Factors Influencing Labor Share: Elasticity of Substitution, Automation, and Task Innovation

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Abstract

In this study, we explore the effects of automation and the creation of new human-exclusive tasks on labor share. We define automation as the advancements allowing robots to carry out tasks they were previously incapable of performing. In contrast, we characterize the emergence of new tasks as task innovations exclusively executable by humans. This research stands at the forefront in empirically examining the ramifications of new task creation on labor share, having developed a rigorous approach to generating variables indicative of new task emergence. Moreover, we introduce a task-based general equilibrium model that discerningly delineates between robot and non-robot capital, thus enriching the existing body of literature. Our research yields four pivotal insights. First, we find that while automation generally diminishes labor share, the creation of new tasks can potentially augment it. Secondly, we note an elasticity of substitution below one between labor and non-robot capital, indicating a gross complementarity. Third, the elasticity of substitution across various tasks closely approximates one, suggesting that labor and robots are neither gross substitutes nor gross complements when viewed across different tasks. Lastly, we note that the innovation in new task development substantially mitigates the negative impact of automation on labor share, a trend conspicuously prominent in the USA, a nucleus of vibrant task innovation.

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

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

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of about five percentage points. The exact reason for this decline remains a topic of debate; however, one potential driving factor could be advancements in automation. If this assumption is correct, the issue of the dwindling labor share takes on an increased urgency in light of the rapid development of automation and artificial intelligence in recent years. For instance, Boston Dynamics has unveiled Atlas, a humanoid robot with impressive speed and capabilities.[1] The recent debut of Chat-GPT 4, which astoundingly achieved a 10% ranking in the United States bar exam, further underscores the rapid evolution of AI systems. [2]

The influence of automation on labor share remains a prominent topic in active research. Several studies such as those by De Vries et al. (2020) and Gregory et al. (2016) propose that automation complements and amplifies labor share. However, findings from research like Acemoglu and Restrepo (2020), Acemoglu et al. (2020), Dauth et al. (2021), and Martinez (2018) suggest the opposite—that automation substitutes for and reduces 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 'emergence of new 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 the 'emergence of new tasks' outstrips the advancement of automation.

Despite its significance, the effect of the emergence of new 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 emergence of new tasks on the labor share. Utilizing the most pertinent data, we measure these two factors.

These two factors 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. 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

[2] https://youtu.be/-e1_QhJ1EhQ
[2] https://youtu.be/EunbKbPV2C0

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, the emergence of new tasks, capital price, robot price, and wage. In this context, the research by Bergholt et al. (2022) closely mirrors our study. They examine rising markups, increased worker bargaining power, a declining investment price, and escalating automation as factors for the falling labor share. While their methodology, employing time series techniques (Structural VAR with sign restriction) and focusing exclusively on the USA, differs from ours, their findings are congruent with our results. They identify automation as a principal driver of labor share reduction, with ascending markups also playing a substantial role. Interestingly, they conclude that a diminishing capital price does not contribute to the decrease in labor share.

Our paper primarily presents three contributions to the literature. First, to the best of our knowledge, we are the first to analyze the influence of the emergence of new tasks on the labor share. We meticulously derived this measure using data from ONET, the US Census, and EU-LFS. Although our approach is grounded in the original method for constructing the emergence of new tasks introduced by Acemoglu and Restrepo (2020), we have further refined the methodology. Our analysis reveals that this development effectively counteracts the adverse repercussions of automation on the labor share. This is particularly evident in the USA, which stands out due to the significant value associated with the emergence of new tasks.

Second, we discover the elasticity of substitution between labor and non-robot capital lies in the range of 0.60 to 0.66, supporting the idea of a gross complementary relationship between the two. Karabarbounis and Neiman (2014) attribute approximately half of the worldwide labor share decrease to the dip in capital price. They employ cross-country variation and robust regression to estimate the elasticity between capital and labor, suggesting they are gross substitutes ($\sigma \approx 1.26$). Contrarily, Glover and Short (2020) argue they are gross complements ($\sigma \approx 0.97$), using cross-country variation with instrumental variables. Recent research resurgence highlights the significance of measuring this elasticity, as indicated by Martinez (2018), Oberfield and Raval (2021), and Zhang (2023).

Lastly, we further contribute to the literature by implementing post-regression accounting exercises. This simple approach allows us to examine various factors influencing changes in labor share. An interesting observation is the country-specific performance within the 'Car and Transport Equipment' sector. For example, the USA and Austria both exhibit a faster machine growth rate compared to their GDP, leading to a negative impact from the Adjusted Penetration of Robots (APR). Conversely, Germany, France, and Italy demonstrate a positive impact from APR, indicative of a slower machine growth rate relative to their GDP. This difference can be traced back to the swift pace of robotization in the USA and Austria, which is in sharp contrast to the slower rate of robotization seen in Germany, France, and Italy since 2012. Furthermore, we observe that the predicted impact on the emergence of new tasks typically surpasses the impact of automation on labor share.

Turning to the subject of 'global' decrease in labor share, it's vital to incorporate data from a wide range of countries. Many studies have concentrated solely on the United States, where the decline in labor share has been more accentuated than in other nations. 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. It's worth noting that while the USA and Sweden 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. 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.

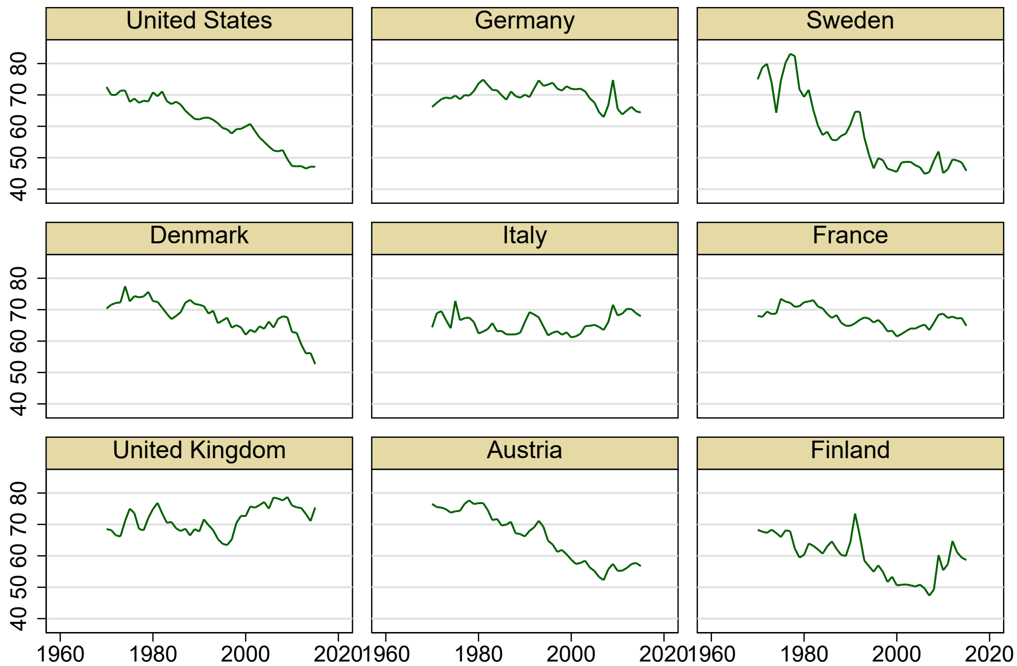
In the following section, we present our general equilibrium model, while Section 3 details the datasets we used. Section 4 conducts the regression analysis, and Section 5 performs various accountings to ascertain which mechanism predominantly explains labor share decline across different countries and industries. Finally, Section 6 provides our concluding remarks. Separately in our Online Appendix,[3] we discuss why the Superstar-firm hypothesis proposed by Autor et al. (2020) falls short of fully explaining the global decline in labor share, even though it adequately accounts for the situation in the USA.

2 Model

Acemoglu and Restrepo (2018) have offered a formal model that outlines how labor share is influenced by automation and the emergence of new tasks. We have refined our model based on their static version. Our key contribution is the distinction we make between

[3]https://github.com/jayjeo/public/blob/main/Laborshare/Online_Appendix.pdf

Figure 1: Labor shares



robots and other capital equipment, a distinction their model does not delineate.

Acemoglu and Restrepo (2020) define robots as "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." They 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.

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 new 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[4]. 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 the emergence of new 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 supplied elastically. For further simplicity, we assume that factors are supplied perfectly elastically at a given factor price at each period.

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

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 algebraic process for this section is provided in 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. This means that whenever firms can technologically replace labor with a robot, they would want to do so.[5]

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:

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

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

[5]This is reasonable considering that robot prices have significantly decreased while wages have steadily increased.

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

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

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

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

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

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

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

, 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 also is 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, denoted dI, changes in the emergence of new tasks, dN, and wage changes, $d\ln\mathbb{W}$, 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 $\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$.[6] 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 (19), the term $-(1-\zeta)+S_K^f(1-\sigma)$ recurs frequently, exerting a significant impact on many coefficients.

Given that we utilize data for robot penetration, as employed in Acemoglu and Restrepo (2020) —which corresponds to $(I-N+1)$— and data for the emergence of new tasks —which corresponds to N in our model— we adjust Equation (18) as follows:

$$
\begin{aligned}
& d\ln S_L^f = \\
& -\left[(1-\zeta)+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\,S_L^T\right] d\ln\gamma \\
& +\left[-\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\frac{1}{1-\zeta}\frac{\psi^{1-\zeta}-\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{P_T^{1-\zeta}}\right] d(I-N+1) \\
& +\Big(S_N^L-S_I^L\Big)\frac{1}{1-\zeta}\left[S_M^T(1-\zeta)+S_L^T S_K^f(1-\sigma)\right] dN \\
& +\left[(1-\zeta)+\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\,S_L^T\right] d\ln\mathbb{W} \\
& -\left[S_K^f(1-\sigma)\right] d\ln R \\
& +\left[\Big(-(1-\zeta)+S_K^f(1-\sigma)\Big)\,S_M^T\right] d\ln\psi
\end{aligned}
\tag{19}
$$

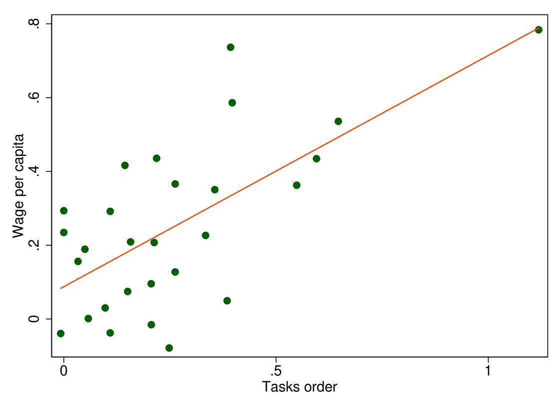
, where $S_L^T \equiv \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{P_T^{1-\zeta}}$ and $S_M^T \equiv \frac{(I-N+1)\psi^{1-\zeta}}{P_T^{1-\zeta}}$ represent the labor share and robot share in the aggregated tasks, respectively. $S_N^L \equiv \frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$ and $S_I^L \equiv \frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$ represent the share of labor income conducting task N and I out of the total labor income, respectively.

