasks above I can only be performed by labor, as follows:

$$t_j(i) = m_j(i) + \gamma_j l_j(i) \ \text{ if } j \leq I \tag{1}$$

$$t_j(i) = \gamma_j l_j(i) \ \text{ if } j > I \tag{2}$$

, where $m_j(i)$ and $l_j(i)$ represent the number of robots and labor used for task j in firm i. γ_j represents the productivity of labor for task j. The productivity, γ_j, increases with a higher task index, j.

Tasks, $t_j(i)$, are aggregated using Constant Elasticity of Substitution (CES) aggregator, and both the aggregated tasks and capital are further combined using another CES function. Therefore, the production function is:

$$Y(i) = \left(T(i)^{\frac{\sigma-1}{\sigma}} + K(i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{3}$$

$$T(i) = \left(\int_{N-1}^{N} t_j(i)^{\frac{\zeta-1}{\zeta}} dj\right)^{\frac{\zeta}{\zeta-1}} \tag{4}$$

, where $T(i)$ and $K(i)$ represent the number of aggregated tasks and capital used for the production of the final good i, denoted as $Y(i)$. Meanwhile, σ and ζ represent the elasticity of substitution between aggregated tasks and capital, and the elasticity of substitution between tasks, respectively.

Factor markets are assumed to be perfectly competitive. Additionally, since we focus on long-run change in labor share, it is reasonable to assume that factors are

[8] Introducing heterogeneity in terms of Hicks-neutral productivity does not change our analysis.

supplied elastically. For further simplicity, we assume that factors are supplied perfectly elastically at a given factor price at each period.

2.1.2 Households

The representative consumer consumes an aggregated continuum of final goods, with the mass of final goods assumed to be 1 for simplicity. It's also assumed that there is no disutility from the supply of labor. The utility function of the representative consumer takes the following form:

$$U = \left(\int_0^1 Y(i)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}} \tag{5}$$

, where η represents the elasticity of substitution between final goods.

The representative consumer's budget constraint is as follows:

$$\int_0^1 P(i)Y(i)di = \int_0^1 \left(\int_{N-1}^{N} W_j l_j(i)dj + \int_{N-1}^{N} \psi m_j(i)dj + RK_i + \Pi_i \right) di \tag{6}$$

, where W_j, ψ, and R represent wage for labor conducting task j, robot price, and capital price, respectively.

2.2 Labor Share

A step-by-step process for this section is provided in Online Appendix A. We set an assumption related to robot and labor productivity for simple algebra in deriving the equilibrium in the model.

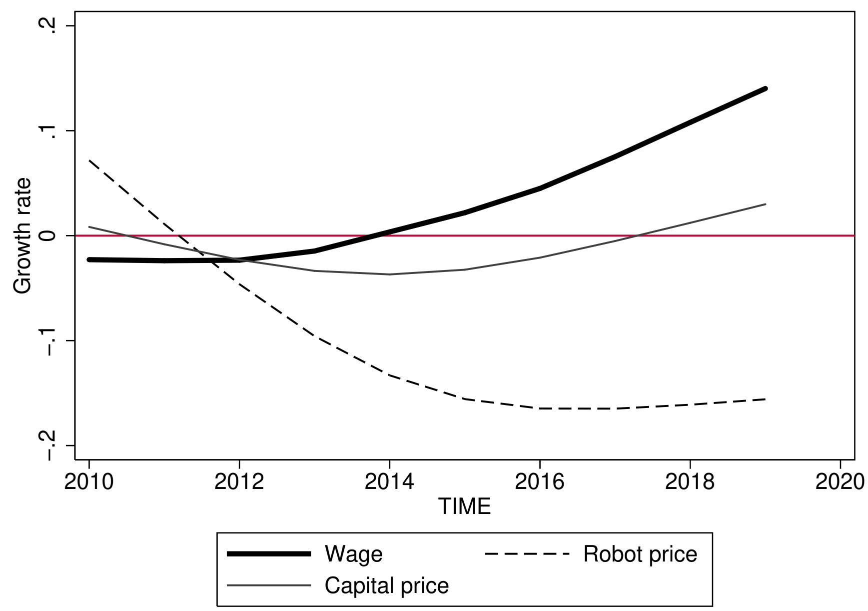
Assumption 1. $\psi < \frac{W_I}{\gamma_I}$

The above assumption implies that it is efficient to use a robot for task j below I. In other words, whenever firms have the technological capability to substitute labor with a robot, they would be inclined to do so. This is a reasonable assumption, especially considering that robot prices have significantly declined, while wages have seen a steady increase. Figure 3 illustrates these trends by depicting the 5-year growth rates of the respective prices.

Based on the Assumption 1 and by solving the firm's cost minimization problem, factor demands, the price for the aggregated task, and the marginal cost of firm i are derived as follows:

$$l_j(i) = 0, \quad \text{if } j \leq I \tag{7}$$

Figure 3: Prices in a 5-year growth rate



$$l_j(i) = \gamma_j^{\zeta-1} \left(\frac{W_j}{P_T}\right)^{-\zeta} T(i), \ \text{ if } j > I \tag{8}$$

$$m_j(i) = \left(\frac{\psi}{P_T}\right)^{-\zeta} T(i), \ \text{ if } j \leq I \tag{9}$$

$$m_j(i) = 0, \ \text{ if } j > I \tag{10}$$

$$T(i) = \left(\frac{P_T}{MC(i)}\right)^{-\sigma} Y(i) \tag{11}$$

$$K(i) = \left(\frac{R}{MC(i)}\right)^{-\sigma} Y(i) \tag{12}$$

$$P_T = \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj\right]^{\frac{1}{1-\zeta}} \tag{13}$$

$$MC(i) = \left[P_T^{1-\sigma} + R^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{14}$$

$$W_j l_j(i) = \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} \cdot P_T^{\zeta} \cdot T_i \tag{15}$$

, where P_T and MC_i represent the price for the aggregated task and marginal cost of firm i, respectively.

Based on Equations (7) to (14), labor share is derived:

$$S_L = \frac{\eta - 1}{\eta} \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{P_T^{1-\zeta}} \frac{P_T^{1-\sigma}}{P_T^{1-\sigma} + R^{1-\sigma}} \tag{16}$$

$$\text{, where } P_T \equiv \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj\right]^{\frac{1}{1-\zeta}}$$

It is worth mentioning that the term, $\frac{\eta-1}{\eta}$, is the inverse of the firm's mark-up. Since we focus on labor income as a fraction of total factor income, we denote it as S_L^f as follows:

$$S_L^f \equiv \frac{\eta}{\eta - 1} S_L = \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{P_T^{1-\zeta}} \frac{P_T^{1-\sigma}}{P_T^{1-\sigma} + R^{1-\sigma}} \tag{17}$$

2.3 Estimating Equations

By taking the natural log of Equation (17) and then computing the total derivative of the resulting equation with respect to the exogenous variables in the model (I, N, R, $\mathbb{W}$, and ψ), we obtain the following estimating equation:

$$
\begin{aligned}
& d\ln S_L^f = \\
& -\left[(1-\zeta)+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\times\frac{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}{P_T^{1-\zeta}}\right]d\ln\gamma \\
& +\left[\underbrace{-\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}}_{\text{Direct loss by } dI\text{: (-)}}+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\times\underbrace{\frac{1}{1-\zeta}\frac{\psi^{1-\zeta}-\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{Change in aggregated task price by } dI\text{: (-)}}\right]dI \\
& +\left[\underbrace{\frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}}_{\text{Direct gain by } dN\text{: (+)}}+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\times\underbrace{\frac{1}{1-\zeta}\frac{-\psi^{1-\zeta}+\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{Change in aggregated task price by } dN\text{: (+)/(-)}}\right]dN \\
& +\left[\underbrace{(1-\zeta)}_{\text{Direct gain by } d\ln\mathbb{W}\text{: (+)}}+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\times\underbrace{\frac{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}{P_T^{1-\zeta}}}_{\text{Change in aggregated task price by } d\ln W\text{: (+)}}\right]d\ln\mathbb{W} \\
& -\left[S_K^f(1-\sigma)\right]d\ln R \\
& +\left[\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\times\underbrace{\frac{(I-N+1)\psi^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{Change in aggregated task price by } d\ln\psi\text{: (+)}}\right]d\ln\psi
\end{aligned}
\tag{18}
$$

, where $\mathbb{W}\equiv\frac{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}{\int_I^N W_j^{-\zeta}\gamma_j^{\zeta-1}dj}$ is the average wage, and assume $d\ln\mathbb{W}=d\ln W_j$ for all j. Additionally, $d\ln\gamma$ represents the change in labor productivity. It is also assumed that $d\ln\gamma=d\ln\gamma_j$ for all j.

The coefficients of the five explanatory variables (dI, dN, $d\ln\mathbb{W}$, $d\ln R$, and $d\ln\psi$) in Equation (18) reflects not only the direct effect caused by the change in the variable, but also the general equilibrium effects that influence the labor share through changes in the price of the aggregated tasks. Changes in automation technology, dI, changes in the emergence of new tasks, dN, and changes in wage, $d\ln\mathbb{W}$, directly affect the labor share. dI directly causes labor to be replaced by robots in task I, which results in a decrease in labor share by $\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$.[9] In contrast, dN and $d\ln \mathbb{W}$ directly increase labor share by $\frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$ and $1-\zeta$ respectively.

All five variables affect the price of the aggregated task, which in turn influences the labor share. The impact of this price change on the labor share is multiplied by the factor $-(1-\zeta) + S_K^f(1-\sigma)$. The sign of this indirect effect hinges on the values of σ and ζ. In Equation (18), the term $-(1-\zeta) + S_K^f(1-\sigma)$ recurs frequently, exerting a significant impact on many coefficients. In the next section, we discuss the datasets used in this paper and the construction of the variables.

3 Data

3.1 Automation and New Tasks by Acemoglu and Restrepo (2019)

Acemoglu and Restrepo (2019) (henceforth referred to as AR) presents a tool for inferring automation and innovation in human tasks (henceforth, IHT). This tool utilizes a relatively small set of variables: labor compensation, employee count, value-added, wage, and investment price. The AR framework enables the inference of automation and IHT.

Fundamentally, the AR framework operates under the assumption that if there is an observed *increase* in labor share (an indicator of the total income in an economy that goes to labor), it must be attributed to IHT. Conversely, if there is a *decrease*, it is attributable to automation. This principle is clearly articulated in Figure 1 of their paper.

The online appendix of the AR paper elaborates on this framework. For ease of reference, we include it in our Online Appendix C. Equation (AR4) represents the percentage change in labor share, which can be broken down into Equations (AR6) and (AR7). The former represents the percentage change in substitution effects, while the latter shows the percentage change in 'task contents.' A positive (negative) result in Equation (AR7) is interpreted as indicative of IHT (automation). Given that the percentage change in substitution effects (Equation AR6) is usually minimal, the percentage change in 'task contents' (Equation AR7) virtually mirrors the percent change in labor share (Equation AR4).

To summarize, AR's inference of automation and IHT is largely based on the percent change in labor share. However, using these inferred variables in our primary analysis presents a challenge due to the expected high correlation with labor share,

[9] This term indicates labor losses of $\gamma(I)^{(\zeta-1)(1-\alpha)}$ in task I out of the total $\int_I^N \gamma(j)^{(\zeta-1)(1-\alpha)} dj$

which could lead to reverse causality. Furthermore, there is no certainty that the inferred variables accurately represent the real-world values of automation and IHT. Consequently, we require variables obtained through direct measurement.

For the purpose of assessing IHT, we will use data from ONET, which offers information on the number of new tasks in the USA, measured at the occupation-year level. This data is collected directly by ONET. To analyze automation, we will use data provided by the International Federation of Robotics (IFR), which gives us the number of automated machines at the country-industry-year level.

3.2 Innovation in Human Tasks

To proxy dN in Equation (18), we will use Innovation in human tasks (IHT), which we elaborate in this subsection. The Occupational Information Network (ONET), managed and maintained by the United States Department of Labor, serves as a comprehensive database of occupational information (National Center for O*NET Development, 2023). For each Standard Occupational Classification (SOC),[10] ONET consistently updates the spectrum of tasks that workers are expected to perform. For example, in 2023, Automotive Engineers were assigned 25 responsibilities, which included the calibration of vehicle systems, control algorithms, and other software systems. When new tasks, previously nonexistent, come to light, ONET increases the number of tasks associated with the Automotive Engineering occupation. Furthermore, ONET periodically reports 'Emerging new tasks' about once or twice annually. These tasks have recently emerged but have not been extensively studied by the ONET department; hence, these specific tasks are not included in the occupational list. We incorporate these 'Emerging new tasks' in addition to our base number of tasks provided by ONET. This process completes our generation of 'task scores' by each occupation.

Meanwhile, AR employs only 'Emerging new tasks' to construct the Task scores. We contend that our method of integrating both the 'base number of tasks' and 'Emerging new tasks' offers a more sophisticated approach than relying solely on Emerging new tasks, as AR does. Specifically, the 'base number of tasks' serves as a primary source of information for capturing new tasks that were nonexistent before, while 'Emerging new tasks' function as supplementary information.

The 'Task scores' vary by Standard Occupational Classification (SOC) and year. AR translated this information into variations by industry and year using the US Census from IPUMS (Ruggles et al., 2020), a dataset comprising individual worker data with specific occupation codes.[11] After associating the 'Task score' with each individual,

[10] SOC is an acronym for Standard Occupational Classification employed by US agencies. The ONET classification system (ONET-code) is a subclassification of the SOC system, hence, every ONET-code has a corresponding SOC. However, the ONET-code does not align perfectly with the Occupational Classification Code (OCC).

an average is calculated at the industry and year level. Subsequently, we compute the 5-year growth rate of this variable, which we denote as 'Innovation in Human Tasks.' IHT can also be formulated for EU countries using the EU Labor Force Survey (EU-LFS) instead of the US Census. It's crucial to recognize that the 'Task scores' from ONET are used to generate IHT for EU countries.

The European Commission has recently initiated a project akin to ONET, named 'European Skills, Competences, Qualifications, and Occupations' (ESCO). ESCO has disclosed the tasks required for workers for a single year and has yet to release a Task score.

In the absence of a European equivalent of the 'Task scores', we depend on data from ONET. A foundational assumption in the creation of the EU's IHT is that the task requirements in the USA mirror similar trends in the EU. For example, if the number of tasks required for Automotive Engineers surged in the USA in 2015, it is assumed that a similar trend occurred in the EU around the same period. Therefore, the variation for the EU originates from the differing composition of workers in each country, occupation, and year; regrettably, the EU-LFS does not offer more detailed industry variation beyond the manufacturing sector.

While we adopt AR's concept when generating IHT, our method offers more refinement. Detailed explanations of this can be found in Online Appendix D. IHT can be compared with the inferred value of IHT proposed by AR. As mentioned earlier, the inferred variable may not be a true representation of the actual value obtained directly from data collection. Consequently, any discrepancies between IHT and the 'inferred value of IHT' do not necessarily indicate that IHT is misleading. Instead, it could suggest that the 'inferred value' is not an effective proxy for the real value.

We compared IHT and the 'inferred value of IHT' in the USA. First, both have fixed differences at the industry level. Therefore, to make meaningful comparisons across industries, the industry-fixed effect must be removed. We regress each variable solely on industry dummies and take the residual. Secondly, as we are interested in long-term growth rates, we convert the variables into 5-year growth rates. Figure 4 presents a scatter plot of the two variables' growth rates. They are highly correlated.

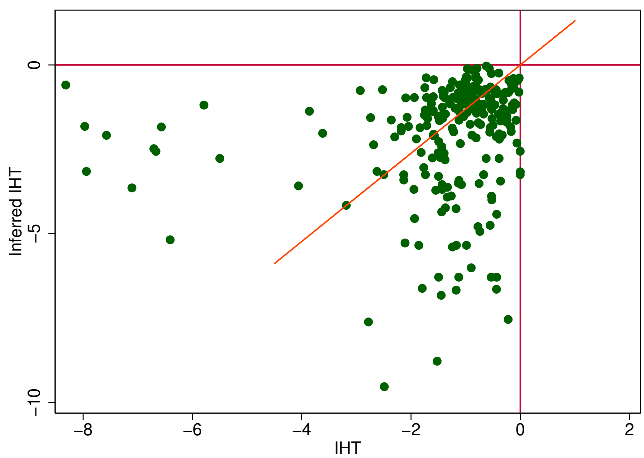
3.3 Innovation in Robots

The International Federation of Robotics (IFR) provides data on the number of automated robots (both flow and stock) at the country-industry-year level. Instead of using the raw data on the number of robots from the IFR, Acemoglu and Restrepo (2020) proposed utilizing the Adjusted Penetration of Robots (APR) to proxy automation. We

[11] Contrary to our approach, AR exclusively utilizes the 'Emerging new tasks' as reported by ONET. They do not combine these with the base number of tasks provided by ONET. We did not favor this method because the 'Emerging new tasks' reported by ONET are sparse and not thorough.

Figure 4

(a) IHT and inferred IHT (5-year growth rate)



will enhance this metric further, referring to it as the Innovation in Robots (IRB), which will serve as a proxy for dI in Equation (18).

3.3.1 Adjusted Penetration of Robots

APR is defined as in Equation (19):

$$\text{APR}_{i,(t5,t1)} \equiv \frac{M_{i,t5} - M_{i,t1}}{L_{i,2005}} - \frac{Y_{i,t5} - Y_{i,t1}}{Y_{i,t1}} \frac{M_{i,t1}}{L_{i,2005}} \tag{19}$$

$$= \left(\frac{M_{i,t5} - M_{i,t1}}{M_{i,t1}} - \frac{Y_{i,t5} - Y_{i,t1}}{Y_{i,t1}}\right) \frac{M_{i,t1}}{L_{i,2005}} \tag{20}$$

$$= (g_M - g_Y) \frac{M_{i,t1}}{L_{i,2005}} \tag{21}$$

, where i is the industry sector (country $\times$ industry in our case), and t5 is 5-year after t1. M is the number of robots (stock), L is the number of employees, Y is value-added (in real terms).

Acemoglu and Restrepo (2020) employs APR as a proxy for $d(I - N + 1)$ primarily because the term dI encapsulates the theoretical concept of a 'pure direction of automation,' which is abstract and not directly observable in empirical settings. The observable growth rate of the number of robots is not a suitable proxy for dI since it reflects an equilibrium outcome in real-world scenarios. Given this, Acemoglu and Restrepo (2020) proposes APR to effectively serve as a proxy for $d(I - N + 1)$.

The second term in Equation (21), $-g_Y$, serves to measure the 'penetration' of robots. In other words, if the growth rate of robots exceeds that of value-added, they interpret this as a positive penetration. This penetration equates to $I - N + 1$ in their terminology, which represents the length between N-1 and I. The inclusion of the second term, (21), $-g_Y$, in Equation (21) is necessary for the following reason: Suppose there is an economic boom. In such a scenario, the growth rate of robot adoption would likely surge, while $d(I-N+1)$ remains unchanged. Therefore, they adjust the growth rate of robot adoption by subtracting the growth rate of value-added, g_Y.

The APR represents the 5-year growth rate of robots adjusted by labor input and the value-added within a given sector. Multiplication by $\frac{M_{i,t1}}{L_{i,2005}}$ is necessary as the raw number of robots does not adequately represent their definition of automation. Consider, for instance, that the IFR began collecting data in many countries starting in 2004. A change from 1 robot to 100 robots between 2004 and 2005 would represent a growth rate of 9900%, whereas an increase from 100 to 200 robots between 2005 and 2006 would only reflect a 100% growth rate. These rates are not useful because the number of machines increased by the same amount (100) in both cases. The term $\frac{M_{i,t1}}{L_{i,2005}}$ is introduced to adjust for this discrepancy. Suppose $L_{i,2005} = 100$. In 2005, $g_M \times \frac{M_{i,t1}}{L_{i,2005}}$ equals 99%, and in 2006, it amounts to 100%, which makes them comparable. The underlying idea is that the 5-year difference in the number of machines across countries and industries is not directly comparable; they needed to normalize it by dividing by the number of employees.[12]

3.3.2 Innovation in Robots

Acemoglu and Restrepo (2020) used APR as a proxy for automation. One issue with this is that APR effectively represents $d(I-N+1)$, not dI, which is the true measure of automation. Our introduction of the proxy for dN, the IHT, as explained in the previous section, enables us to address this issue in the following manner.

From Equation (18),

$$d \ln S_L^f = \alpha_0 d \ln \gamma + \alpha_1 dI + \alpha_2 dN + \alpha_3 d \ln \mathbb{W} + \alpha_4 d \ln R + \alpha_5 d \ln \psi$$

Therefore, on the right-hand side,

$$\begin{aligned} \alpha_1 dI + \alpha_2 dN &= \alpha_1 d(I - N + 1) + \alpha_1 dN + \alpha_2 dN \\ &= \alpha_1 \text{APR} + \alpha_1 \text{IHT} + \alpha_2 \text{IHT} \\ &= \alpha_1 (\text{APR} + \text{IHT}) + \alpha_2 \text{IHT} \\ &= \alpha_1 \text{IRB} + \alpha_2 \text{IHT} \end{aligned} \tag{22}$$

In short, we use the Innovation in Robots (IRB) to proxy automation, dI. IRB is essentially a summation of APR and IHT. One might wonder why we don't simply use dI

[12] Instead of dividing by $L_{i,2005}$, dividing by 'quantity' would be more accurate, but it will not change the results significantly.

from the beginning instead of using $d(I - N + 1) + dN$. The issue here is that there is no effective alternative to proxy dI. As mentioned earlier, the number of robots used is the result of economic equilibrium and is not the abstract concept of dI.

3.4 Robot Price

Unfortunately, the International Federation of Robotics (IFR) no longer provides information on the prices of robots. IFR provided robot prices in the form of an average unit price until 2009, and as a price index until 2005. Klump et al. (2021) and Jurkat et al. (2022) provide in-depth information on this topic.[13] An alternative method to obtain robot prices is by following the approach of Fernandez-Macias et al. (2021), which involves the use of UN Comtrade data.[14]

We adopted this method by Fernandez-Macias et al. (2021), who illustrate in their Figures 3 and A1 that the robot price trends based on IFR and UN Comtrade data are similar. Furthermore, they demonstrate that the robot price has been steadily declining. The data generation process is as follows: UN Comtrade provides annual import and export values in dollar for 'Machinaery and mechanical appliances; industrial robot, n.e.c. or included.'[15] They also provide the quantity of these values for both imports and exports. Hence, we infer the robot prices by dividing the dollar values by their quantities.

3.5 Estimation of S_M^T

S_M^T represents the share of robot cost in the total combined task cost, which comprises both labor and robot costs. This metric is vital for our analysis in the Regression section. Unfortunately, no official data is available that directly quantifies this value, requiring us to rely on multiple sources for an accurate estimation.

Denote Ψ, M, W, and L as robot price, number of robots, wage, and employment, respectively. Then S_M^T can be expressed as follows:

$$
\begin{aligned}
S_M^T &= \frac{\Psi M}{\Psi M + WL} \\
&= \frac{1}{1 + \frac{WL}{\Psi M}} \\
&= \frac{1}{1 + \left(\frac{M}{L}\right)^{-1} \frac{W}{\Psi}}
\end{aligned}
$$

[13]They noted, "Due to the considerable effort involved and owing to compliance issues, the IFR no longer continues to construct the price indices."

[14]https://comtradeplus.un.org/

[15]HS847950

Unfortunately, the International Federation of Robotics (IFR) provided robot prices in the form of an average unit price until 2009 and discontinued this practice thereafter. Access to robot price information prior to 2009 is also restricted for those who have purchased IFR data after this point. Nonetheless, Fernandez-Macias et al. (2021) offers a comprehensive method to approximate the missing price information from the IFR dataset. Specifically, they provide values for M/L as well as Ψ. We supplement these data with wage information from the OECD STAN database to complete the S_M^T value in the equation above.

It is important to note that the equipment cost for robots is estimated to constitute around 33.04% of the total robot costs[16], covering elements like operation, training, software, maintenance, and disposal (Zhao et al., 2021). The figures provided by Fernandez-Macias et al. (2021) pertain only to equipment cost. Therefore, we have accounted for this information accordingly.

By synthesizing all available information, we estimate S_M^T to be 2.813% for the total manufacturing sectors. An alternative method detailed in Appendix A estimates the S_M^T value at 2.104%. However, we consider the method outlined in this section to be more accurate and reliable, leading us to conclude that the S_M^T value is 2.813%.

3.6 KLEMS

Aside from the IFR dataset, the ONET dataset, and Robot Price, we will use data from KLEMS.[17] KLEMS comes in two different versions: one follows national accounts, and the other follows growth accounts. The main difference between these versions is that the national accounts allow room for a markup greater than one, while the growth accounts do not. The latter assumes that the sum of labor cost and capital cost equals the value-added, implying that the markup is exactly one. As allowing for a markup is critical for our analysis, we use the national accounts when using KLEMS.

KLEMS shares similar characteristics with OECD STAN in terms of many national account variables at a country-industry-year level. Table 1 presents descriptive statistics. Predominantly, the values for OECD STAN and KLEMS are comparable, albeit not identical. In some instances, the values are in fact identical. This alignment is a result of collaborative projects aimed at fostering more consistent values between the two.