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

Labor Share by Task Determining the value of the elasticity of substitution between aggregated tasks and capital, as well as between tasks is crucial[7]. This understanding provides substantial insights into how the labor share changes due to the influence of robots or capital. In Equation (19), the sign of the term $S_N^L - S_I^L$ in the coefficient of dN is not specified by the model or the estimation results. Given the difficulty in defining the range of elasticity of substitution between tasks without knowing this term's sign, we aim to empirically analyze how labor share evolves as tasks become more advanced.

Wage per capita is heterogeneous by tasks throughout the model, as Figure 2 proves. We define 'high order of occupations' as occupations that demonstrate a higher growth rate of the number of tasks. In the figure, wages rise as the order of *occupations* ascends (We were unable to validate Figure 2 in terms of the order of *tasks*, as the most granular wage information available is associated with occupations, not individual tasks).

Figure 2: Wage per capita and Tasks order



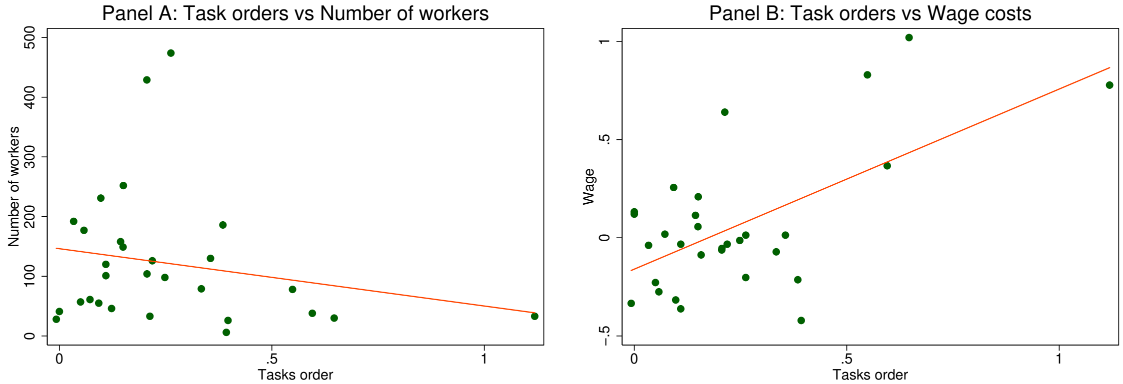
Wage data from IPUMS CPS (Flood et al., 2021)

As the occupation order index escalates, depicted in Figure 3, the number of employees correspondingly decreases. In contrast, wage cost —the product of wage per capita and the number of workers— heightens in line with the occupation ordering index, substantiated by Equation (15) and Panel B of Figure 3. This dynamic stems from the increasing wage per capita and decreasing worker count with rising task orders. Despite fewer workers, the total wage cost increases as the growth in wage per capita overpowers the reduction in worker numbers.

Given these dynamics, we infer a positive correlation between wage cost (wage $\times$ number of workers) and higher-order tasks. This inference allows us in Equation (19) to determine that the sign of $\big(S_L(N) - S_L(I)\big)$ is positive since $N > I$ as a task index. Next

[7]Especially, it is important to assess whether σ and ζ are greater than 1 or not.

Figure 3: Task orders



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 the emergence of new tasks (henceforth, ENT). 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 ENT.

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

For the purpose of assessing 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. To analyze ENT, 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.

3.2 The International Federation of Robotics

The International Federation of Robotics (IFR) provides data on the number of automated machines (both flow and stock) at the country-industry-year level. They define an 'industrial robot' as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (Müller, 2022) [8] . Therefore, their definition of robots aligns closely with our conceptualization of automated machines.

Rather than using the raw data on the number of robots from the IFR, we could utilize the Adjusted Penetration of Robots (APR), as proposed by Acemoglu and Restrepo (2020). The APR is defined as in Equation (20):

$$\mathrm{APR}_{i,(t5,t1)} = \frac{M_{i,t5} - M_{i,t1}}{L_{i,2005}} - \frac{Y_{i,t5} - Y_{i,t1}}{Y_{i,t1}} \frac{M_{i,t1}}{L_{i,2005}} \tag{20}$$

$$= \Big(\frac{M_{i,t5} - M_{i,t1}}{M_{i,t1}} - \frac{Y_{i,t5} - Y_{i,t1}}{Y_{i,t1}}\Big) \frac{M_{i,t1}}{L_{i,2005}} \tag{21}$$

$$= \big(g_M - g_Y\big) \frac{M_{i,t1}}{L_{i,2005}} \tag{22}$$

, 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). 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 our definition of automation. Consider, for instance, that the IFR began collecting data in many countries starting

[8] IFR's definition strictly follows the ISO standard 8373:2012.

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; we need to normalize it by dividing by the number of employees.[9]

The second term in Equation (22), $-g_Y$, serves to measure the 'penetration' of robots. In other words, if the growth rate of robots exceeds that of value-added, we interpret this as a positive penetration. Within the AR framework, this penetration equates to $I-N+1$ in their terminology, which represents the length between N-1 and I.

3.3 The Occupational Information Network

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.

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

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

[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).

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, an average is calculated at the industry and year level. We denote this variable as Raw New Tasks (RNT). RNT 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 RNT 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 RNT 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.

Upon generating the RNT data for the USA and EU countries, we proceed to establish the ANT, which will be employed in our regression as follows:

$$\mathrm{ANT} = \frac{\mathrm{RNT}_{t5} - \mathrm{RNT}_{t0}}{\mathrm{RNT}_{t0}} \tag{23}$$

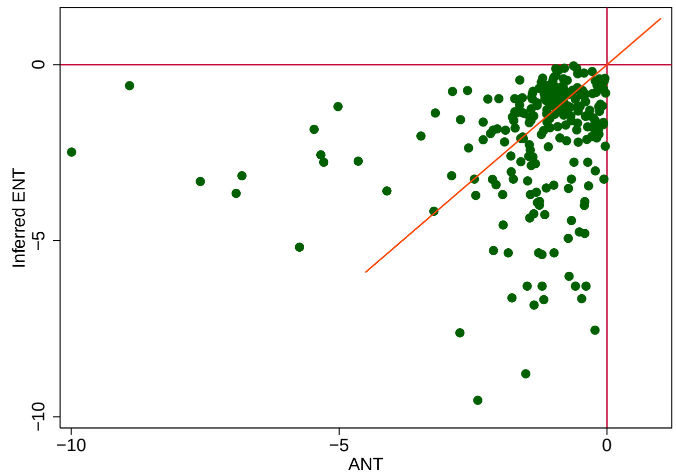
While we adopt AR's concept when generating ANT, our method offers more refinement. Detailed explanations of this can be found in Appendix D. ANT can be compared with the inferred value of ENT (Emergence of New Tasks) proposed by AR. As mentioned earlier, the inferred variable may not be a true representation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

We compared ANT and the 'inferred value of ENT' 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

[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) ANT and inferred ENT (5-year growth rate)



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.

Before concluding this section, it's worth noting that 'task contents' constitute the sum of 'inferred ENT' and 'inferred Automation', which nearly matches the labor share (refer to Panel B of Figure 5 in AR). In Figure 4, we compared ANT and inferred ENT at the country and year level. Acemoglu and Restrepo (2020) performed a similar comparison at the industry level in the USA, focusing solely on the year 2018 (the growth rate from 1990 to 2018). Interestingly, they compared their version of ANT with 'task contents', while we believe that a comparison between ANT and 'inferred ENT' would be more appropriate. Using their replication code, we compared their version of ANT with the 'inferred ENT' they computed. The similarity was found to be insignificant. Our explanation for their insignificant comparison is provided in Appendix E. In essence, the reason lies in their comparison of ANT with the inferred ENT across industries at a single point in time (2018). As will be elaborated on in the appendix, the magnitude of inferred ENT across industries at a specific point in a year is meaningless. Consequently, the insignificant result is expected.

3.4 Capital Price

In our paper, we utilize the replicated values for capital price from Karabarbounis and Neiman (2014) (specifically, the their KLEMS version). 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:

$$R_t = \xi_{t-1}(1+i_t) - \xi_t(1-\delta_t) \tag{24}$$

In this equation, R represents the capital price, ξ is the investment price, i is the nominal interest rate, and δ is the depreciation rate. Equation (24) 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.

3.5 Robot Price

Unfortunately, the International Federation of Robotics (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. They noted, "Due to the considerable effort involved and owing to compliance issues, the IFR no longer continues to construct the price indices." 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.[12] We adopted this method, though, unfortunately, as they did not provide a replication code and data, there may be slight differences in our results.

UN Comtrade provides annual import and export values for HS847950.[13] They also provide the number of HS847950 for both imports and exports. Hence, we infer the robot prices by dividing the values by their numbers. Fernandez-Macias et al. (2021) 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.

3.6 KLEMS

Aside from the IFR dataset, the ONET dataset, and Robot Price, we will use data from KLEMS.[14] 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

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

[13] Machinaery and mechanical appliances; industrial robot, n.e.c. or included.

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.

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

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).

4 Regressions

Based on the specification in Equation (19), we provide consistent regression equations. Equation (26) is for the corresponding regression. It should be noted that the coefficient of $d\ln\mu$ is required to be -1, as directed by Equation (25). Given that our emphasis is not on measuring the coefficient of $d\ln\mu$, we have transposed this term to the left-hand side, as depicted in Equation (26). This adjustment is consistent with the specification

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

outlined in Equation (19).

$$
\begin{aligned}
\text{gr\_laborshare} =& -\text{gr\_markup} \\
& + \alpha_1 \text{APR} + \alpha_2 \text{ANT} \\
& + \alpha_3 \text{gr\_labor price} + \alpha_4 \text{gr\_robot price} \\
& + \alpha_5 \text{gr\_capital price} + \gamma_i + \gamma_j + \gamma_t + \gamma_{ij} + \varepsilon_{ijt} \qquad (25) \\
\Leftrightarrow \text{gr\_(laborshare} \times \text{markup)} =& \alpha_1 \text{APR} + \alpha_2 \text{ANT} \\
& + \alpha_3 \text{gr\_labor price} + \alpha_4 \text{gr\_robot price} \\
& + \alpha_5 \text{gr\_capital price} + \gamma_i + \gamma_j + \gamma_t + \gamma_{ij} + \varepsilon_{ijt} \qquad (26)
\end{aligned}
$$

, where *gr* indicates the variables are in a 5-year growth rate. APR and ANT stand for Adjusted Penetration of Robots and Adjusted New Tasks, respectively. We exclude the notation of *gr* from APR and ANT, as by definition, they already represent a 5-year growth rate (refer to Equation (22)). Within this context, i, j, and t correspond to country, industry, and year, respectively.