All nominal values are converted to real values through division by the chain-linked price index provided by KLEMS (VA_PI), following the methodology implemented by Karabarbounis and Neiman (2014).

[16] $33.04\% = 35.73\% \times (1 - 0.075)$, where 0.075 represents taxes, transactions, and after-sales fees. The cost share of robot equipment accounts for 35.73% of the total cost for using robots, as estimated by Zhao et al. (2021).

[17] KLEMS: EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs.

Table 1: Descriptive Statistics

Country	WL (labor comp)		RK (capital comp)		Value added		Labor Share	
	STAN	KLEMS	STAN	KLEMS	STAN	KLEMS	STAN	KLEMS
USA	867,789	851,834	292,456	308,662	1,647,140	1,593,719	52.85	53.60
DEU	366,787	366,806	104,117	104,034	569,189	570,196	64.67	64.57
SWE	256,507	256,540	115,040	124,370	502,728	502,728	51.17	51.18
DNK	219,076	226,496	199,337	220,713	410,478	426,533	55.33	54.87
ITA	140,568	140,568	57,107	54,924	253,368	253,353	55.60	55.60
FRA	135,093	135,098	52,379	41,244	226,181	226,181	59.74	59.74
GBR	110,603	109,347	26,230	25,535	171,778	170,498	64.45	64.19
AUT	28,106	29,959	9,427	12,090	51,011	54,254	55.22	55.31
FIN	17,100	17,979	7,512	7,204	33,112	34,848	51.91	51.85
PRT	11,537	12,897	3,166	3,166	20,575	23,030	56.06	55.99
Total	215,317	214,753	86,677	90,194	388,556	385,534	56.75	56.69

3.7 Capital Price

In our paper, we utilize the replicated values for capital price from Karabarbounis and Neiman (2014) (hereinafter KN). To calculate this, we initially require the investment price, which the KLEMS data provides, including industry variations.

It's important to note that we don't directly observe the capital price, which represents the *usage* cost of one unit of capital. We do, however, observe the investment price, which signifies the *purchase* cost of one unit of capital. In accordance with the theory of investment by Jorgenson (1963), we can calculate the capital price as follows:

$$R_t = \xi_{t-1}(1 + i_t) - \xi_t(1 - \delta_t) \tag{23}$$

$$R_t = \xi_t \left(\frac{1}{\beta} - 1 + \delta \right) \tag{24}$$

In this Equation (23), R represents the capital price, ξ is the investment price, i is the interest rate, and δ is the depreciation rate. All values are expressed in real terms. This equation signifies that investors are indifferent between paying a *usage* cost for capital (R_t) and *purchasing* capital, paying interest, and then selling the depreciated capital at a later date.

To simplify Equation (23) into the form presented in Equation (24), we follow a specific process. This involves the assumption of a constant interest rate, i, and approximating $1 + i$ as $\frac{1}{\beta}$. Additionally, we assume that $\xi_{t-1} = \xi_t$. Equation (24), as employed by KN in their KLEMS version of the capital price variable, assumes a depreciation rate of 10%. This rate aligns closely with the 10.8% rate assumed by Stehrer et al. (2019), an official KLEMS document. Throughout this paper, we strictly adhere to the approach by KN.

It is important to note that KN employed a β value of 0.909 (corresponding to an interest rate, $i = 0.100$), reflecting the high real interest rates prevalent in the 1970s. In contrast, our study adopts a β of 0.988 (equivalent to $i = 0.012$), derived from averaging the real interest rates from 2005 to 2019 across ten countries. However, the specific value of β does not influence the regression outcomes in our analysis, as we focus on the growth rate of the capital price, which effectively cancels out the impact of β.

3.8 Non-robot Capital Price

Denote total capital that includes robot and non-robot as K. Also, denote robot capital and non-robot capital as M and R, respectively. Then it follows that

$$\text{gr\_Price}_K = \text{gr\_Price}_M \frac{\text{Cost}_M}{\text{Cost}_K} + \text{gr\_Price}_R \frac{\text{Cost}_R}{\text{Cost}_K}$$

, where 'gr' denotes the growth rate. The implication of this equation is that the level and scale of the prices do not matter in this growth rate relationship. The above equation can be rearranged to

$$\text{gr\_Price}_R = \frac{\text{gr\_Price}_K - \text{gr\_Price}_M \times \alpha}{1 - \alpha}$$

, where α is $\frac{\text{Cost}_M}{\text{Cost}_K}$. We have values for Cost_K from KLEMS data. This completes the derivation of the growth rate of price for the non-robot capital.

We can estimate Cost_M by sector and country through two approaches. The first approach employs the value obtained using the approach introduced in Section 3.5. This approach yields the ratio $\frac{\text{Robot Cost}}{\text{Labor Cost}} = 2.813\%$, and labor cost information is available from the KLEMS dataset. Consequently, we can calculate Cost_M based on this information. However, this approach is contingent on labor cost values, raising concerns that the ratio $\frac{\text{Robot Cost}}{\text{Labor Cost}} = 2.813\%$ may vary significantly across sectors and countries. Therefore, we propose an alternative approach.

The alternative approach leverages information from the alternative method detailed in Appendix A. In this method, we have determined the cost ratio between OMach and robots to be $13.595 : 2.149$, where 'OMach' refers to the machinery and equipment in the KLEMS. Given that we possess detailed OMach cost data by sector and country, we can subsequently estimate Cost_M. This approach circumvents the need for labor cost data. By using this approach, we complete our derivation of the growth rate of non-robot capital price, which will be used in our regression analysis.

3.9 Capital Cost

The KLEMS data has one limitation: it lacks RK (rental cost for capital stock) and profit (operating surplus and mixed income). If either RK or Profit were available, we could deduce the other because Value-added is calculated as WL + RK + Profit. Regrettably, the absence of both presents a challenge. This issue is addressed by utilizing OECD STAN data.

In particular, the KLEMS dataset lacks RK. It does include I_GFCF (Investment in Gross Fixed Capital Formation) and K_GFCF (Capital Stock of Gross Fixed Capital Formation), but these do not provide the necessary RK information. I_GFCF represents the net investment in fixed assets —a flow metric indicating capital goods investment. K_GFCF, on the other hand, denotes the total value of all fixed assets available for production —a stock variable. Consequently, although RK can be estimated based on K_GFCF, this method lacks precision. This is because K_GFCF represents the purchase cost, not the rental cost. To convert the purchase cost into rental cost, the real interest rate and depreciation rate as shown in Equation (23) are required. Notably, the depreciation rate requires numerous assumptions, and we lack this information.

A pertinent question arises: why not use OECD STAN initially, instead of KLEMS? The response lies in the fact that OECD STAN does not contain R (capital price) data. Therefore, we resort to using R obtained from KLEMS. However, integrating this with other data from OECD STAN, particularly wage variables, poses complications. Furthermore, STAN does not provide industry-specific Producer Price Index (PPI). To enhance the accuracy of our analysis, we prefer to use industry-specific PPI, specifically the VA_PI variable from KLEMS.

Hence, an alternative approach is to employ RK from OECD STAN. This is feasible because the value-added and WL (labor compensation) figures are nearly identical in both STAN and KLEMS datasets (as illustrated in Appendix Figures 1 and 2). Consequently, it is highly probable that RK, along with operating surplus and mixed income, are consistent across both KLEMS and STAN. Therefore, in this paper, we assume that the markups in KLEMS and STAN are identical, denoted by $\frac{\text{Value-added}}{\text{WL+RK}}$. Based on this assumption, we are able to recover RK for KLEMS as below:

$$\frac{\text{Value-added}_{\text{STAN}}}{\text{WL}_{\text{STAN}} + \text{RK}_{\text{STAN}}} = \frac{\text{Value-added}_{\text{KLEMS}}}{\text{WL}_{\text{KLEMS}} + \mathbf{RK}_{\mathbf{KLEMS}}}.$$

4 Regressions

4.1 Regression Results

Based on the specification in Equation (18), we provide consistent regression equations. Equation (26) is for the corresponding regression. It is important to note that the coefficient of $d \ln \mu$ must be -1, as dictated by Equation (25). Since our focus is not on exploring the impact of markup on labor share, we employ the markup-adjusted labor share, as represented in Equation (26). This adjustment aligns with the specification provided in Equation (18).

$$\begin{aligned}
\text{gr_laborshare} =& -\text{gr_markup} \\
& + \alpha_1 \text{IRB} + \alpha_2 \text{IHT} \\
& + \alpha_3 \text{gr_labor price} + \alpha_4 \text{gr_robot price} \\
& + \alpha_5 \text{gr_non-robot capital price} \\
& + \gamma_i + \gamma_j + \gamma_t + \gamma_{ij} + \varepsilon_{ijt} \qquad (25) \\
\Leftrightarrow \text{gr_(laborshare} \times \text{markup)} =& \alpha_1 \text{IRB} + \alpha_2 \text{IHT} \\
& + \alpha_3 \text{gr_labor price} + \alpha_4 \text{gr_robot price} \\
& + \alpha_5 \text{gr_non-robot capital price} \\
& + \gamma_i + \gamma_j + \gamma_t + \gamma_{ij} + \varepsilon_{ijt}. \qquad (26)
\end{aligned}$$

gr indicates the variables are in a 5-year growth rate, and i, j, and t correspond to country, industry, and year, respectively. IRB and IHT stand for the growth rate of Innovation in Robots and Innovation in human tasks, respectively. We exclude the notation of *gr* from IRB and IHT, as by definition, they already represent a 5-year growth rate.

To facilitate the explanation of the intuitions behind the regression results, we have rewritten Equation (18) as Equation (27) below. In Equation (27), S_L^f represents labor share times markup, I is automation, N is innovation in human tasks, $\mathbb{W}$ is wage, ψ is robot price, and R is non-robot capital price.

$$
\begin{aligned}
&d\ln S_L^f = \\
&-\left[(1-\zeta)+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)S_L^T\right]d\ln\gamma \\
&+\underbrace{\left[\underbrace{-\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}}_{\text{(A)}}+\underbrace{\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)}_{\text{(B)}}\underbrace{\frac{1}{1-\zeta}\frac{\psi^{1-\zeta}-\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{(C)}}\right]}_{(\alpha_1)}dI \\
&+\underbrace{\left[\underbrace{\frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}}_{\text{(D)}}+\underbrace{\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)}_{\text{(B)}}\underbrace{\frac{1}{1-\zeta}\frac{-\psi^{1-\zeta}+\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{(E)}}\right]}_{(\alpha_2)}dN \\
&+\underbrace{\left[(1-\zeta)+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)S_L^T\right]}_{(\alpha_3)}d\ln\mathbb{W} \\
&+\underbrace{\left[\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)S_M^T\right]}_{(\alpha_4)}d\ln\psi \\
&\underbrace{-\left[S_K^f(1-\sigma)\right]}_{(\alpha_5)}d\ln R.
\end{aligned}
\tag{27}
$$

Meanwhile, the sum of the coefficients of $d\ln\mathbb{W}$, $d\ln\psi$, and $d\ln R$ is equal to zero (i.e. $(\alpha_3)+(\alpha_4)+(\alpha_5)=0$). Therefore, we prefer to impose this restriction on our regression. Table 2 is the regression result. To improve readability, both the coefficients and standard errors have been multiplied by 100. Column (1) shows the Ordinary Least Squares (OLS) results without the coefficient restriction; Column (2) displays the OLS results with the coefficient restriction. In both Column (1) and (2), standard errors are clustered by country and sector to account for the serial correlation. Lastly, Columns (3-5) present the quantile regressions with the restriction. The coefficients across different quantiles retain the same sign as in the OLS regressions. This suggests that the implications hold steady across different quantiles of labor share.

Table 2: Regressions

	OLS		Quantile		
	(1)	(2)	(3)	(4)	(5)
Restrction	No	Yes	Yes	Yes	Yes
Quantile			0.3	0.5	0.7
α_1: IRB	-0.076***	-0.062**	-0.091***	-0.070**	-0.043
	(0.021)	(0.023)	(0.006)	(0.026)	(0.029)
α_2: IHT	0.165***	0.156***	0.188***	0.166***	0.124***
	(0.042)	(0.044)	(0.019)	(0.033)	(0.035)
α_3: gr_labor price	12.559***	12.777***	9.383***	11.223***	14.149***
	(3.423)	(3.626)	(1.083)	(1.431)	(0.901)
α_4: gr_robot price	0.646	0.777	0.781*	0.829	0.081
	(1.014)	(1.035)	(0.354)	(0.606)	(0.335)
α_5: gr_non robot capital price	-18.917***	-13.553***	-10.164***	-12.052***	-14.230***
	(3.681)	(3.338)	(1.037)	(1.451)	(0.878)
N	911	911	911	911	911
R^2	0.621	0.609			
pseudo R^2			0.480	0.446	0.455

Standard errors in parenthesis are clustered by country and sector (OLS); heteroskedasticity-robust (Quantile)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The coefficients and the standard errors have been multiplied by 100 for better readability.

In assessing the congruence between the regression results and the model's predictions, two findings are noteworthy. First, the model delineates the coefficient for robot price as α_4, with the term $S_M^T = 2.81\%$ included. The model thus anticipates this coefficient to be of an insignificantly small value. In line with this prediction, the regression coefficient for robot price is not statistically significant, and the point estimate lacks precision. Second, the OLS results maintain consistency in both magnitude and direction, regardless of whether the restriction is applied. Utilizing OLS without the restriction (as shown in Column 1), we test the null hypothesis that the restriction is non-binding. This hypothesis is rejected at the 0.05 significance level, suggesting a certain degree of misalignment between the data and the model's predictions. In subsequent analyses, we refer to the OLS results from Column (2) as our baseline.

4.2 Estimation of σ and ζ

Before delving into the implications of the regression results, it is essential to first estimate the values of σ and ζ. These parameters are pivotal in governing the mechanisms through which five explanatory variables influence labor share via price channels. By utilizing Equation (27) along with the regression results, we can estimate the values of σ and ζ. Specifically, given that $S_K^f > 0$ and the coefficient for $d \ln R$ is negative, we can infer that $\sigma < 1$. Further, by substituting the value $S_K^f = 0.494$ that we obtained from the data, we calculate $\sigma = 0.726$, as illustrated in Equation (28). We conduct a Wald test on the null hypothesis that $\sigma = 0$ and find that it can be rejected at the 0.05 significance level. The confidence interval for σ is $(0.593, 0.858)$. Consequently, we can conclude with confidence that σ lies within the range of 0 to 1.

$$- \underbrace{S_K^f}_{0.494}(1 - \sigma) = \underbrace{\textcircled{\alpha_5}}_{-0.18917} \tag{28}$$

$$\Rightarrow \sigma = 1 + \frac{\textcircled{\alpha_5}}{S_K^f} \tag{Sigma}$$

The derivation of the value for ζ proceeds as follows. From Equation (27), utilizing coefficients $\textcircled{\alpha_3}$ and $\textcircled{\alpha_5}$, we arrive at Equation (Zeta).

$$\zeta = 1 - \frac{\textcircled{\alpha_3} + \textcircled{\alpha_5} S_L^T}{1 - S_L^T} \tag{Zeta}$$

As demonstrated earlier in Section 3.5, we estimate S_L^T to be 0.972. Upon substituting $S_L^T = 0.972$ into Equation (Zeta), we obtain an estimate for ζ of 1.141. We then conduct a Wald test on the null hypothesis that $\zeta = 0$ and find it can be rejected at the 0.05 significance level. Specifically, the confidence interval is from 0.407 to 1.874. Consequently, we can conclude with confidence that ζ lies within the range of this interval. Additionally, we conduct a Wald test on the null hypothesis that $\zeta - 1 = 0$ and find it cannot be rejected at the 0.05 significance level, yielding a confidence interval of $(-0.593, 0.874)$. This result suggest that ζ is one. Many papers, including those by Autor (2013), have assumed this value to be 1 and used the Cobb-Douglas function, but there has been no concrete basis for this. By providing a basis for such an assumption, we make an additional contribution to literature.

4.3 Estimation of $-(1 - \zeta) + S_K^f(1 - \sigma)$

As indicated in Equation (18), the term $-(1 - \zeta) + S_K^f(1 - \sigma)$ plays a crucial role as it governs the aggregate task price channel. This, in turn, affects how factors such as automation, the innovation in human tasks, wages, and robot prices influence labor share. Substituting the point estimates for σ and ζ acquired from the regression results in Column (2), this term evaluates to $2.260 > 0$. To test its significance, we use stochastic variables for σ and ζ and perform a Wald test on the null hypothesis that $-(1-\zeta)+S_K^f(1-\sigma) = 0$. The confidence interval for it is $(1.359, 3.161)$. Consequently, The test reveals that we can reject this null hypothesis at the 0.05 significance level, which allows us to make a reasonable inference that the term $-(1-\zeta)+S_K^f(1-\sigma)$ is positive.

4.4 Direct and Indirect Effects for Automation and Innovation in Human Tasks

The coefficients of the five explanatory variables (dI, dN, $d\ln\mathbb{W}$, $d\ln R$, and $d\ln\psi$) in Equation (27) capture not just the direct effects of changes in these variables, but also the indirect effects that operate through the price of aggregated tasks. This subsection aims to show that the indirect effects of both automation and innovation in human tasks serve to amplify their direct impacts on labor share. First, automation and innovation in human tasks alter the composition of tasks performed by robots and those performed by labor. Second, this change in composition affects the aggregate task price. Finally, the change in the aggregate task price, in turn, affects labor share through substitution among labor, robots, and non-robot capital.

Automation: The term Ⓐ in Equation (27) denotes the direct effect of automation on labor share, which is negative. Concurrently, the term Ⓑ×Ⓒ captures the indirect effect. Specifically, Ⓒ is negative under Assumption 1, irrespective of the sign of ζ. This indicates that the price of the aggregated task, denoted by P_T, falls when robots take over tasks previously performed by humans. This change in P_T is then scaled by the factor $-(1-\zeta)+S_K^f(1-\sigma)$, which represents the partial derivative of labor share with respect to the aggregated task price. Therefore, the sign of the indirect effect on labor share hinges critically on the sign of $-(1-\zeta)+S_K^f(1-\sigma)$, which we have estimated to be positive. In summary, given that Ⓑ >0 and Ⓒ <0, the indirect effect of automation on labor share is also negative, serving to amplify its direct impact.

Innovation in Human Tasks: The term Ⓓ in Equation (27) denotes the direct effect of Innovation in human tasks (IHT) on labor share, which is positive. Concurrently, the term Ⓑ×Ⓔ captures the indirect effect. Specifically, Ⓔ is positive under Assumption 1, with the proof provided in Appendix B. This indicates that the price of the aggregated task, denoted by P_T, rises when there is innovation in human tasks. Since Ⓑ>0, the indirect effect of IHT on labor share is also positive, serving to amplify its direct impact.

4.5 Effects of Price Factors on Labor Share

Essentially, the elasticity of substitution between aggregated tasks and non-robot capital ($\sigma<1$) fundamentally influences the relationship between wage and capital price with labor share. The logic is demonstrated in the equations below, and the explanations are provided as follows: The robot cost share, denoted by S_M^T, is a very small value, specifically 0.028. Hence, the labor cost share, denoted by $S_L^T\equiv 1-S_M^T$, is

0.972. Also, ζ is close to one. As a result, the term $(1-\zeta)$ largely cancels out, as detailed below.

$$
\begin{aligned}
\textcircled{\alpha_3} =& (1-\zeta) + \Big(-(1-\zeta) + S_K^f(1-\sigma)\Big) S_L^T \\
=& (1-\zeta)(1-S_L^T) + S_K^f(1-\sigma)S_L^T \\
=& -0.004 + S_K^f(1-\sigma)S_L^T \\
\approx&\ S_K^f(1-\sigma)S_L^T = 0.132 > 0.
\end{aligned}
$$

Consequently, the model anticipates a positive association between labor price and labor share. The regression results align with this prediction.

Similarly, the model predicts a negative association between the price of non-robot capital and labor share, as detailed below. The regression results are in alignment with this prediction.

$$
\textcircled{\alpha_5} = -\Big[S_K^f(1-\sigma)\Big] < 0 \tag{29}
$$

The underlying intuition stems from the gross complementarity between labor and non-robot capital. Specifically, when wages rise, employment levels do not decrease proportionally, leading to an increase in labor share. Similarly, a decline in the price of non-robot capital results in an increase in labor share.

Meanwhile, the model predicts a positive, albeit small, association between robot price and labor share, which is consistent with current empirical findings. This insignificance is attributed to the low share of the robot cost ($S_M^T = 2.8\%$). This means that even if robot prices change, their impact on labor share will inevitably be small. The positive correlation is primarily dependent on the condition $-(1-\zeta)+S_K^f(1-\sigma) > 0$, as demonstrated in Section 4.3.

$$
\textcircled{\alpha_4} = \Big(-(1-\zeta) + S_K^f(1-\sigma)\Big) S_M^T > 0 \tag{30}
$$

The positive association between robot price and labor share is fundamentally attributed to $\zeta = 1$ and $\sigma < 1$. The underlying logic is as follows: (1) A decrease in robot price results in a reduction in the price for aggregate tasks, a relationship that holds true under all conditions, as indicated by a positive S_M^T. (2) A lower price for aggregate tasks leads to a decreased cost share of these tasks, primarily due to $\sigma < 1$, as demonstrated in Equation (3). Specifically, with $\sigma < 1$, the cost of non-robot capital rises relative to the cost of aggregate tasks. (3) Given that $\zeta = 1$, the cost share of labor remains constant within the aggregate tasks. In other words, the ratio of labor to robot costs remains unchanged. The combination of processes (2) and (3) can be expressed as $\Big(-(1-\zeta) + S_K^f(1-\sigma)\Big) > 0$. Therefore, a decrease (increase) in robot price leads to a corresponding decrease (increase) in the price of aggregate tasks and, consequently, a decrease (increase) in the cost of these tasks. This results in a reduction (increase) in labor costs, culminating in a decrease (increase) in the labor share.

This model's prediction is consistent with the observed positive association in the regression coefficient of robot prices. The positive relationship with robot prices in our model uncovers two pivotal mechanisms that impact labor share as advancements in robotics occur. First, enhanced robotic capabilities allow for the execution of tasks previously exclusive to humans, thereby reducing labor share. Second, a decline in the price of robots, without a corresponding enhancement in functionality, also exerts a negative impact on the labor share.

In the future, we anticipate that the coefficient for robot price will become more prominent, yielding a positive association as the share of robots in society increases. This expectation is attributable to the term S_M^T, the share of robot costs. It is important to note that, among the three price factors in Equation (27), S_M^T is uniquely associated with the price of robots.

4.6 Estimation of the Elasticity of Substitution between Labor and Non-robot Capital

The condition $\sigma < 1$ indirectly confirms that capital and labor are gross complementary, a result that aligns with the findings reported by Glover and Short (2020). Conversely, this result contradicts the hypothesis of gross substitutability ($\sigma > 1$) posited by Karabarbounis and Neiman (2014) (henceforth referred to as KN). We clarify that the term σ in our general equilibrium model does not align exactly with the definition of σ in the work of KN as well as Glover and Short (2020). The divergence stems from our model's distinction between robots and capital. Specifically, in our model, σ represents the elasticity of substitution between 'non-robot capital' and 'aggregated tasks', where the latter encompasses both robot and labor inputs.

Hence, in this subsection, we introduce the elasticity of substitution between labor and non-robot capital, denoted by μ, a measure that closely aligns with the findings of both KN and Glover and Short (2020). The solution for μ is given in Equation (31), and its derivation can be found in Online Appendix B.

$$\mu \equiv \frac{d\left(\frac{L}{K}\right)}{d\left(\frac{R}{\mathbb{W}}\right)} \frac{\frac{R}{\mathbb{W}}}{\frac{L}{K}} \text{ , where} \tag{31}$$

$$d\Big(\frac{L}{K}\Big) = \Big(\frac{\mathbb{W}_1}{R_1}\Big)^{-\sigma}\left[\frac{S_M^T}{1-S_M^T}\Big(\frac{\mathbb{W}_0}{\mathbb{W}_1}\Big)^{1-\zeta}+1\right]^{\frac{\zeta-\sigma}{1-\zeta}} - \Big(\frac{\mathbb{W}_0}{R_0}\Big)^{-\sigma}\left[\frac{S_M^T}{1-S_M^T}+1\right]^{\frac{\zeta-\sigma}{1-\zeta}}$$

$$\frac{L}{K} = \Big(\frac{\mathbb{W}_0}{R_0}\Big)^{-\sigma}\left[\frac{S_M^T}{1-S_M^T}+1\right]^{\frac{\zeta-\sigma}{1-\zeta}}$$

$$\Rightarrow \ \mu = \sigma \ \text{ if } S_M^T = 0.$$

Differentiating Equation (31) is infeasible. However, we can employ numerical approximation to estimate μ. We use actual $\mathbb{W}$ and R values from the dataset (all possible combinations of these), along with $\sigma = 0.726$ as established in Equation (28). We introduce small random variations to each $\mathbb{W}$ and R and consider scenarios where $|\Delta \frac{R}{\mathbb{W}}|$ is approximately 0.01. These values are then plugged into Equation (31) to obtain an approximated μ.