For convenience, we have rewritten Equation (19) as Equation (28) below. Ⓐ represents 'the share of the effective wage for task I' times -1. Ⓑ represents the task price channel (the partial derivative). Lastly, Ⓒ represents the price drop in the aggregate task (T) when robots replace human labor.

In Equation (28), the sum of the coefficients of $d \ln \mathbb{W}$ and $d \ln \psi$ is equal to the negative coefficient of $d \ln R$ (i.e. $\alpha_3 + \alpha_4 = -\alpha_5$). Therefore we prefer to put this restriction accordingly to our regression.

Table 2 is the regression result. Column (1) is OLS without the coefficient restriction ($\alpha_3 + \alpha_4 = -\alpha_5$); Column (2) is OLS with the restriction; Column (3) is Non-linear Least Square (NLS) with the restriction; Lastly, Column (4) is the two-step GMM with the restriction. For the rest of our paper, we will use the result from Column (2).

Using Equation (28), we can determine the signs of ζ and σ. Specifically, $S_K^f > 0$ and the coefficient for $d \ln R$ is negative, implying that $\sigma < 1$. Additionally, by plugging in $S_K^f = 0.494$ that we acquired from dataset, we infer $\sigma = 0.594$ as shown in Equation (27).

$$
-\left[\underbrace{S_K^f}_{0.494} (1 - \sigma) \right] = \underbrace{\text{coefficient}}_{\text{-0.200}} \qquad (27)
$$

$$
\begin{aligned}
&d\ln S_L^f = \\
&-\left[(1-\zeta)+\left(-(1-\zeta)+S_K^f(1-\sigma)\right)S_L^T\right]d\ln\gamma \\
&+\underbrace{\left[\underbrace{-\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N\left(\frac{W_j}{\gamma_j}\right)^{1-\zeta}dj}}_{\text{A}}+\underbrace{\left(-(1-\zeta)+S_K^f(1-\sigma)\right)}_{\text{B}}\underbrace{\frac{1}{1-\zeta}\frac{\psi^{1-\zeta}-\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{C}}\right]}_{\alpha_1}d(I-N+1) \\
&+\underbrace{\underbrace{\left(S_N^L-S_I^L\right)}_{\text{D}}\underbrace{\frac{1}{1-\zeta}}_{\text{E}}\underbrace{\left[S_M^T(1-\zeta)+S_L^TS_K^f(1-\sigma)\right]}_{\text{F}}}_{\alpha_2}dN \\
&+\underbrace{\left[(1-\zeta)+\left(-(1-\zeta)+S_K^f(1-\sigma)\right)S_L^T\right]}_{\alpha_3}d\ln\mathbb{W} \\
&+\underbrace{\left[\left(-(1-\zeta)+\underbrace{S_K^f(1-\sigma)}_{\text{G}}\right)S_M^T\right]}_{\alpha_4}d\ln\psi \\
&\underbrace{-\left[S_K^f(1-\sigma)\right]}_{\alpha_5}d\ln R
\end{aligned}
\tag{28}
$$

The derivation of the value of ζ is as follows. From Equation (28), using α_3, α_4, and α_5, we derive Equation (Zeta), which we illustrate in Figure 5. To keep things concise, denote $\alpha_2 = 0.015$; $\alpha_3 = 0.195$; and $\alpha_4 = 0.005$, then

$$
\zeta = 1 - \alpha_3 + \alpha_4 \frac{S_L^T}{1-S_L^T} \tag{Zeta}
$$

As we will demonstrate at the end of this section, we estimate S_L^T, which represents the share of labor cost out of the aggregated task cost (i.e. labor cost + robot cost), to be 0.979. By substituting $S_L^T = 0.979$ into Equation (Zeta), we derive an estimate of $\zeta = 1.051$, which is a value close to one. It's important to note that ζ signifies the

Table 2: Regressions

	OLS	OLS	NLS	GMM
	(1)	(2)	(3)	(4)
APR	-0.003*	-0.002*	-0.002*	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
ANT	0.015***	0.015***	0.015***	0.015***
	(0.004)	(0.004)	(0.004)	(0.003)
gr_capital price	-0.235***	-0.200***	-0.200***	-0.248***
	(0.031)	(0.038)	(0.038)	(0.034)
gr_labor price	0.202***	0.195***	0.195***	0.204***
	(0.024)	(0.025)	(0.025)	(0.026)
gr_robot price	0.010	0.005	0.005	0.044
	(0.026)	(0.030)	(0.030)	(0.025)
N	1027	1027	1027	1027
R^2	0.565		0.563	

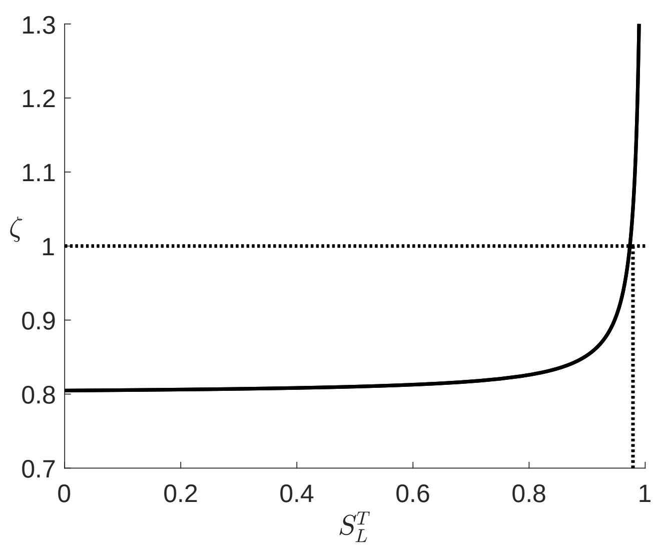
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

elasticity of substitution *between different tasks* and does not pertain to the elasticity between labor and robots *with in the same task*. We will provide further elaboration on this matter in this section.

Meanwhile, ζ consistently falls within the range of 0.8 and 1.3, regardless of the sensitivity of our estimated value for S_L^T. This observation is primarily attributed to the fact that α_4, the coefficient for robot price, is approximately zero.

Figure 5: Equation (Zeta)



To validate the reliability of ζ, we have conducted sensitivity tests. Rather than relying on point estimates, we've used intervals encompassing one standard deviation around these estimates. For the coefficient of gr_labor price, denoted as α_3, the interval is $(0.183, 0.208)$, resulting in ζ falling within the interval of $(1.038, 1.063)$. If we instead consider the interval for the coefficient of gr_robot price, represented by α_4, as $(-0.009, 0.007)$, then ζ falls within the interval of $(0.364, 1.137)$. Finally, by considering intervals for both α_3 and α_4, we find that ζ falls within the interval of $(0.352, 1.149)$. From this analysis, we can conclude that the uncertainty associated with ζ predominantly arises due to the low significance of α_4, gr_robot price.

Finally, the sign of the coefficient for $d(I - N + 1)$ is negative. To elaborate, Ⓐ < 0 by the definition of productivity-adjusted wage; We have demonstrated that Ⓑ is indeed greater than zero.[15] ; and, as per Assumption 1, Ⓒ < 0. Therefore, Ⓑ $\times$ Ⓒ < 0. This means that both the direct effect (Ⓐ) and indirect effect (Ⓑ $\times$ Ⓒ) are negative. Here, we define the 'direct effect' as the effect that does not operate through the 'task price' channel. Conversely, we define the 'indirect effect' as the effect that necessarily passes through this channel.

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. 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 'tasks', where tasks encompass both robot and labor inputs. Assuming a Cobb-Douglas production function between robot and labor input brings our definition of σ closer to that of KN (considering the estimated value of $\zeta = 1.051$, the plausibility of Cobb-Douglas formation is reasonable).

Let μ denote the elasticity of substitution between labor and non-robot capital. Given that our model incorporates two layers of production functions —Equation (3) and (4)— it is not possible to derive a closed-form solution for μ. Assuming that ζ converges to one, we can temporarily treat Equation (4) as a Cobb-Douglas function. It then follows

[15] Specifically, upon substituting the values, it amounts to 0.25

that (the derivation process is provided in Appendix B):

$$
\begin{aligned}
\mu &\equiv \frac{d\left(\frac{L}{K}\right)}{d\left(\frac{R}{\mathbb{W}}\right)} \frac{\frac{R}{\mathbb{W}}}{\frac{L}{K}} \\
&= \frac{d\left(\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}\right)}{d\left(\frac{R}{\mathbb{W}}\right)} \frac{\frac{R}{\mathbb{W}}}{\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}} \qquad (29) \\
&\Rightarrow \ \sigma \ \text{ if } N-I=1.
\end{aligned}
$$

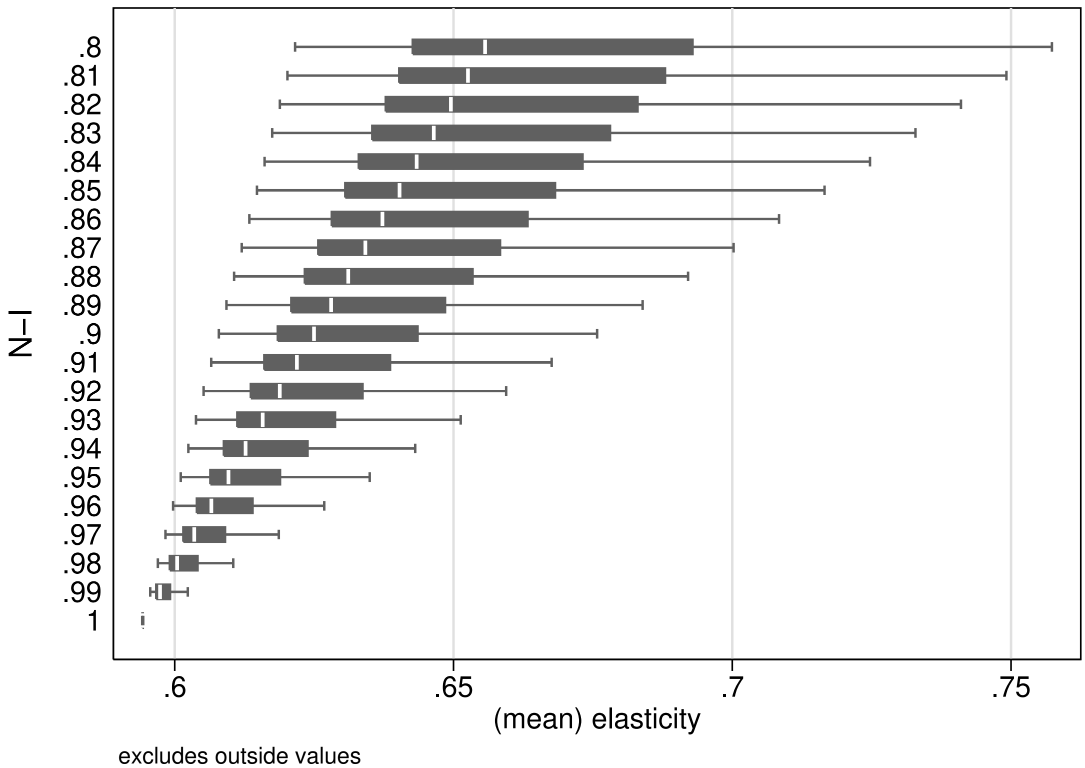
Consequently, when I is positioned at $N-1$ (indicating the absence of automation tasks and all tasks being executed by labor), then $\mu = \sigma$. Otherwise, $\sigma < \mu$ as depicted in Figure 6. Specifically, when $I > N-1$, differentiating Equation (29) becomes infeasible. However, we can employ numerical approximation to estimate μ. We use actual $\mathbb{W}$ and R values from the dataset (all possible combinations of these), along with $\sigma = 0.594$ as established in Equation (27). 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 (29) to obtain an approximated μ.

Figure 6 presents the results. When $N-I=1$ (i.e. $I=N-1$), we find that $\mu=\sigma=0.594$, which aligns with our expectations. Even when we assume $N-I=0.8$ (meaning 20% of tasks are automated), the divergence from σ is minimal, at most $\mu = 0.656$. 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 0.594 and 0.656, supporting the idea of a gross complementary relationship between the two.

Meanwhile, it's important to understand that $\zeta < 1$ doesn't imply a gross complementary relationship between robots and labor *within a task*; our model considers robots and labor as perfect substitutes within a task. Instead, $\zeta = 1.051 \simeq 1$ denotes the elasticity of substitution *across different tasks*, which we deduce neither gross substitution nor gross complementarity. Considering all of these factors together, we deduce a gross substitutive relationship between robots and labor in a general sense: When the price of robots decreases —a trend that can be observed in actual data— the quantity of robot usage experiences a more significant increase compared to the reduction in price. As a result, the labor share declines.

The negative coefficient associated with robot price in our regression model offers intriguing insights into the ramifications of advancements in robotics. These advancements can be comprehended through two distinct mechanisms: first, the augmentation

Figure 6: Elasticity of Substitution between Labor and Non-robot Capital



of robots' capabilities, which empowers them to execute tasks that were previously unachievable; and second, a reduction in the price of robots without corresponding enhancements in functionality. Our findings suggest that as robots become capable of performing tasks previously undertaken by humans, the share of labor decreases. On the other hand, when the robot price decreases, labor share also decreases. Together, these effects create a negative impact on the labor share, indicative of a degree of gross substitutability between labor and robots (Since we consider robots as regular goods, their utilization will increase as their prices drop. This increase will be more than proportionate to the price decrease, resulting in an elevation of the costs associated with robots and subsequently leading to a reduction in the labor share).

Table 3 represents the regressions, which are analogous to those in Table 2, with the exception that it utilizes ANT_USdetail instead of ANT. ANT remains constant across sectors in both the EU and the USA. In contrast, ANT_USdetail is sector-specific in the USA but uniform in EU countries. This distinction stems from the EU-LFS's limitation in offering variations beyond the primary manufacturing sector. Conversely, the US Census provides differentiation at the two-digit sector level. When formulating ANT, we aligned

Table 3: Regressions using ANT_USdetail

	OLS	OLS	NLS	GMM
	(1)	(2)	(3)	(4)
APR	-0.002*	-0.002*	-0.002*	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
ANT_detail	0.006**	0.006**	0.006**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
gr_capital price	-0.250***	-0.213***	-0.213***	-0.262***
	(0.033)	(0.040)	(0.040)	(0.036)
gr_labor price	0.204***	0.197***	0.197***	0.204***
	(0.024)	(0.025)	(0.025)	(0.026)
gr_robot price	0.021	0.016	0.016	0.059*
	(0.027)	(0.030)	(0.030)	(0.026)
N	1027	1027	1027	1027
R^2	0.555		0.552	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

with the broader manufacturing sector representation of the EU-LFS for both the EU and the USA to maintain consistency. However, in creating ANT_USdetail, we incorporated the detailed sector classifications from the US Census for the USA, while preserving the more generalized manufacturing sector for the EU countries. For consistency between the USA and EU, we prefer using ANT.

The coefficients for both ANT and ANT_USdetail consistently outweigh those for APR. Notably, the coefficients for ANT_USdetail are significantly smaller than those for ANT. This suggests that if we had access to an EU-LFS dataset offering more granular sector variations, the dominance might diminish. Investigating this remains a task for future work.

Estimation of S_L^T: Before concluding this section, let us explain how we estimated S_L^T, which denotes the share of labor cost out of the combined task cost (i.e., labor cost + robot cost). There isn't official data available that directly provides this value, but it is necessary to infer ζ. As a result, we must rely on various sources to accurately estimate this value. 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,[16] and separately calculating the total export values of HS Code 8479 (which pertains to robots),[17] 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.

It is essential to acknowledge that the equipment cost for robots is estimated to be around 33.04%[18] of the total robot costs, covering aspects such as operation, training, software, maintenance, and disposal (Zhao et al., 2021). The UN Comtrade estimate of 0.71 corresponds to the equipment cost. Therefore, the total cost of the robot amounts to $0.71/0.33 = 2.149$. Finally, we compute $S_L^T = 97.90$ by performing the calculation $100/(100 + 2.149)$.

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) of Table 2, we have assembled a series of accounting tables. These comprehensive contents can be accessed in the Excel file, which is provided in the associated footnote.[19] This file contains information on 'Average variables' and their contribution to change in labor shares.

$$\text{chg\_APR} = \text{Coefficient of APR} \times \text{Average APR}. \tag{30}$$

For instance, the term 'Average APR' refers to the APR value averaged over the period from 2005 to 2019. We use this average to mitigate short-term fluctuations in the variable. The 'Coefficient of APR' is the regression result in Column (1) of Table 2. Finally, chg_APR quantifies how the five-year growth rate of labor share (S_L^f) has changed due to automation (APR).[20]

In the Excel file, odd-numbered sheets correspond to 'Average variables,' and even-numbered sheets correspond to 'chg_variables.' Sheets 1 and 2 present data by country $\times$ sector, with samples provided in Tables 4 and 5, respectively. Sheets 5 and 6 are

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

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

[18] $33.04\% = 35.73\% \times (1 - 0.075)$, where 0.075 represents taxes, transactions, and after-sales fees.

[19] https://github.com/jayjeo/public/blob/main/Laborshare/accounting.xlsx

[20] S_L^f is defined in Equation (19) in the Model section.

aggregated by country (Tables 6 and 7, respectively). Sheets 9 and 10 are aggregated by sector (Tables 8 and 9, respectively). Aggregation is based on 'Average variables' from the country $\times$ sector data in Excel Sheet 1. These values are then aggregated using the corresponding value-added as weights.

The remaining sheets in the Excel file —Sheets 3, 4, 7, 8, 11, and 12— are structured similarly, but they use ANT_USdetail instead of ANT.[21] For readability, our focus remains on the sheets using ANT. For more information, please refer to the 'Readme' sheet in the Excel file.

The tables reveal patterns not readily discernible through regression results alone. Starting from Table 4 (Excel Sheet 1), we observe that APR is mostly positive. This implies that automation is outpacing value-added growth in most countries and sectors. Meanwhile, ANT is generally positive, indicating that task indices are increasing over time. Robot prices are predominantly declining, suggesting that robots become more affordable. Contrary to robot trend, capital prices and wages vary across countries and sectors.

Shifting our attention to Table 5 (Excel Sheet 2), in the analysis of chg_APR, patterns vary by country and industry. For instance, results for the 'Car and Transport Equipment' sector show variation between countries. Austria and the USA display negative signs, indicating deeper penetration of robots (APR) —that is, a faster growth of robots compared to value-added in this particular industry. In contrast, countries like Germany, France, and Italy show positive signs, indicating lighter penetration of robots— a slower pace of robots growth relative to value-added in the same industry. Figure 7 further elucidates this trend, revealing that the USA, South Korea, and Austria are experiencing more accelerated robot growth relative to their value-added.

In Table 5, both chg_APR and chg_robot price are mostly negative. The results for chg_gr_capital prices are mixed, displaying both positive and negative signs across various countries and industries. This suggests a more complex influence of ordinary capital —such as buildings, equipment, and non-robot machinery— on labor share. This distinction underscores the need to consider different types of capital separately when examining their effects on labor share.

As we turn to chg_ANT, a distinct pattern emerges. chg_ANT surpasses chg_APR in most instances. This suggests that the advent of new tasks exerts a stronger influence on labor share than does automation. Notably, the USA exhibits a considerably larger chg_ANT than chg_APR, signifying robust innovation in terms of new task creation.

[21] The meaning of ANT_USdetail is explained in detail in the paragraph following Table 3.