Panel (a) of Figure 5 displays the approximation results. When S_M^T is zero, we find that $\mu = \sigma = 0.726$. This stage indicates a complete absence of automation tasks, with all tasks being performed by labor. When $S_M^T = 2.813\%$, which corresponds to our estimate presented in Section 3.5, we obtain $\mu = 0.735$. Even when we assume $S_M^T = 10\%$, the divergence from σ is minimal, reaching at most $\mu = 0.755$. Consequently, we argue that in the context of the KN model, the elasticity of substitution between labor and non-robot capital closely approximates σ. Our analysis suggests that μ ranges between 0.726 and 0.755, supporting the idea of a gross complementary relationship between the two. In the future, as automated robots come to constitute a larger portion of tasks, the elasticity of substitution between labor and non-robot capital may move closer to one. However, making this prediction with accuracy would require more comprehensive research.

The above estimation of μ is contingent upon the value of $\zeta = 1.141$, which is our point estimate as derived in Section 4.2. However, the confidence interval for ζ varies: it spans from 0.407 to 1.874. To demonstrate the robustness of our μ estimate, we examine its sensitivity across a wide range of ζ values. This analysis is presented in Panel (b) of Figure 5. Within the ζ range of 0.407 to 1.874, μ varies between 0.719 and 0.750, confirming the robustness of our μ estimation.

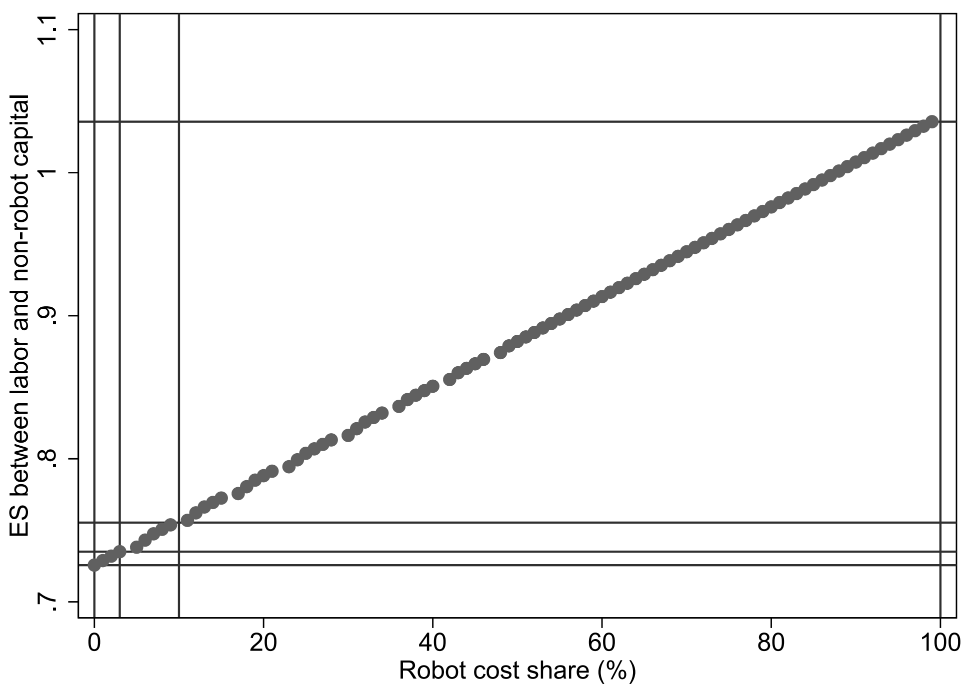
Recent research underscores the importance of quantifying this elasticity of substitution between labor and capital, as highlighted by Martinez (2018), Oberfield and Raval (2021), and Zhang (2023). Many studies report an elasticity less than one, endorsing the concept of gross complementarity. However, Piketty and Zucman (2014) suggest the potential for gross substitutability. They observed an escalating capital-output ratio and argued that this trend could consistently account for the declining labor share if the elasticity of substitution between labor and capital exceeds one —a claim our estimates do not corroborate.

Our finding also does not support the hypothesis proposed by Karabarbounis and Neiman (2014), who argue that the falling price of capital accounts for half of the recent decline in labor share. For their argument to hold, the elasticity of substitution between labor and capital must be greater than one (gross substitutes). They directly measured the correlation between the trend of capital price and labor share without using instrumental variables.

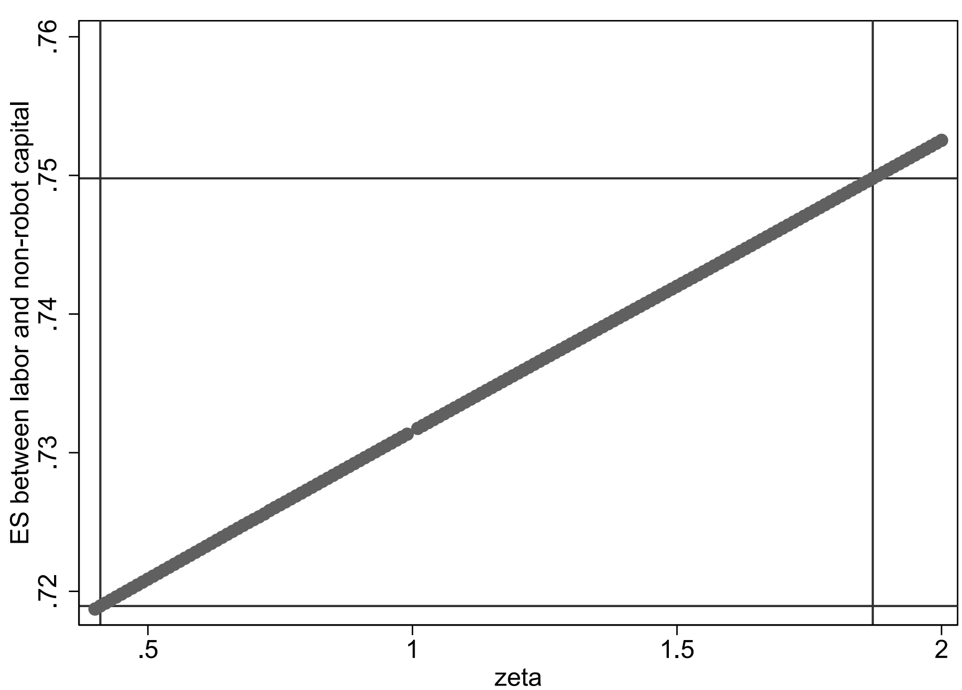
In contrast, Glover and Short (2020) reached a different conclusion, that of gross complements, by using cross-country variation with instrumental variables. They ar-

Figure 5: Elasticity of Substitution between Labor and Non-robot Capital

(a) Fixing ζ to be 2.873; Moving S_M^T



(b) Fixing S_M^T to be 2.813%; Moving ζ



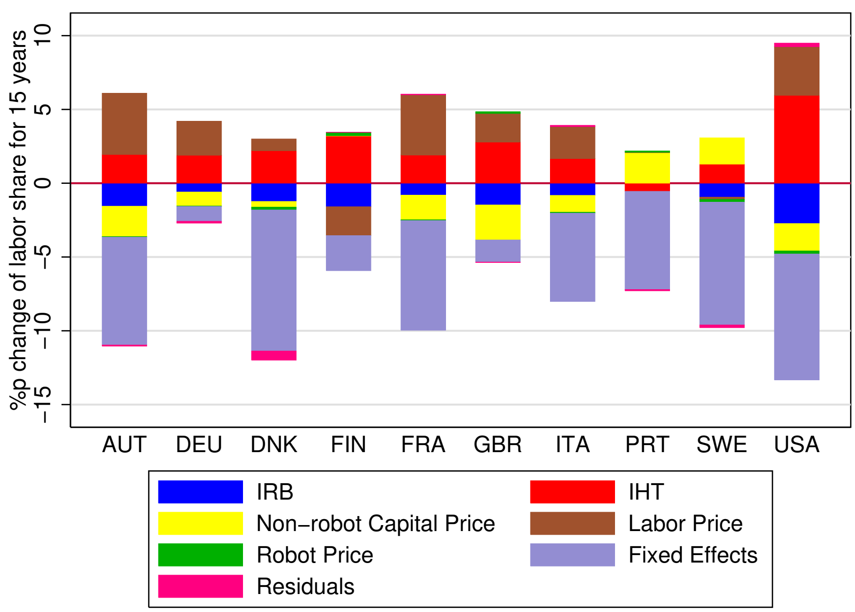
gue that correcting for bias is critical when estimating the correlation between the capital price and labor share. Our paper addresses omitted variable bias using a control function approach. We regress automation, the emergence of new tasks, wages, and robot price, along with capital price, on labor share, believing that this approach corrects for omitted variable bias. Our study supports Glover and Short (2020).

To explore the implications of the regression results further, we will now shift to the accounting exercise.

5 Accounting Exercise

Based on the regression results from Column (1) in Table 2, we have generated Figures 6, 7, and 8. In this paper, we exclusively focus on country-level variation to maintain brevity. Accordingly, the values in these figures are derived by aggregating data at the country level. During this aggregation process, 'Average variables' are consolidated by weighting the value-added in each sector and year. Intuitively, the values illustrated in Figures 6, 7, and 8 quantify the extent to which each factor influences the growth rate of the markup-adjusted labor share (S_L^f) for 15 years.[18]

Figure 6: Labor shares



[18] S_L^f is defined in Equation (17) in the Model section.

Figure 7: Labor shares (NET)

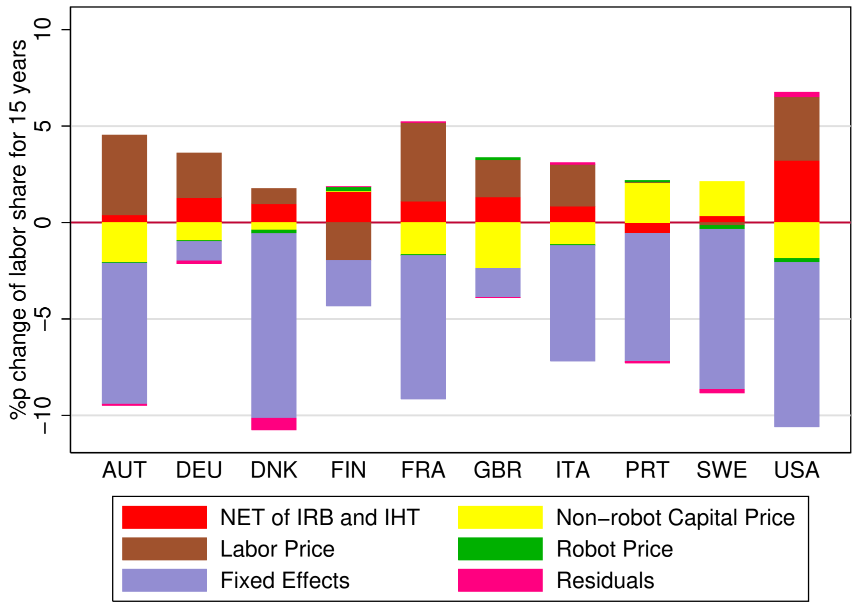


Figure 8: Labor shares (Zoom out)

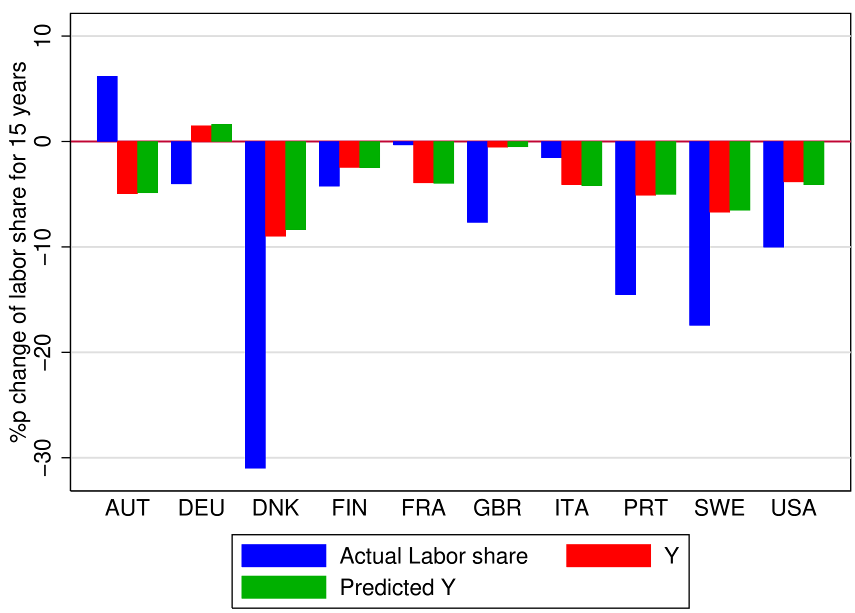


Figure 6 illustrates these values, showing that IRB and IHT are not significantly larger than other price factors. This indicates that automation and innovation in human tasks are not the sole primary drivers of changes in labor share. Consequently, this finding does not support Acemoglu and Restrepo (2019)'s hypothesis that automation and innovation in human tasks can be deduced by decomposing the labor share.[19]

Figure 7 differs from Figure 6 in that it nets out IRB and IHT, thereby canceling out effects in opposite directions. In most countries, innovation in human tasks (IHT) predominates over automation (IRB), particularly in the USA. This adjustment allows us to concentrate on other variables. The trends for Non-robot Capital Price are mostly negative. Given its negative coefficient, the findings suggest that Non-robot Capital Prices have generally increased over the past 15 years, as illustrated in Figure 9. In Figure 9, KN's Capital Price replicates the capital price derivation from their KLEMS data version, making this variable identical to KN's, which is used throughout Section 4 and 5.