Table 4: Average Variables

location	sector	gr_S_L^f	APR	ANT	gr_capital price	gr_labor price	gr_robot price
AUT	10-12	-0.117	0.179	0.844	1.050	6.297	-6.329
AUT	13-15	-1.138	0.010	0.844	4.247	-6.828	-0.269
AUT	16-18	1.133	0.093	0.844	8.614	7.769	4.088
AUT	20-21	-0.092	0.005	0.844	7.983	29.063	2.271
AUT	22-23	-0.785	1.588	0.844	2.904	6.136	-3.634
AUT	24-25	-0.492	1.622	0.844	-2.119	3.285	-8.967
AUT	26-27	-4.332	0.605	0.844	6.693	13.105	1.870
AUT	28	-1.731	0.532	0.844	1.102	15.561	-4.435
AUT	29-30	-1.850	3.111	0.844	6.732	18.560	1.394
AUT	31-33	0.054	0.449	0.844	-0.615	10.690	-6.559
DEU	10-12	0.887	0.240	0.866	0.327	4.385	-8.220
DEU	13-15	1.455	0.016	0.866	-1.175	6.638	-8.417
DEU	16-18	1.363	-0.285	0.866	4.886	8.845	-1.630
DEU	19	-0.431	0.263	0.866	-27.546	-28.091	-39.132
DEU	20-21	2.617	0.006	0.866	1.309	5.617	-9.444
DEU	22-23	1.544	1.222	0.866	1.623	5.949	-6.842
DEU	24-25	0.715	0.794	0.866	4.053	8.588	-4.858
DEU	26-27	2.096	-0.091	0.866	9.482	14.893	0.193
DEU	28	0.731	0.783	0.866	-4.410	-0.925	-14.783
DEU	29-30	-1.136	-2.512	0.866	1.370	7.288	-8.982
DEU	31-33	-0.101	-0.176	0.866	-4.635	-2.412	-14.182
ITA	10-12	0.958	1.261	0.740	3.239	6.690	-9.521
ITA	13-15	-0.799	-0.010	0.740	7.401	8.281	-9.742
ITA	16-18	-1.230	0.145	0.740	4.422	7.198	-7.637
ITA	19	-12.079	0.386	0.740	-21.279	-32.843	-32.373
ITA	20-21	-0.577	0.021	0.740	0.778	3.375	-11.734
ITA	22-23	-2.164	0.857	0.740	2.693	6.952	-9.869
ITA	24-25	0.165	0.820	0.740	4.655	10.120	-7.668
ITA	26-27	-1.610	0.119	0.740	-7.317	-1.766	-18.731
ITA	28	0.212	0.709	0.740	-1.078	4.907	-12.576
ITA	29-30	-4.697	-2.286	0.740	-0.022	5.243	-11.992
ITA	31-33	0.975	0.034	0.740	-2.031	1.273	-14.446
USA	10-12	0.242	0.060	2.555	-7.774	-5.949	-16.491
USA	13-15	-0.177	0.001	2.555	-3.711	2.706	-9.983
USA	16-18	-0.530	0.004	2.555	-2.363	1.841	-8.808
USA	19	-3.414	0.032	2.555	2.938	9.504	-6.019
USA	22-23	-0.100	0.066	2.555	-3.510	-0.021	-11.694
USA	24-25	-0.366	0.078	2.555	2.311	6.349	-5.663
USA	26-27	0.167	0.184	2.555	21.149	37.001	15.158
USA	28	-0.418	0.025	2.555	-4.846	0.530	-12.613
USA	29-30	-1.493	0.475	2.555	-0.417	0.900	-8.770
USA	31-33	0.049	0.079	2.555	-2.198	8.760	-7.501

Table 5: Chg_Variables

location	sector	gr_S_L^f	chg_sum	chg _fixed effects	chg_APR	chg_ANT	chg_gr _capital price	chg_gr _labor price	chg_gr _robot price
AUT	10-12	-0.117	0.939	-1.255	-0.042	1.251	-0.210	1.229	-0.033
AUT	13-15	-1.138	-0.081	0.856	-0.002	1.251	-0.852	-1.333	-0.001
AUT	16-18	1.133	2.189	1.149	-0.022	1.251	-1.727	1.516	0.022
AUT	20-21	-0.092	0.964	-4.370	-0.001	1.251	-1.600	5.673	0.012
AUT	22-23	-0.785	0.272	-1.203	-0.373	1.251	-0.582	1.198	-0.019
AUT	24-25	-0.492	0.565	-1.324	-0.381	1.251	0.425	0.641	-0.047
AUT	26-27	-4.332	-3.275	-5.610	-0.142	1.251	-1.342	2.558	0.010
AUT	28	-1.731	-0.675	-4.594	-0.125	1.251	-0.221	3.037	-0.023
AUT	29-30	-1.850	-0.793	-3.594	-0.731	1.251	-1.350	3.623	0.007
AUT	31-33	0.054	1.110	-2.211	-0.106	1.251	0.123	2.087	-0.035
DEU	10-12	0.887	1.943	-0.032	-0.056	1.284	-0.065	0.856	-0.043
DEU	13-15	1.455	2.511	-0.256	-0.004	1.284	0.236	1.296	-0.044
DEU	16-18	1.363	2.419	0.330	0.067	1.284	-0.980	1.726	-0.009
DEU	19	-0.431	0.626	-0.429	-0.062	1.284	5.523	-5.483	-0.207
DEU	20-21	2.617	3.674	1.607	-0.002	1.284	-0.262	1.096	-0.050
DEU	22-23	1.544	2.600	0.804	-0.287	1.284	-0.325	1.161	-0.036
DEU	24-25	0.715	1.772	-0.164	-0.186	1.284	-0.813	1.676	-0.026
DEU	26-27	2.096	3.152	0.840	0.021	1.284	-1.901	2.907	0.001
DEU	28	0.731	1.787	0.062	-0.184	1.284	0.884	-0.181	-0.078
DEU	29-30	-1.136	-0.079	-3.054	0.590	1.284	-0.275	1.423	-0.047
DEU	31-33	-0.101	0.955	-0.753	0.041	1.284	0.929	-0.471	-0.075
ITA	10-12	0.958	2.015	0.608	-0.296	1.097	-0.649	1.306	-0.050
ITA	13-15	-0.799	0.258	-0.922	0.002	1.097	-1.484	1.616	-0.051
ITA	16-18	-1.230	-0.173	-1.714	-0.034	1.097	-0.887	1.405	-0.040
ITA	19	-12.079	-11.023	-9.713	-0.091	1.097	4.266	-6.411	-0.171
ITA	20-21	-0.577	0.480	-1.053	-0.005	1.097	-0.156	0.659	-0.062
ITA	22-23	-2.164	-1.108	-2.768	-0.201	1.097	-0.540	1.357	-0.052
ITA	24-25	0.165	1.221	-0.684	-0.193	1.097	-0.933	1.975	-0.041
ITA	26-27	-1.610	-0.553	-2.645	-0.028	1.097	1.467	-0.345	-0.099
ITA	28	0.212	1.268	-0.769	-0.167	1.097	0.216	0.958	-0.066
ITA	29-30	-4.697	-3.641	-6.239	0.537	1.097	0.004	1.023	-0.063
ITA	31-33	0.975	2.032	0.364	-0.008	1.097	0.407	0.248	-0.076
USA	10-12	0.242	1.298	-2.786	-0.014	3.788	1.559	-1.161	-0.087
USA	13-15	-0.177	0.879	-4.128	-0.000	3.788	0.744	0.528	-0.053
USA	16-18	-0.530	0.527	-4.047	-0.001	3.788	0.474	0.359	-0.047
USA	19	-3.414	-2.358	-7.373	-0.007	3.788	-0.589	1.855	-0.032
USA	22-23	-0.100	0.956	-3.454	-0.015	3.788	0.704	-0.004	-0.062
USA	24-25	-0.366	0.690	-3.826	-0.018	3.788	-0.463	1.239	-0.030
USA	26-27	0.167	1.223	-5.584	-0.043	3.788	-4.240	7.222	0.080
USA	28	-0.418	0.639	-4.152	-0.006	3.788	0.972	0.103	-0.067
USA	29-30	-1.493	-0.437	-4.326	-0.112	3.788	0.084	0.176	-0.046
USA	31-33	0.049	1.106	-4.775	-0.019	3.788	0.441	1.710	-0.040

Table 6: Average Variables (Country)

location	$gr\_S_L^f$	APR	ANT	gr_capital price	gr_labor price	gr_robot price
AUT	-1.070	0.888	0.844	3.225	11.194	-2.607
DEU	0.755	-0.248	0.866	1.195	5.722	-8.392
DNK	-1.613	0.515	0.905	0.543	3.226	-10.233
FIN	0.084	0.114	1.296	3.701	-3.846	-2.480
FRA	-0.203	0.055	0.847	3.084	11.117	-1.664
GBR	0.192	0.160	1.349	2.991	4.502	-11.483
ITA	-0.808	0.286	0.740	1.177	5.125	-11.464
PRT	-0.114	0.254	-0.213	-4.991	-1.902	-3.538
SWE	2.083	0.474	0.641	-2.740	0.055	-5.962
USA	-0.675	0.140	2.555	2.690	9.188	-4.854

Table 7: Chg_Variables (Country)

location	$gr\_S_L^f$	chg_sum	chg _fixed effects	chg_APR	chg_ANT	chg_gr _capital price	chg_gr _labor price	chg_gr _robot price
AUT	-1.070	-4.492	-7.059	-0.209	1.251	-0.647	2.185	-0.014
DEU	0.755	-4.344	-6.519	0.058	1.284	-0.240	1.117	-0.044
DNK	-1.613	-0.929	-2.617	-0.121	1.342	-0.109	0.630	-0.054
FIN	0.084	-1.920	-2.308	-0.027	1.921	-0.742	-0.751	-0.013
FRA	-0.203	-3.307	-6.093	-0.013	1.255	-0.618	2.170	-0.009
GBR	0.192	-3.542	-5.724	-0.038	2.000	-0.600	0.879	-0.061
ITA	-0.808	-7.970	-9.704	-0.067	1.097	-0.236	1.000	-0.061
PRT	-0.114	-3.504	-3.739	-0.060	-0.316	1.001	-0.371	-0.019
SWE	2.083	-6.142	-7.510	-0.111	0.951	0.549	0.011	-0.032
USA	-0.675	-2.808	-7.792	-0.033	3.788	-0.539	1.794	-0.026

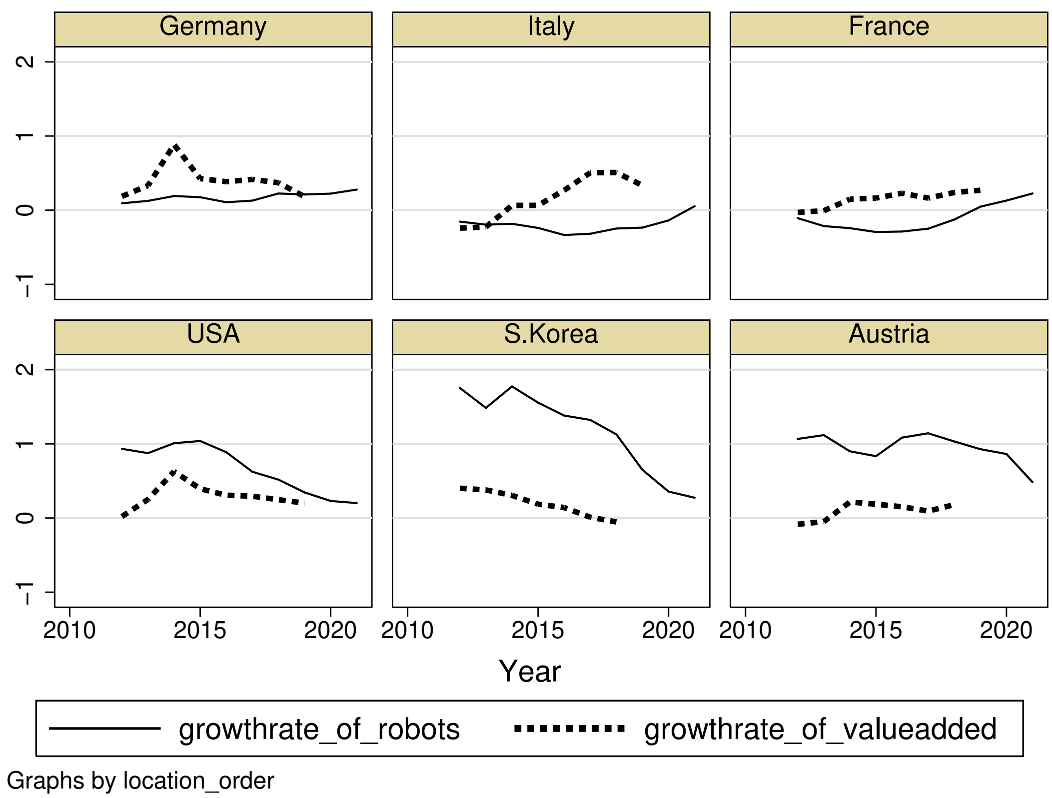
Table 8: Average Variables (Sector)

sector	$gr\_S_L^f$	APR	ANT	gr_capital price	gr_labor price	gr_robot price
10-12 Food products	0.268	0.408	1.634	-3.941	-1.696	-11.569
13-15 Textiles, wearing apparel	0.092	0.002	1.288	1.904	5.285	-7.046
16-18 Wood and paper products	-0.432	0.065	1.522	1.359	1.255	-4.661
19 Coke and refined petroleum	-2.828	0.068	2.246	-0.083	7.053	-7.974
20-21 Chemicals	-0.259	0.020	0.905	2.112	13.004	-8.738
22-23 Rubber and plastics	0.072	0.612	1.532	-0.681	2.424	-8.652
24-25 Basic metals	-0.141	0.439	1.534	2.103	6.294	-5.866
26-27 Electrical and optical	3.206	0.053	1.851	16.359	26.709	9.709
28 Machinery and equipment	-0.779	0.762	1.370	-4.151	-0.978	-12.671
29-30 Car and Transport equipment	-1.668	-0.612	1.563	-1.300	2.589	-9.756
31-33 Other manufacturing	0.031	0.158	1.482	-2.691	2.863	-9.860

Table 9: Chg_Variables (Sector)

sector	$gr\_S_L^f$	chg_sum	chg _fixed effects	chg_APR	chg_ANT	chg_gr _capital price	chg_gr _labor price	chg_gr _robot price
10-12 Food products	0.268	-0.772	-3.497	-0.096	2.423	0.790	-0.331	-0.061
13-15 Textiles, wearing apparel	0.092	-1.198	-3.721	-0.001	1.910	-0.382	1.032	-0.037
16-18 Wood and paper products	-0.432	-0.946	-3.135	-0.015	2.257	-0.272	0.245	-0.025
19 Coke and refined petroleum	-2.828	0.771	-3.894	-0.016	3.330	0.017	1.377	-0.042
20-21 Chemicals	-0.259	1.548	-1.858	-0.005	1.342	-0.423	2.538	-0.046
22-23 Rubber and plastics	0.072	0.031	-2.661	-0.144	2.272	0.137	0.473	-0.046
24-25 Basic metals	-0.141	-0.681	-3.629	-0.103	2.275	-0.422	1.228	-0.031
26-27 Electrical and optical	3.206	2.092	-2.626	-0.012	2.744	-3.280	5.213	0.051
28 Machinery and equipment	-0.779	-0.976	-3.403	-0.179	2.032	0.832	-0.191	-0.067
29-30 Car and Transport equipment	-1.668	-3.344	-6.519	0.144	2.317	0.261	0.505	-0.052
31-33 Other manufacturing	0.031	-1.012	-4.219	-0.037	2.198	0.540	0.559	-0.052

Figure 7: Robot and GDP in manufacturing (5-year growth rate)



Our accounting analysis reveals that the emergence of new tasks (ANT) has had a positive impact on labor share, despite the negative effects of increasing automation.

This suggests a balancing act between robots and the emergence of new tasks, with the latter currently holding more sway. Tables 6 and 7 illuminate this dominance (Excel Sheets 5 and 6). We obtain these tables by aggregating data to the country level. During this aggregation, we base our calculations on the 'Average variables' from Table 4 and use value-added by country $\times$ sector as weights. We then apply relevant coefficients derived from the regression in Column (2) of Table 2 to generate 'chg_variables'.

The data presented in Table 7 delineate the directional tendencies of each variable: chg_gr_capital prices predominantly register negative values, whereas chg_gr_labor prices are mainly positive. This trend suggests a consistent increase in both the capital and labor prices since at least 2005. This finding is notable, especially considering that we derived the capital price through an exact replication of the KLEMS version code presented in Karabarbounis and Neiman (2014).

Lastly, we examine Tables 8 and 9 (Excel Sheets 9 and 10), which are aggregated at the sector level using value-added as weights. Similar to the previous tables, APR generally exhibits positive values, indicating a faster rate of automation relative to the growth of value-added. This trend is most pronounced in the 'Machinery and Equipment' sector, which showcases a significantly high APR. In contrast, the 'Car and Transport Equipment' sector is the sole sector to record a negative APR. Given the analysis period, which spans from 2005 to 2019, this implies that automation in the 'Car and Transport' sector has largely stagnated since 2005. While the rate of automation has increased in many other sectors, this sector appears to have seen a relatively slower pace of technological integration compared to its value-added growth.

It is important to exercise caution in interpreting these results. Specifically, this analysis does not provide information about the absolute level of automation within each sector. Instead, it sheds light on the relative penetration of automation in comparison to value-added growth. That is, a negative APR indicates a slower growth rate of automation relative to value-added growth, not necessarily a low level of automation in absolute terms.

6 Concluding Remarks

Our research primarily focused on the two opposing forces of automation and the emergence of new tasks, both of which contribute to changes in labor share. While empirical measurements of automation's effects on labor share are plentiful in current literature (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Dauth et al., 2021; De Vries et al., 2020; Humlum, 2019), we contribute to the literature by empirically measuring the impact of the emergence of new tasks on labor share, an area which, to the best of our knowledge, has yet to be explored in existing studies.

Our analysis focused on exploring multiple reasons for changes in labor share within a single framework, as opposed to most studies which concentrate on a single cause to formally establish causality. In this respect, our work aligns with that of Bergholt et al. (2022), who 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."

In contrast to their study that employs time series techniques, we utilize a general equilibrium model based on Acemoglu and Restrepo (2018). Our contribution to this model involves differentiating between robots and capital. In their model, only robots are considered, with capital not taken into account.

We add to the literature on the substitutability between capital and labor (Karabarbounis and Neiman, 2014; Glover and Short, 2020; Martinez, 2018; Oberfield and Raval, 2021; Zhang, 2023) by indirectly providing evidence that the elasticity is less than one, indicating a gross complementary relationship. However, some caution is required when interpreting this elasticity (σ) as it is not defined identically to other studies. The reason for this difference lies in the fact that our model incorporates both capital and robots. Nevertheless, if we further assume our production function for robots and labor to be Cobb-Douglas, the interpretation of our σ becomes more aligned with the general understanding.

Our paper seeks to answer the question: Will the labor share continue to decline, or will it stabilize and perhaps even rebound?[22] We propose that the future labor share will be determined by the tug-of-war between automation and the emergence of new tasks. We conjecture that task innovation is more prominent in the USA compared to EU countries. This is corroborated by Tables 4 through 7, where the impact of ANT (New Tasks), as well as the fitted value for ANT on labor share, are particularly substantial in the USA.

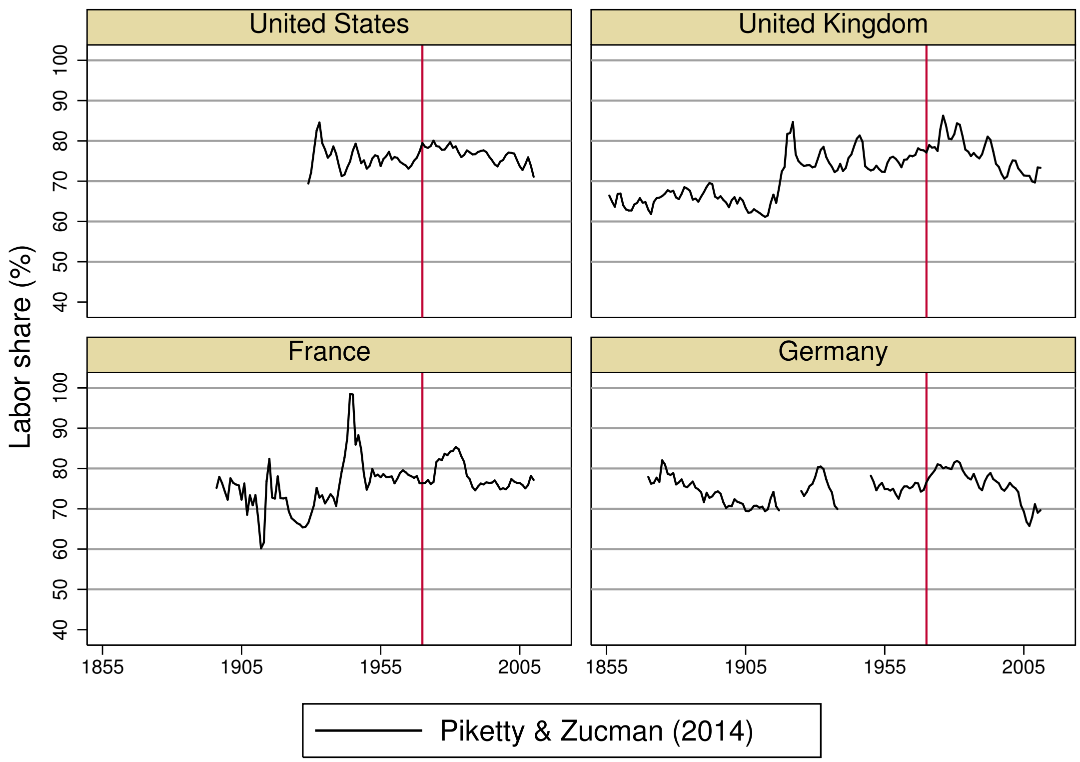
However, the labor share in the USA has experienced a particularly steep decline, which we attribute to rising concentration (Autor et al., 2020). Further in our online appendix,[23] we provide an analysis showing that this increase in concentration, leading

[22] Piketty and Zucman (2014) also discusses this and emphasizes that the recent decline in labor share falls within the historical range of fluctuations. For convenience, we present historical values of labor shares in Figure 8.