This observation might initially appear contradictory to the claims of Karabarbounis and Neiman (2014) (hereafter KN), who reported a rapid global decline in capital prices (see Figure 7 of their paper). However, our Figure 9 is consistent with their findings, considering that capital prices began to rise from round year 2000. Furthermore, their figure aggregates data from all countries worldwide, whereas our analysis is more focused, presenting data at the country level for only ten selected countries.

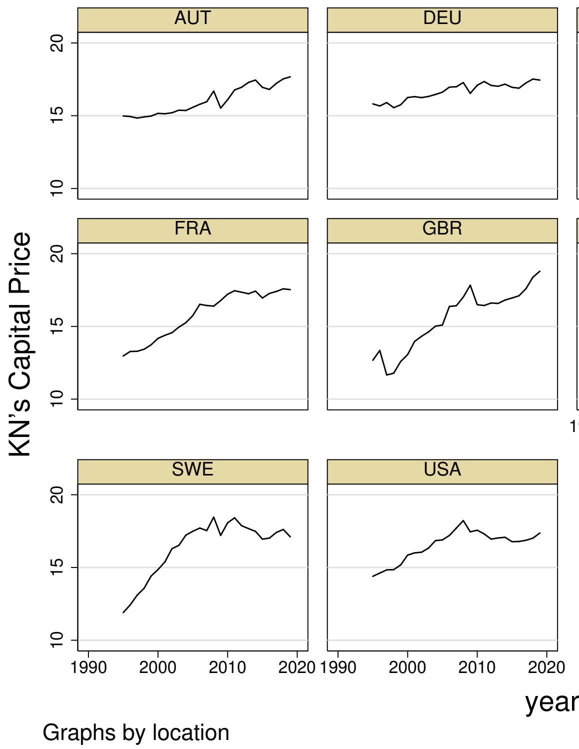
Meanwhile, Figure 7, Labor Price (Robot Price) is mostly positive (negative). Given that their coefficients are both positive, this suggests that labor prices have increased globally over a 15-year period, while robot prices have declined. Finally, Figure 7 presents a substantial portion of fixed effects. We interpret these fixed effects as primarily arising from the productivity not included in our regression as control variables as shown in Equation (18).

Figure 8 shows even more zoomed out view. Y represents the left hand side of the regression, the markup adjusted labor share (S_L^f). Predicted Y represents Y minus residuals. Actual Labor Share is the one without markup adjusted. We can notice that 'Actual Labor Share' and Y are much different. We ascribe this gap to the markup. For instance, in USA, the gap is a large negative value, implying that markup negatively affected the labor share.

The negative impact of markup on labor share is comprehensively detailed by Autor et al. (2020). They demonstrated that an increase in market concentration in the USA has led to a rise in markup. Given the negative correlation between markup and labor share (a coefficient of -1), this increased concentration has consequently resulted in a decrease in labor share. However, in a separate study, Jeong (2024) presents a contrasting perspective for the EU. Utilizing CompNet data, he highlights two key findings: firstly, market concentration in the EU has overall declined, and secondly, the relationship between market concentration and labor share in the EU is not significant.

[19] Fundamentally, there is a contrast in approaches; our analysis elucidates the factors driving the labor share, whereas their study infers these factors through decomposition of the labor share.

Figure 9: KN's Capital Prices



6 Concluding Remarks

In summary, this paper aims to unravel the factors contributing to the recent downtrend in labor share, placing a special emphasis on the roles of automation and innovation in human tasks. While existing literature presents a mosaic of conflicting viewpoints (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Dauth et al., 2021; De Vries et al., 2020; Humlum, 2019), our empirical analysis corroborates the adverse impact of automation on labor share.

Uniquely, our study is the first to explore how innovation in human tasks influences labor share. Our findings suggest that this factor effectively mitigates the negative repercussions of automation on labor share, a finding that is highly relevant in the context of the United States, where the proliferation of new tasks is notably significant.

Our quantified estimates indicate that the elasticity of substitution *between labor and non-robot capital* is below one, while the elasticity of substitution *between tasks* is one. These estimates facilitate a nuanced understanding of how factor prices—namely, labor, robots, and non-robot capital—affect labor share. Specifically, we observe that both the negative effect of automation and the positive effect of innovation in human tasks are amplified through the aggregated task price channel: First, automation and innovation in human tasks alter the composition of tasks performed by robots and those performed by labor. Second, this change in composition affects the aggregate task price. Finally, the change in the aggregate task price, in turn, affects labor share through substitution among labor, robots, and non-robot capital.

In addition, the elasticities we have calculated permit us to offer consistent predictions concerning the directional influence of three key prices —wages, the price of non-robot capital, and the price of robots— on labor share, all grounded in our general equilibrium framework. The directional trends and magnitudes related to labor price, non-robot capital price, and robot price, as suggested by our model, are further substantiated by our regression analyses.

Our model foresees a positive correlation between labor costs and labor share, and a negative correlation between the price of non-robot capital and labor share. The underlying intuition stems from the gross complementarity between labor and non-robot capital. Specifically, when wages rise, employment levels do not decrease proportionally, leading to an increase in labor share. Similarly, a decline in the price of non-robot capital results in an increase in labor share.

In our model, we posit a positive, albeit small, correlation between the price of robots and labor share. This implies that a decrease in robot prices is associated with a reduction in labor share. The weak nature of this correlation can be attributed to the relatively minor contribution of robot costs to the total costs, encompassing both labor and robot expenses.

Lastly, our model highlights two key mechanisms that become increasingly relevant as robotic technology progresses. The first is that increased capabilities in robotics permit them to undertake tasks that were previously human-exclusive, thereby diminishing labor share. The second is that a reduction in robot prices, without any corresponding improvements in functionality, also exerts a downward pressure on labor share. According to our general equilibrium model, the influence of this latter mechanism—termed the robot price channel—is expected to become more pronounced as robots gain wider adoption. Consequently, our regression coefficient for robot prices is poised to grow both in magnitude and statistical significance as automation continues to proliferate.

Meanwhile, we would like to clarify that the focus of this paper is not to investigate whether this decline in labor share exacerbates income inequality or necessitates policy interventions. Although some studies have posited a correlation between a declining labor share and increasing income inequality, a more comprehensive examination of causality is necessary. (ILO and OECD, 2015; Torres et al., 2011). As such, we set these topics aside and concentrate on identifying the reasons for the decline within a unified framework.

However, as a policy recommendation, we suggest that governments implement ONET programs aimed at keeping people updated on task requirements for specific occupations. Providing such information will enable individuals to identify emerging labor demands and prepare accordingly, thus improving the alignment between labor supply and demand. This, in turn, could bolster labor share. While the USA is the only country currently offering ONET, the EU has recently initiated a similar project.[20] However, many countries, such as South Korea with its Korea Employment Information Service (KELS), offer job information and matching services but lack ONET-style service.

In the current landscape, our paper shows that while automation contributes to a declining labor share, innovation in human tasks exerts a significantly more positive impact on labor share. Drawing on our general equilibrium model, we anticipate that in the future, the robot price channel will gain greater importance as the prevalence of robot usage increases.

[20] The European Commission has recently initiated a project akin to ONET, named 'European Skills, Competences, Qualifications, and Occupations' (ESCO). ESCO has disclosed the tasks required for workers for a single year and has yet to release a Task score.

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A An Alternative Approach to Estimating the S_M^T

Let's assume labor cost to be 100 without loss of generality. According to KLEMS data, the rental cost for OMach is recorded as 13.595. But it's important to note that OMach encompasses not just robots but also a range of other items, including equipment, machinery, engines, and turbines (Stehrer et al., 2019; Gouma and Timmer, 2013). Therefore, the challenge is to determine the share of robots within the broader category of OMach. The most reliable approach we can consider involves utilizing UN Comtrade data, which offers information about import and export values by detailed commodity categories. By calculating the total export values of commodities corresponding to OMach,[21] and separately calculating the total export values of HS Code 8479 (which pertains to robots),[22] we find that the ratio between these values is 13.595 : 0.71. In brief, the ratio between labor cost, OMach cost, and robot cost is 100 : 13.595 : 0.71.

The equipment cost for robots is estimated to be around 33.04% of the total robot costs (Zhao et al., 2021), and the UN Comtrade estimate of 0.71 corresponds to the equipment cost. Therefore, the total cost of the robot amounts to $0.71/0.33 = 2.149$. Hence, S_M^T is estimated to be 2.104%.[23]

B Appendix: Proof of $E > 0$

Here, we explain why Ⓔ is positive. To do this, we rewrite Equation (18) as below:

$$d \ln S_L^f = \ ... \ d \ln \gamma + \textcircled{\alpha_1} dI + \textcircled{\alpha_2} dN + ... \ d \ln \mathbb{W} + ... \ d \ln R + ... \ d \ln \psi.$$

We can rearrange $\textcircled{\alpha_1} dI + \textcircled{\alpha_2} dN$ as follows:

$$\begin{aligned} & \textcircled{\alpha_1} dI + \textcircled{\alpha_2} dN \\ = & \textcircled{\alpha_1} dI - \textcircled{\alpha_1} dN + \textcircled{\alpha_1} dN + \textcircled{\alpha_2} dN \\ = & \textcircled{\alpha_1} d(I - N + 1) + (\textcircled{\alpha_1} + \textcircled{\alpha_2}) dN \\ = & \textcircled{\alpha_1} d(I - N + 1) + \textcircled{\beta_2} dN \end{aligned}$$

, where $\textcircled{\beta_2}$ is

$$\textcircled{\beta_2} = \underbrace{\left(S_N^L - S_I^L\right) \frac{1}{1-\zeta}}_{\text{Ⓕ}} \underbrace{\left[S_M^T (1-\zeta) + S_L^T S_K^f (1-\sigma)\right]}_{\text{Ⓖ}} \tag{32}$$

[21] HS Classification 84 excluding 8401, 8402, 8403, 8404, 8405, 8429, 8440, 8443, 8470, 8471, and 8472.

[22] Machinery and mechanical appliances; having individual functions, n.e.c. in this chapter.

[23] $2.104\% = \frac{2.149}{2.149+100}$

We can estimate this $\textcircled{\beta_2}$ by a regression. We perform the identical regression in Column (2) of Table 2 except that we use APR instead of IRB. The regression result is provided in Appendix C Table 3, in which $\textcircled{\beta_2} = 0.095 > 0$. The sign of Ⓖ in Equation (32) is positive because the robot cost share, denoted as S_M^T, is a very small value, specifically 0.028. Given that $\textcircled{\beta_2}$ is positive, Ⓕ in Equation (32) is also positive. Since S_N^L and S_I^L are defined as $\frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$ and $\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$, respectively, the sign of $\left(S_N^L - S_I^L\right)\frac{1}{1-\zeta}$ is the same as that of $\left[\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta} - \left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}\right]\frac{1}{1-\zeta}$, which is a positive value. Assumption 1 asserts that $\psi < \frac{W_I}{\gamma_I}$. This assumption is reasonable, given the observed decline in robot prices and the corresponding increase in wages (Figure 3). Combining this assumption with $\left[\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta} - \left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}\right]\frac{1}{1-\zeta}$ establishes that the sign of $\frac{1}{1-\zeta}\left[-\psi^{1-\zeta} + \left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}\right]$ is positive. In summary, Ⓔ in Equation (27) is positive.