[23] https://github.com/jayjeo/public/blob/main/Laborshare/Online_Appendix.pdf

to the decline in labor share, is not a trend that extends to EU countries, but rather seems to be specific to the USA. This observation prompts further investigation, which should include analyzing firm-level data from EU countries and utilizing resources like Amadeus for the EU. This also suggests a deeper exploration of the effect of automation on concentration as initiated by Firooz et al. (2022).

Figure 8: Historical Labor Share



A Appendix: Model Derivations

A.1 Environment

There is a representative household with utility function in Equation (31):

$$U = \left(\int_0^1 Y(k)^{\frac{\eta-1}{\eta}} dk \right)^{\frac{\eta}{\eta-1}}. \tag{31}$$

There are infinite number of identical firms i with production functions in Equation (34) and (35):

$$t_j(i) = m_j(i) + \gamma_j l_j(i) \text{ if } j \leq I \tag{32}$$

$$t_j(i) = \gamma_j l_j(i) \text{ if } j > I \tag{33}$$

$$T(i) = \left(\int_{N-1}^{N} t_j(i)^{\frac{\zeta-1}{\zeta}} dj \right)^{\frac{\zeta}{\zeta-1}} \tag{34}$$

$$Y(i) = \left(T(i)^{\frac{\sigma-1}{\sigma}} + K(i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{35}$$

By Assumption 1, Equation (32) simplifies to Equation (36). 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.

$$t_j(i) = m_j(i) \text{ if } j \leq I \tag{36}$$

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.

$$\min \text{cost(i) for } T(i) \text{ s.t. Equation(36), (33), and (34)}$$

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

$\Rightarrow$ This finds optimal inputs for robot* and labor* to produce T(i)

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

$$\Rightarrow P_T = \left[(I - N + 1)\psi^{1-\zeta} + \int_{I}^{N} \left(\frac{w_j}{\gamma_j} \right)^{1-\zeta} dj \right]^{\frac{1}{1-\zeta}} \tag{37}$$

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 $Y(i)$.

$$
\begin{aligned}
&\min \text{cost(i) for } Y(i) \text{ s.t. Equation(35)} \\
\Leftrightarrow &\min P_T \cdot T(i) + R \cdot K(i) \text{ s.t. Equation(35)} \\
\Rightarrow &\text{This finds optimal inputs for T(i)* and K(i)* to produce Y(i)} \\
\Rightarrow &\text{Specifically, the minimization solution is the minimum cost for producing } Y(i) \\
\Rightarrow &\begin{cases} T(i)^* = Y(i) P_T^{-\sigma} \\ K(i)^* = Y(i) R^{-\sigma} \\ \text{Cost for } Y(i) = Y(i) \left[P_T^{1-\sigma} + R^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \\ \qquad\quad = Y(i) \times \text{AC} \\ \qquad\quad = Y(i) \end{cases}
\end{aligned}
$$

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.

$$
\begin{aligned}
&\min \text{cost for consumption s.t. Equation(31)} \\
\Leftrightarrow &\min \int_0^1 P(i) Y(i) di \text{ s.t. Equation(31)} \\
\Rightarrow &\text{Specifically, this yields a demand function for } Y(i) \\
\Leftrightarrow &Y(i) = \left(\frac{P(i)}{\mathbb{P}} \right)^{-\eta}, \text{ where } \mathbb{P} \equiv \left[\int_0^1 P(i)^{1-\eta} di \right]^{\frac{1}{1-\eta}}
\end{aligned}
$$

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 $T(i)$.

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

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. We have two layers of production fuctions:

$$Y(i) = \left(T(i)^{\frac{\sigma-1}{\sigma}} + K(i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{38}$$

$$T(i) = \left(\int_{N-1}^{N} t_j(i)^{\frac{\zeta-1}{\zeta}} dj \right)^{\frac{\zeta}{\zeta-1}} \tag{39}$$

, 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 $Y(i)$. Tasks, $t_j(i)$ are as follows:

$$t_j(i) = m_j(i) + \gamma_j l_j(i) \ \text{ if } j \leq I \tag{40}$$

$$t_j(i) = \gamma_j l_j(i) \ \text{ if } j > I \tag{41}$$

With Assumption 1 in Model section, Equation (40) becomes Equation (42):

$$t_j(i) = m_j(i) \ \text{ if } j \leq I \tag{42}$$

Combining Equations (39), (41), and (42), we get Equation (43):

$$T(i) = \left(\int_{N-1}^{I} m_j(i)^{\frac{\zeta-1}{\zeta}} dj + \int_I^N (\gamma_j l_j(i))^{\frac{\zeta-1}{\zeta}} dj \right)^{\frac{\zeta}{\zeta-1}} \tag{43}$$

Next, we assume $\lim_{\zeta \to 1}$ and convert Equation (43) to Equation (44) below:

$$\exp\left\{\int_{N-1}^{I} \ln m_j dj + \int_{I}^{N} \ln\bigl(\gamma_j l_j\bigr) dj\right\}. \tag{44}$$

Under the Cobb-Douglas production function, it is necessary to derive P_T, which will differ from the P_T derived in the CES case. Essentialy, we will do the same procedure of Step 1 in Appendix A except that we now use Cobb-Douglas production function (Equation 44).

$$\min \int_{N-1}^{I} \psi m_j dj + \int_{I}^{N} w_j l_j dj \quad \text{s.t. Equation(44)} = 1 \tag{45}$$

We derive optimal l_j^* and m_j^* as follows:

$$\forall j, \;\; m_j^* = m = \frac{1}{\psi^{N-1}} \prod_{I}^{N} \frac{w_j}{\gamma_j} \tag{46}$$

$$\forall j, \;\; l_j^* = \frac{\psi^{I-N+1}}{w_j} \prod_{I}^{N} \frac{w_j}{\gamma_j} \tag{47}$$

Plugging in m_j^* and l_j^* into $\int_{N-1}^{I} \psi m_j dj + \int_{I}^{N} w_j l_j dj$, we derive P_T:

$$P_T = \psi^{I-N+1} \prod_{I}^{N} \frac{w_j}{\gamma_j} \tag{48}$$

We introduce a parameter β_j to act as a weight for the wage distribution corresponding to each worker indexed by j. Employing β_j allows us to define a representative wage measure, $\mathbb{W}$, whose properties we will elucidate in subsequent discussions.

$$w_j \equiv \beta_j \mathbb{W} \tag{49}$$

A representative wage, $\mathbb{W}$, is total labor cost for producing $Y(i)$ divided by total number of workers to produce $Y(i)$:

$$\mathbb{W} \equiv \frac{\left(\int_{I}^{N} w_j l_j^* dj\right) T(i)}{\left(\int_{I}^{N} l_j^* dj\right) T(i)} \tag{50}$$

$$= \frac{N-I}{\int_{I}^{N} \frac{1}{w_j} dj} \tag{51}$$

$$= \mathbb{W} \frac{N-I}{\int_{I}^{N} \frac{1}{\beta_j} dj} \tag{52}$$

$$\therefore \;\; \frac{N-I}{\int_{I}^{N} \frac{1}{\beta_j} dj} = 1 \tag{53}$$

Hence, it is evident that β_j functions as the weight of the wage pertaining to the individual indexed by j. It holds that β_j varies with the index j, oscillating around a value of one:

We make an assumption that an infinitesimal change in the representative wage, $\mathbb{W}$, does not alter the distribution of the wage weight, β_j. In other words,

Assumption 2. $\forall j, \ \ \frac{\partial \beta_j}{\partial \mathbb{W}} = 0$

We resume the discussion of P_T in Equation (48). Inserting $w_j \equiv \beta_j \mathbb{W}$ into the equation yields:

$$P_T = \psi^{I-N+1} \cdot \prod_I^N \left(\frac{\beta_j}{\gamma_j} \right) \cdot \mathbb{W}^{N-I} \tag{54}$$

We define $L(i)$ as total number of workers to produce $Y(i)$. Therefore it satisfy the following equation:

$$\mathbb{W}L(i) = \int_I^N w_j l_j^* dj \times T(i) \tag{55}$$

Specifically, the term $\mathbb{W}L(i)/P_T T(i)$ represents the share of labor cost in the aggregate task cost for producing $Y(i)$:

$$\begin{aligned} \frac{\mathbb{W}L(i)}{P_T T(i)} &= \frac{\int_I^N w_j l_j^* dj \times T(i)}{P_T T(i)} && (56) \\ &= N - I && (57) \end{aligned}$$

This result confirms the well-known property of Cobb-Douglas function that the share of costs that goes to labor is always equal to the power of the Cobb-Douglas function, $N - I$.

From the equation discussed above, we derive the expression for $L(i)$:

$$L(i) = (N - I)\frac{P_T T(i)}{\mathbb{W}} \tag{58}$$

, where $T(i)$ is as follows. We detailed this derivation in Step 2 of Appendix A.

$$T(i) = \left(\frac{P_T}{MC} \right)^{-\sigma} Y(i) \tag{59}$$

Combining Equations (58) and (59) yields:

$$L(i) = \frac{(N - I)P_T}{\mathbb{W}} \left(\frac{P_T}{MC} \right)^{-\sigma} Y(i). \tag{60}$$

In Step 2 in Appendix A, we derived:

$$K(i) = \left(\frac{R}{MC}\right)^{-\sigma} Y(i). \tag{61}$$

Hence, combining Equations (54), (60), and (61) yields:

$$\frac{L(i)}{K(i)} = (N-I)\psi^{(I-N+1)(1-\sigma)} \left(\prod_{I}^{N} \frac{\beta_j}{\gamma_j}\right)^{1-\sigma} \left(\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}\right) \tag{62}$$

$$= \alpha \left(\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}\right) \tag{63}$$

, where we denote $\alpha \equiv (N-I)\psi^{(I-N+1)(1-\sigma)} \left(\prod_{I}^{N} \frac{\beta_j}{\gamma_j}\right)^{1-\sigma}$ for notational convenience. This is without loss of generality because α is not a function of R or $\mathbb{W}$.

Finally, we denote μ as the elasticity of substitution between non-robot capital and labor:

$$\mu \equiv \frac{d\alpha\left(\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}\right)}{d\left(\frac{R}{\mathbb{W}}\right)} \frac{\frac{R}{\mathbb{W}}}{\alpha\left(\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}\right)} \tag{64}$$

$$= \frac{d\left(\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}\right)}{d\left(\frac{R}{\mathbb{W}}\right)} \frac{\frac{R}{\mathbb{W}}}{\left(\frac{R^{\sigma}}{\mathbb{W}^{1-(N-I)(1-\sigma)}}\right)} \tag{65}$$

$$\Rightarrow \sigma \ \text{ if } N-I=1.$$

C Appendix: Acemoglu and Restrepo (2019)

Let me first introduce their notations in Table 10.

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 10

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 $(1-\sigma)(1-s_{it0}^L)\Big(\ln\frac{W_{it}}{W_{it0}}-\ln\frac{R_{it}}{R_{it0}}-g_{i,t0,t}^A\Big)$ as $\text{Substitution}_{i,t0,t}$, we can rewrite Equation (AR5) as AR8; Denote $\big(\ln s_{it}^L-\ln s_{it0}^L\big)-\text{Substitution}_{i,t0,t}$ as $\text{ChangeTaskContent}_{i,t0,t}$, we can rewrite Equation (AR8) as (AR9).

$$\approx \ln\Big(\frac{Y_t}{N_t}\Big)-\ln\Big(\frac{Y_{t0}}{N_{t0}}\Big) \tag{AR5}$$

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

$$+\sum_i \ell_{it0}\Big[(1-\sigma)(1-s_{it0}^L)\Big(\ln\frac{W_{it}}{W_{it0}}-\ln\frac{R_{it}}{R_{it0}}-g_{i,t0,t}^A\Big) \tag{AR6}$$

$$+\frac{1-s_{it0}^L}{1-\Gamma_{it0}}(\ln\Gamma_{it}-\ln\Gamma_{it0})\Big] \tag{AR7}$$

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

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

$$+\sum_i \ell_{it0}\Big[\text{Substitution}_{i,t0,t}$$

$$+\frac{1-s_{it0}^L}{1-\Gamma_{it0}}(\ln\Gamma_{it}-\ln\Gamma_{it0})\Big]$$

$$\approx \ln\Big(\frac{Y_t}{N_t}\Big)-\ln\Big(\frac{Y_{t0}}{N_{t0}}\Big) \tag{AR8}$$

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

$$+\sum_i \ell_{it0}\Big[\text{Substitution}_{i,t0,t}$$

$$+\big(\ln s_{it}^L-\ln s_{it0}^L\big)-\text{Substitution}_{i,t0,t}\Big]$$

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

$\sum_i \ell_{it0}[\text{ChangeTaskContent}_{i,t0,t}]$ 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.

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

D Appendix: Generation of ANT

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 ANT variable only for the year 2018 in the USA, while our ANT varies by country×year (and industry×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).[24] 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.

E Appendix: Why AR's comparison was insignificant

We argue that the reason for their insignificant result is that they used just one time point (2018) and compared the 'inferred emergence of new tasks' across industries. In contrast, our comparison utilized yearly variation.

As we will explain carefully now, the size of 'inferred emergence of new tasks' across industries at a given point in a year has no meaningful interpretation. Equation (AR10) in Appendix C clearly demonstrates this. For simplicity, let's assume that $l_{i,t0}$ are equal across industries. Suppose there are five subsectors within, say, the automotive industry, and we focus on just one year. Suppose the 'change in task contents' in the automotive industry is given as Table 11. Then the 'inferred emergence of new tasks' for the automotive industry is 6, and 'inferred Automation' is 8. It is important to note that each sector's 'change in task contents' is the result of combining (summing) 'inferred emergence of new tasks' and 'inferred Automation' in its sub-subcategory. For example, the 'change in task contents' for Sector A in this instance was -7, which would be a combination of 2 and -9. What if, in Sector A, the 'change in task contents'

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

is -2, which was a combination of 30 and -32? Even though -7 is larger than -2, the 'inferred emergence of new tasks' and 'inferred Automation' in the subcategory of Sector A were much larger in the case of -2. This case is shown in the second row of Table 11, which yields 'inferred emergence of new tasks' as 1.6 and 'inferred Automation' as -1.8. Comparing the two examples (in the first and second rows), 'inferred emergence of new tasks' in the first row is larger than in the second row. However, it does not mean that the automotive industry has lower 'inferred emergence of new tasks' in the second row. Therefore, the inference method by AR is meaningful only as the relative size between 'inferred emergence of new tasks' and 'inferred Automation' (the first row is $\frac{6}{6+8} = 0.43$ and the second row is $\frac{1.6}{1.6+1.8} = 0.47$). Additionally, it is meaningful in the relative size across years. For example, for the automotive industry, when did it experience a rapid increase, and when was it flat? However, it is crucial to understand that it is not meaningful across industries at a given year. This is why our version of the comparison removed the fixed effects and used only error terms.

Table 11: Example for Equation (AR10)

Decomposition result			Inferred conclusion	
Sectors	Change in task contents in labor		Inferred Emerging new tasks	Inferred Automation
A	-7		0	-7
B	20	⇒	20	0
C	-3		0	-3
D	10		10	0
E	-30		0	-30
			6	-8

Decomposition result			Inferred conclusion	
Sectors	Change in task contents in labor		Inferred Emerging new tasks	Inferred Automation
A	-2		0	-2
B	5	⇒	5	0
C	-1		0	-1
D	3		3	0
E	-6		0	-6
			1.6	-1.8

References

Daron Acemoglu and Pascual Restrepo. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review*, 108(6):1488–1542, 2018. ISSN 0002-8282.

Daron Acemoglu and Pascual Restrepo. Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30, 2019. ISSN 0895-3309.

Daron Acemoglu and Pascual Restrepo. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244, 2020. ISSN 0022-3808.

Daron Acemoglu and Pascual Restrepo. Tasks, automation, and the rise in US wage inequality. *Econometrica*, 90(5):1973–2016, 2022. ISSN 0012-9682.

Daron Acemoglu, Claire Lelarge, and Pascual Restrepo. Competing with robots: Firm-level evidence from France. In *AEA Papers and Proceedings*, volume 110, pages 383–388. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, 2020. ISBN 2574-0768.

David Autor, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen. The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709, 2020. ISSN 0033-5533.

David H. Autor. Why are there still so many jobs? the history and future of workplace automation. In *Journal of Economic Perspectives*, volume 29, pages 3–30. American Economic Association, June 2015. doi: 10.1257/jep.29.3.3.

Andrew Berg, Edward F Buffie, and Luis-Felipe Zanna. Should we fear the robot revolution?(The correct answer is yes). *Journal of Monetary Economics*, 97:117–148, 2018. ISSN 0304-3932.

Drago Bergholt, Francesco Furlanetto, and Nicolò Maffei-Faccioli. The decline of the labor share: New empirical evidence. *American Economic Journal: Macroeconomics*, 14(3):163–98, 2022. ISSN 1945-7707.

Wolfgang Dauth, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6):3104–3153, 2021. ISSN 1542-4766.

Gaaitzen J De Vries, Elisabetta Gentile, Sébastien Miroudot, and Konstantin M Wacker. The rise of robots and the fall of routine jobs. *Labour Economics*, 66:101885, 2020. ISSN 0927-5371.

Stephen J DeCanio. Robots and humans–complements or substitutes? *Journal of Macroeconomics*, 49: 280–291, 2016. ISSN 0164-0704.

Enrique Fernandez-Macias, David Klenert, and Jose-Ignacio Anton. Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe. *Structural Change and Economic Dynamics*, 58:76–89, 2021. ISSN 0954-349X.

Hamid Firooz, Zheng Liu, and Yajie Wang. Automation and the Rise of Superstar Firms. *Available at SSRN 4040235*, 2022.

Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, J Robert Warren, and Michael Westberry. Integrated Public Use Microdata Series, Current Population Survey: Version 9.0 [dataset]. Minneapolis, MN: IPUMS, 2021. 2021.

Pamela Frugoli and ESCO. The crosswalk between ESCO and O*NET (Technical Report), 2022.

Andrew Glover and Jacob Short. Can capital deepening explain the global decline in labor's share? *Review of Economic Dynamics*, 35:35–53, 2020. ISSN 1094-2025.

Reitze Gouma and Marcel Timmer. World KLEMS Growth and Productivity Accounts Japan: Sources and notes. *Groningen Growth and Development Centre*, 8, 2013.

Georg Graetz and Guy Michaels. Robots at work. *Review of Economics and Statistics*, 100(5):753–768, 2018. ISSN 0034-6535.

Terry Gregory, Anna Salomons, and Ulrich Zierahn. Racing with or against the machine? Evidence from Europe. *Evidence from Europe (July 15, 2016). ZEW-Centre for European Economic Research Discussion Paper*, (16-053), 2016.

Gene M. Grossman and Ezra Oberfield. The elusive explanation for the declining labor share. *Annual Review of Economics*, 14:93–124, 2022.

Germán Gutiérrez and Sophie Piton. Revisiting the global decline of the (non-housing) labor share. *American Economic Review: Insights*, 2(3):321–338, 2020. ISSN 2640-205X.

Joachim Hubmer and Pascual Restrepo. Not a typical firm: The joint dynamics of firms, labor shares, and capital–labor substitution. Technical report, National Bureau of Economic Research, 2021.

Anders Humlum. Robot adoption and labor market dynamics. *Princeton University*, 2019.

Dale W Jorgenson. Capital theory and investment behavior. *The American Economic Review*, 53(2):247–259, 1963. ISSN 0002-8282.

Anne Jurkat, Rainer Klump, and Florian Schneider. Tracking the Rise of Robots: The IFR Database. 242 (5-6):669–689, 2022. doi: 10.1515/jbnst-2021-0059.

Loukas Karabarbounis and Brent Neiman. The global decline of the labor share. *The Quarterly journal of economics*, 129(1):61–103, 2014. ISSN 1531-4650.

Rainer Klump, Anne Jurkat, and Florian Schneider. Tracking the rise of robots: A survey of the IFR database and its applications. 2021.

Joseba Martinez. Automation, growth and factor shares. In *2018 Meeting Papers*, volume 736. Society for Economic Dynamics, 2018.

Christopher Müller. World Robotics 2022 - Industrial Robots, 2022.

National Center for O*NET Development. O*NET Resource Center, 2023.

Ezra Oberfield and Devesh Raval. Micro data and macro technology. *Econometrica*, 89(2):703–732, 2021. ISSN 0012-9682.

Thomas Piketty and Gabriel Zucman. Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly journal of economics*, 129(3):1255–1310, 2014. ISSN 0033-5533.

Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 10.0 [dataset]. *Minneapolis, Mn: Ipums*, 10:D010, 2020.

Robert Stehrer, Alexandra Bykova, Kirsten Jäger, Oliver Reiter, and Monika Schwarzhappel. Industry level growth and productivity data with special focus on intangible assets. *Vienna Institute for International Economic Studies Statistical Report*, 8, 2019.

Pengfei Zhang. Endogenous capital-augmenting R&D, intersectoral labor reallocation, and the movement of the labor share. *Journal of Economics*, pages 1–36, 2023. ISSN 0931-8658.

Xuyang Zhao, Cisheng Wu, and Duanyong Liu. Comparative Analysis of the Life-Cycle Cost of Robot Substitution: A Case of Automobile Welding Production in China. *Symmetry*, 13(2):226, 2021. ISSN 2073-8994.