C Appendix: Tables and Figures

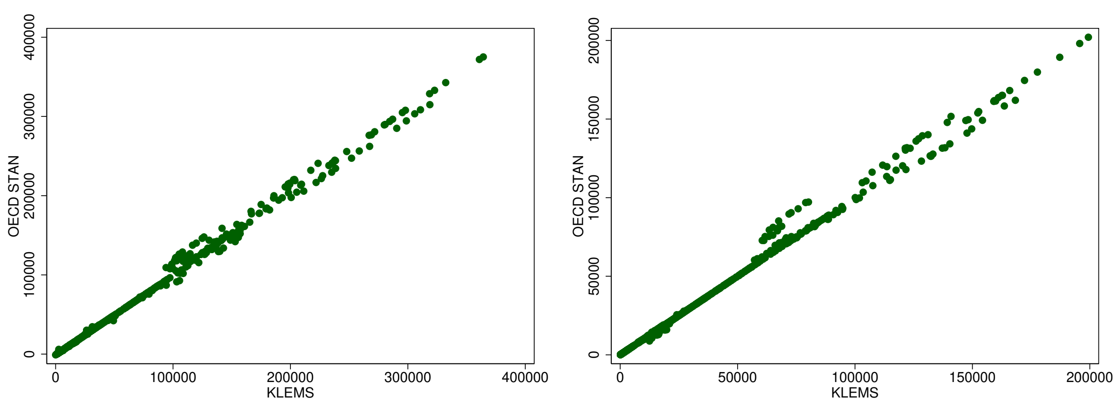
Table 3: Regressions using APR

	OLS		Quantile		
	(1)	(2)	(3)	(4)	(5)
Restrction	No	Yes	Yes	Yes	Yes
Quantile			0.3	0.5	0.7
α_1: APR	-0.076***	-0.062**	-0.091***	-0.070**	-0.043
	(0.021)	(0.023)	(0.006)	(0.026)	(0.029)
β_2: IHT	0.089*	0.095*	0.097***	0.095***	0.082***
	(0.036)	(0.037)	(0.019)	(0.020)	(0.018)
α_3: gr_labor price	12.559***	12.777***	9.383***	11.223***	14.149***
	(3.423)	(3.626)	(1.083)	(1.431)	(0.901)
α_4: gr_robot price	0.646	0.777	0.781*	0.829	0.081
	(1.014)	(1.035)	(0.354)	(0.606)	(0.335)
α_5: gr_non robot capital price	-18.917***	-13.553***	-10.164***	-12.052***	-14.230***
	(3.681)	(3.338)	(1.037)	(1.451)	(0.878)
N	911	911	911	911	911
R^2	0.621	0.609			
pseudo R^2			0.480	0.446	0.455

Standard errors in parenthesis are clustered by country and sector (OLS); heteroskedasticity-robust (Quantile)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The coefficients and the standard errors have been multiplied by 100 for better readability.

Figure 10: Values by Country, Sector, and Year

(a) Value-added (b) Labor Compensation[24]



Online Appendix of Automation, Human Task Innovation, and Labor Share: Unveiling the Role of Elasticity of Substitution

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A Appendix: Model Derivations

A.1 Environment

There is a representative household with utility function in Equation (1):

$$U = \left(\int_0^1 Y(k)^{\frac{\eta-1}{\eta}} dk \right)^{\frac{\eta}{\eta-1}}. \tag{1}$$

There are infinite number of identical firms i with production functions in Equation (4) and (5):

$$t_j(i) = m_j(i) + \gamma_j l_j(i) \ \text{ if } j \leq I \tag{2}$$

$$t_j(i) = \gamma_j l_j(i) \ \text{ if } j > I \tag{3}$$

$$T(i) = \left(\int_{N-1}^{N} t_j(i)^{\frac{\zeta-1}{\zeta}} dj \right)^{\frac{\zeta}{\zeta-1}} \tag{4}$$

$$Y(i) = \left(T(i)^{\frac{\sigma-1}{\sigma}} + K(i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{5}$$

By Assumption 1, Equation (2) simplifies to Equation (6). Without this assumption, the algebra becomes too complex to yield a closed-form solution. The implication of this assumption is that whenever robot operation is technically feasible, firms opt for robots over labor. This is because, according to Assumption 1, the cost of using a robot is lower than the cost of labor for unit of production.

$$t_j(i) = m_j(i) \ \text{ if } j \leq I \tag{6}$$

A.2 Step 1: derive P_T, and optimal inputs for robot* and labor*

We derive P_T, the price for an aggregated task, $T(i)$, by solving the cost minimization problem. We assume perfectly competitive market.

$$\min \text{cost(i) for } T(i) \text{ s.t. Equation(6), (3), and (4)}$$

$$\Rightarrow \min \int_{N-1}^{I} \psi m_j dj + \int_{I}^{N} w_j l_j dj \;\text{ s.t. } \left(\int_{N-1}^{I} m_j^{\frac{\zeta-1}{\zeta}} dj + \int_{I}^{N} (\gamma_j l_j)^{\frac{\zeta-1}{\zeta}} dj \right)^{\frac{\zeta}{\zeta-1}} = T(i)$$

⇒ This finds optimal inputs for robot* and labor* to produce T(i)

⇒ Specifically, letting T(i)=1 means the minimization solution is the price for T(i), P_T :

$$\Rightarrow P_T = \left[(I - N + 1)\psi^{1-\zeta} + \int_{I}^{N} \left(\frac{w_j}{\gamma_j} \right)^{1-\zeta} dj \right]^{\frac{1}{1-\zeta}} \tag{7}$$

A.3 Step 2: find optimal inputs for $T(i)$ and $K(i)$

Next, we find optimal inputs for $T(i)$ and $K(i)$ to produce $Y(i)$.

$\min$ cost(i) for $Y(i)$ s.t. Equation(5)

⇔ $\min P_T \cdot T(i) + R \cdot K(i)$ s.t. Equation(5)

⇒This finds optimal inputs for T(i)* and K(i)* to produce Y(i)

⇒Specifically, the minimization solution is the minimum cost for producing $Y(i)$

$$\Rightarrow \begin{cases} T(i)^* = Y(i) P_T^{-\sigma} \\ K(i)^* = Y(i) R^{-\sigma} \\ \text{Cost for } Y(i) = Y(i) \left[P_T^{1-\sigma} + R^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \\ \qquad = Y(i) \times \text{AC} \\ \qquad = Y(i) \end{cases}$$

We let $\left[P_T^{1-\sigma} + R^{1-\sigma} \right]^{\frac{1}{1-\sigma}} = 1$ as a numeraire. This numeraire significantly simplifies the algebraic complexity. Since we let AC$= 1$, MC is also one.

A.4 Step 3: find a demand function for $Y(i)$

Next, we find a demand function for $Y(i)$ by minimizing consumption cost.

$\min$ cost for consumption s.t. Equation(1)

⇔ $\min \int_0^1 P(i) Y(i) di$ s.t. Equation(1)

⇒Specifically, this yields a demand function for $Y(i)$

$$\Leftrightarrow Y(i) = \left(\frac{P(i)}{\mathbb{P}} \right)^{-\eta}, \text{ where } \mathbb{P} \equiv \left[\int_0^1 P(i)^{1-\eta} di \right]^{\frac{1}{1-\eta}}$$

A.5 Step 4: find firm(i)'s profit

The final goods market is the monopolistic competition that allows firms' positive profit. Until now, we know two things: (1) a demand function for $Y(i)$, and (2) the minimum cost for producing $Y(i)$. Firm's profit maximization problem yields:

$$\begin{aligned} P(i)^* &= \frac{\eta}{\eta - 1} \\ \Rightarrow \Pi(i) &= \frac{1}{\eta - 1} Y(i)^* \end{aligned}$$

Meanwhile, we naturally get optimal $Y(i)$ as below, but this is redundant for this paper.

$$Y(i)^* = \left(\frac{\eta}{(\eta - 1)\mathbb{P}} \right)^{-\eta}, \text{where } \mathbb{P} \equiv \left[\int_0^1 P(i)^{1-\eta} di \right]^{\frac{1}{1-\eta}}$$

A.6 Step 5: derive the labor cost for producing optimal $Y(i)$

In Step 1, we already found optimal inputs of $l_j(i)$ to produce $T(i)$. Therefore we can also know the optimal labor cost at task j for firm i to produce $T(i)$.

$$\begin{aligned} l_j(i)^* &= \left(\frac{W_j(i)}{\gamma_j P_T} \right)^{-\zeta} \gamma_j^{-1} T(i) \\ \Rightarrow W_j(i) l_j(i)^* &= \left(\frac{W_j(i)}{\gamma_j} \right)^{1-\zeta} P_T^{\zeta} T(i) \end{aligned} \tag{8}$$

And we also derived optimal $T(i)$ while in Step 2: $T(i)^* = Y(i) P_T^{-\sigma}$. Plugging in this to the equation above,

$$W_j(i) l_j(i)^* = \left(\frac{W_j(i)}{\gamma_j} \right)^{1-\zeta} P_T^{\zeta-\sigma} Y(i)$$

Therefore, the optimal labor cost for firm i to produce $Y(i)$ by using every task from I to N is:

$$\begin{aligned} \int_I^N W_j(i) l_j(i)^* dj &= \int_I^N \left(\frac{W_j(i)}{\gamma_j} \right)^{1-\zeta} P_T^{\zeta-\sigma} Y(i) dj \\ &= \int_I^N \left(\frac{W_j(i)}{\gamma_j} \right)^{1-\zeta} dj \cdot P_T^{\zeta-\sigma} Y(i) \end{aligned}$$

A.7 Step 6: derive an expression for labor share

Until now, we have figured out (1) labor cost, (2) total cost, and (3) profit. Putting all together, we find labor share. Since we prefer not to focus on $\frac{\eta-1}{\eta}$, we move this term to the left-hand side.

$$\begin{aligned} S_L(i) &= \frac{\text{Labor cost(i)}}{\text{Total cost(i)} + \text{Profit(i)}} = \frac{\text{Labor cost(i)}}{Y(i) + \frac{1}{\eta-1}Y(i)} \\ &= \frac{\eta-1}{\eta}\frac{\text{Labor cost(i)}}{\text{Total cost(i)}} \\ \Leftrightarrow \frac{\eta}{\eta-1}S_L(i) &= \frac{\text{Labor cost(i)}}{\text{Total cost(i)}} \\ &\equiv S_L^f(i) \end{aligned}$$

After substituting the expressions for Labor cost(i) and Total cost(i) that we derived earlier, we finally construct a detailed expression for $S_L^f(i)$.

$$\begin{aligned} S_L^f(i) &= \frac{\text{Labor cost(i)}}{\text{Total cost(i)}} \\ &= \frac{\int_I^N W_j(i)l_j(i)dj}{Y(i)} \\ &= \frac{\int_I^N W_j(i)l_j(i)dj}{P_T T(i) + RK(i)} \\ &= \frac{\int_I^N \left(\frac{W_j(i)}{\gamma_j}\right)^{1-\zeta}dj \cdot P_T^{\zeta-\sigma}Y(i)}{P_T^{1-\sigma}Y(i) + R^{1-\sigma}Y(i)} \\ &= \frac{\int_I^N \left(\frac{W_j(i)}{\gamma_j}\right)^{1-\zeta}dj}{P_T^{1-\zeta}}\frac{P_T^{1-\sigma}}{P_T^{1-\sigma} + R^{1-\sigma}} \\ &\text{, where } P_T \equiv \left[(I-N+1)\psi^{1-\zeta} + \int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj\right]^{\frac{1}{1-\zeta}} \end{aligned}$$

B Appendix: Derivation of μ

Let μ denote the elasticity of substitution between labor and non-robot capital. The concept of elasticity of substitution formally defines μ as follows:

$$\mu \equiv \frac{d\left(\frac{L}{K}\right)}{d\left(\frac{R}{\mathbb{W}}\right)}\frac{\frac{R}{\mathbb{W}}}{\frac{L}{K}}. \tag{9}$$

To proceed, we must express L and K in terms of W and R, respectively. Equation (8), derived in Appendix A.6, provides the formulation for L as follows:

$$
\begin{aligned}
l_j(i)^* &= \left(\frac{W_j(i)}{\gamma_j P_T}\right)^{-\zeta} \gamma_j^{-1} T(i) \\
\Rightarrow L &= \int_I^N l_j(i)^* dj \\
&= \int_I^N \left(\frac{W_j(i)}{\gamma_j P_T}\right)^{-\zeta} \gamma_j^{-1} T(i) dj. \qquad (10)
\end{aligned}
$$

We introduce a parameter β_j to serve as a weight for the wage distribution corresponding to each worker, indexed by j. Utilizing β_j enables us to establish a representative measure for wages, $\mathbb{W}$.

$$W_j \equiv \beta_j \mathbb{W} \qquad (11)$$

Consequently, Equation (10) can be restructured to yield Equation (12). To streamline the notation, we define $A = \int_I^N \gamma_j^{\zeta-1} \beta_j^{-\zeta} dj$.

$$
\begin{aligned}
L &= \int_I^N \gamma_j^{\zeta-1} \beta_j^{-\zeta} dj \; \cdot T(i) \Big(\frac{\mathbb{W}}{P_T}\Big)^{-\zeta} \qquad (12) \\
&= A \cdot T(i) \Big(\frac{\mathbb{W}}{P_T}\Big)^{-\zeta} \qquad (13)
\end{aligned}
$$

We have derived $T(i)$ in Appendix A.3 and P_T in Appendix A.2. For the sake of clarity, we restate these formulations here:

$$
\begin{aligned}
T(i) &= Y(i) P_T^{-\sigma} \\
P_T &= \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{w_j}{\gamma_j}\right)^{1-\zeta} dj \right]^{\frac{1}{1-\zeta}}
\end{aligned}
$$

By substituting $T(i)$ and P_T into Equation (13),

$$
\begin{aligned}
L &= A \cdot Y(i) P_T^{-\sigma} \Big(\frac{\mathbb{W}}{P_T}\Big)^{-\zeta} \\
&= A \cdot Y(i) P_T^{\zeta-\sigma} \mathbb{W}^{-\zeta} \\
&= A \cdot Y(i) \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{w_j}{\gamma_j}\right)^{1-\zeta} dj \right]^{\frac{\zeta-\sigma}{1-\zeta}} \mathbb{W}^{-\zeta}.
\end{aligned}
$$

$(I-N+1)\psi^{1-\zeta}$ and $\int_I^N \left(\frac{w_j}{\gamma_j}\right)^{1-\zeta} dj$ correspond to the cost share of robots and human labor, respectively. Consequently, we can reformulate these expressions as follows:

$$(I-N+1)\psi^{1-\zeta} \equiv S_M^T$$
$$\int_I^N \left(\frac{w_j}{\gamma_j}\right)^{1-\zeta} dj \equiv S_L^T$$

Therefore, L can be reformulated as follows:

$$\begin{aligned} L =& A \cdot Y(i) \left[S_M^T + S_L^T\right]^{\frac{\zeta-\sigma}{1-\zeta}} \mathbb{W}^{-\zeta} \\ =& A \cdot Y(i) \left[\frac{S_M^T}{S_L^T} + 1\right]^{\frac{\zeta-\sigma}{1-\zeta}} \mathbb{W}^{-\zeta} \end{aligned} \tag{14}$$

We derived the optimal value of K in Appendix A.3, given by $K = Y(i)R^{-\sigma}$. Consequently, we complete our derivation of $\frac{L}{K}$ as follows:

$$\begin{aligned} \frac{L}{K} =& \frac{A \cdot Y(i) \left[\frac{S_M^T}{S_L^T} + 1\right]^{\frac{\zeta-\sigma}{1-\zeta}} \mathbb{W}^{-\zeta}}{Y(i)R^{-\sigma}} \\ =& \frac{A \cdot \left[\frac{S_M^T}{S_L^T} + 1\right]^{\frac{\zeta-\sigma}{1-\zeta}} \mathbb{W}^{-\zeta}}{R^{-\sigma}} \end{aligned}$$

Thus, the expression for $d\left(\frac{L}{K}\right)/\frac{L}{K}$ is given below. This concludes our derivation of μ.

$$\frac{d\left(\frac{L}{K}\right)}{\frac{L}{K}} = \frac{\left(\frac{\mathbb{W}_1}{R_1}\right)^{-\sigma} \left[\frac{S_M^T}{1-S_M^T}\left(\frac{\mathbb{W}_0}{\mathbb{W}_1}\right)^{1-\zeta} + 1\right]^{\frac{\zeta-\sigma}{1-\zeta}} - \left(\frac{\mathbb{W}_0}{R_0}\right)^{-\sigma} \left[\frac{S_M^T}{1-S_M^T} + 1\right]^{\frac{\zeta-\sigma}{1-\zeta}}}{\left(\frac{\mathbb{W}_0}{R_0}\right)^{-\sigma} \left[\frac{S_M^T}{1-S_M^T} + 1\right]^{\frac{\zeta-\sigma}{1-\zeta}}}$$

C Appendix: Acemoglu and Restrepo (2019)

Let me first introduce their notations in Table 4.

The decomposition starts from the percent change in the wage bill normalized by population (Equation (AR1)). Since $\ln\left(\frac{W_t L_t}{N_t}\right)$ can be expressed as $\ln\left(Y_t \sum_i \chi_{it} s_{it}^L\right)$, Equation (AR1) can be decomposed as Equation (AR2);

Table 4

Notation	Meaning
i	Industry sector
P_i	The price of the goods produced by sector i
Y_i	Output (value added) of sector i
$Y = \sum_i P_i Y_i$	Total value added (GDP) in the economy
$\chi_i = \frac{P_i Y_i}{Y} = \frac{P_i Y_i}{\sum_i P_i Y_i} = \frac{\text{GDP}_i}{\text{GDP}}$	The share of sector i's GDP
W_i	Wage per worker in sector i
L_i	Number of workers in sector i
$W_i L_i$	Total wage bill in sector i
$WL = \sum_i W_i L_i$	Total wage bill in the economy
$\ell_i = \frac{W_i L_i}{WL}$	The share of the wage bill in sector i
$s_i^L = \frac{W_i L_i}{P_i Y_i} = \frac{\text{Total wage bill}_i}{\text{GDP}_i}$	The labor share in sector i
$s^L = \frac{WL}{Y} = \frac{\text{Total wage bill}}{\text{GDP}}$	The labor share in the economy
$\Gamma_i = \Gamma(N_i, I_i)$	The task content of production with regards to labor in sector i
γ_i^L	The comparative advantage schedules for labor in sector i
γ_i^K	The comparative advantage schedules for captial in sector i

$$\ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t0} L_{t0}}{N_{t0}}\right) \tag{AR1}$$

$$= \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right) \tag{AR2}$$

$$+ \ln\left(\sum_i \chi_{it} s_{it}^L\right) - \ln\left(\sum_i \chi_{it0} s_{it0}^L\right)$$

$$= \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right)$$

$$+ \ln\left(\sum_i \chi_{it} s_{it}^L\right) - \ln\left(\sum_i \chi_{it0} s_{it}^L\right)$$

$$+ \ln\left(\sum_i \chi_{it0} s_{it}^L\right) - \ln\left(\sum_i \chi_{it0} s_{it0}^L\right)$$

$$\approx \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right)$$

$$+ \sum_i \frac{s_{it}^L}{\sum_j \chi_{jt0} s_{jt}^L}(\chi_{it} - \chi_{it0})$$

$$+ \ln\left(\sum_i \chi_{it0} s_{it}^L\right) - \ln\left(\sum_i \chi_{it0} s_{it0}^L\right)$$

$$\approx \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right) \tag{AR3}$$

$$+ \sum_i \frac{s_{it}^L}{\sum_j \chi_{jt0} s_{jt}^L}(\chi_{it} - \chi_{it0})$$

$$+ \sum_i \ell_{it0}(\ln s_{it}^L - \ln s_{it0}^L) \tag{AR4}$$

The first-order Taylor expansion of the last term of Equation (AR3) yields Equation (AR5); Denote $(1-\sigma)(1-s^L_{it0})\Big(\ln\frac{W_{it}}{W_{it0}}-\ln\frac{R_{it}}{R_{it0}}-g^A_{i,t0,t}\Big)$ as $\text{Substitution}_{i,t0,t}$, we can rewrite Equation (AR5) as AR8; Denote $\big(\ln s^L_{it}-\ln s^L_{it0}\big)-\text{Substitution}_{i,t0,t}$ as $\text{ChangeTaskContent}_{i,t0,t}$, we can rewrite Equation (AR8) as (AR9).

$$
\begin{aligned}
&\approx \ln\left(\frac{Y_t}{N_t}\right)-\ln\left(\frac{Y_{t0}}{N_{t0}}\right) && \text{(AR5)}\\
&+\sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0}s^L_{jt}}\big(\chi_{it}-\chi_{it0}\big)\\
&+\sum_i \ell_{it0}\Bigg[(1-\sigma)(1-s^L_{it0})\Big(\ln\frac{W_{it}}{W_{it0}}-\ln\frac{R_{it}}{R_{it0}}-g^A_{i,t0,t}\Big) && \text{(AR6)}\\
&\qquad+\frac{1-s^L_{it0}}{1-\Gamma_{it0}}(\ln\Gamma_{it}-\ln\Gamma_{it0})\Bigg] && \text{(AR7)}\\
&\approx \ln\left(\frac{Y_t}{N_t}\right)-\ln\left(\frac{Y_{t0}}{N_{t0}}\right)\\
&+\sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0}s^L_{jt}}\big(\chi_{it}-\chi_{it0}\big)\\
&+\sum_i \ell_{it0}\Bigg[\text{Substitution}_{i,t0,t}\\
&\qquad+\frac{1-s^L_{it0}}{1-\Gamma_{it0}}(\ln\Gamma_{it}-\ln\Gamma_{it0})\Bigg]\\
&\approx \ln\left(\frac{Y_t}{N_t}\right)-\ln\left(\frac{Y_{t0}}{N_{t0}}\right) && \text{(AR8)}\\
&+\sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0}s^L_{jt}}\big(\chi_{it}-\chi_{it0}\big)\\
&+\sum_i \ell_{it0}\Bigg[\text{Substitution}_{i,t0,t}\\
&\qquad+\big(\ln s^L_{it}-\ln s^L_{it0}\big)-\text{Substitution}_{i,t0,t}\Bigg]
\end{aligned}
$$

$$\begin{aligned}
&\approx \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right) \\
&+ \sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0} s^L_{jt}} (\chi_{it} - \chi_{it0}) \\
&+ \sum_i \ell_{it0} \Big[\text{Substitution}_{i,t0,t} \\
&\qquad + \text{ChangeTaskContent}_{i,t0,t} \Big] \\
&\approx \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right) \\
&+ \sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0} s^L_{jt}} (\chi_{it} - \chi_{it0}) \\
&+ \text{Substitution}_{t0,t} \\
&+ \sum_i \ell_{it0} \Big[\text{ChangeTaskContent}_{i,t0,t} \Big]
\end{aligned} \tag{AR9}$$

$\sum_i \ell_{it0}[\text{ChangeTaskContent}_{i,t0,t}]$ can be decomposed again into Equation (AR10), assuming that over five-year windows, an industry engages in either automation or the creation of new tasks but not in both activities.

$$\begin{aligned}
\text{Displacement}_{t-1,t} &= \sum_{i \in \mathcal{I}} \ell_{i,t0} \min\left\{0, \frac{1}{5} \sum_{\gamma=t-2}^{t+2} \text{ChangeTaskContent}_{i,\gamma-1,\gamma}\right\} \\
\text{Reinstatement}_{t-1,t} &= \sum_{i \in \mathcal{I}} \ell_{i,t0} \max\left\{0, \frac{1}{5} \sum_{\gamma=t-2}^{t+2} \text{ChangeTaskContent}_{i,\gamma-1,\gamma}\right\}
\end{aligned} \tag{AR10}$$

To sum up, starting from Equation (AR1), it can be decomposed into 1) productivity, 2) composition, 3) substitution, 4) displacement, and 5) reinstatement effects.

$$\begin{aligned}
&\ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t0} L_{t0}}{N_{t0}}\right) && \text{[Wage bill per capita]} \\
&\approx \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right) && \text{[Productivity effect]} \\
&+ \sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0} s^L_{jt}} (\chi_{it} - \chi_{it0}) && \text{[Composition effect]} \\
&+ \text{Substitution}_{t0,t} && \text{[Substitution effect]} \\
&+ \text{Displacement}_{t0,t} && \text{[Displacement effect (Automation)]} \\
&+ \text{Reinstatement}_{t0,t} && \text{[Reinstatement effect (New tasks)]}
\end{aligned} \tag{AR11}$$

D Appendix: Generation of IHT

Our detailed work differs from that of Acemoglu and Restrepo (2019) in several ways. They generated a 'Task score' only for 2018, whereas we generated it on a yearly basis. Additionally, they provided their version of the IHT variable only for the year 2018 in the USA, while our IHT varies by country$\times$year (and industry$\times$year in the USA).

Our matching procedure from 'Task score' to the US Census also differs. They convert the 'Task score' from SOC to OCC. In contrast, we use SOC as it is. The US Census provides both SOC and OCC for occupational taxonomy, allowing us to simply use SOC to match the US Census with the 'Task score'.

Moreover, when matching 'Task score' to EU-LFS, using SOC is more advantageous than using OCC. EU-LFS uses ISCO for occupational taxonomy, and ISCO (4-digits) matches with SOC (6-digits).[25] This granular level of crosswalk matching is made possible by the recent work of Frugoli and ESCO (2022). They used machine learning and natural language processing for the initial matching, followed by human experts cross-checking to generate the final crosswalks.

[25]The excel file for the crosswalk between ISCO and SOC is in this link. This is publicly released by ONET and ESCO.