Accounting Analysis for Labor Share: The Tug of War Between Automation and Emergence of New Tasks

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Abstract

In this study, we explore the effects of automation and the emergence of new tasks on labor share. We propose a task-based model that differentiates between robots and other forms of capital. This model incorporates several factors that influence labor share, including automation and the introduction of new tasks, within a unified framework. We are among the first to empirically examine the impact of new tasks on labor share, benefiting from a diverse dataset spanning various countries and industries. Our study unveils four insights. First, although automation usually shrinks the labor share, the inception of new tasks can elevate it. Second, we identified two distinct ways in which robots affect the labor share: by innovating to accomplish tasks previously deemed unfeasible for them and through their increased cost-effectiveness. Notably, the former tends to decrease the labor share, whereas the latter promotes its growth. Third, our results suggest that the elasticity of substitution between labor and traditional capital is likely below one, signaling a complementarity. Lastly, we found that the elasticity of substitution across various tasks is also less than one. This implies that while labor and robots might be perfect substitutes within a single task, they act more as complements when viewed across multiple tasks. Overall, the integration of new tasks appears to have mitigated the effect of automation on labor share, particularly in the USA, where we note stronger task innovation.

1 Introduction

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

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Karabarbounis and Neiman (2014) and Autor et al. (2020) have noted that the global labor share has followed a declining trend since the early 1980s, with an average decrease of about five percentage points. 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), 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.

Automation and the emergence of new tasks are not the only factors contributing to changes in labor share. Many other reasons have been meticulously examined in literature, 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

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

equilibrium model, an approach that represents a contribution to the existing literature. The study most akin to ours is that of Acemoglu and Restrepo (2022). They too utilize a general equilibrium model, though their main focus is on wage inequality rather than the decline in labor share.

Our analysis incorporates five potential determinants within our general equilibrium model —automation, 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 investment price does not contribute to the decrease in labor share.

We enrich the existing literature by distinguishing the two mechanisms through which robots affect labor share. Robots can either develop the capability to perform tasks that were previously impossible (automation), or they can become cheaper without any functional improvement. Both our model and regression results consistently illustrate that the first mechanism tends to lower labor share, while the latter mechanism boosts it.

We also discover a negative correlation between capital price and labor share. 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).

Our notable contribution to the literature is the implementation of 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. This is particularly evident in the USA, which stands out due to the significant value associated with the emergence of new tasks, as measured using ONET data.

Transitioning to the subject of triggers behind the '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.

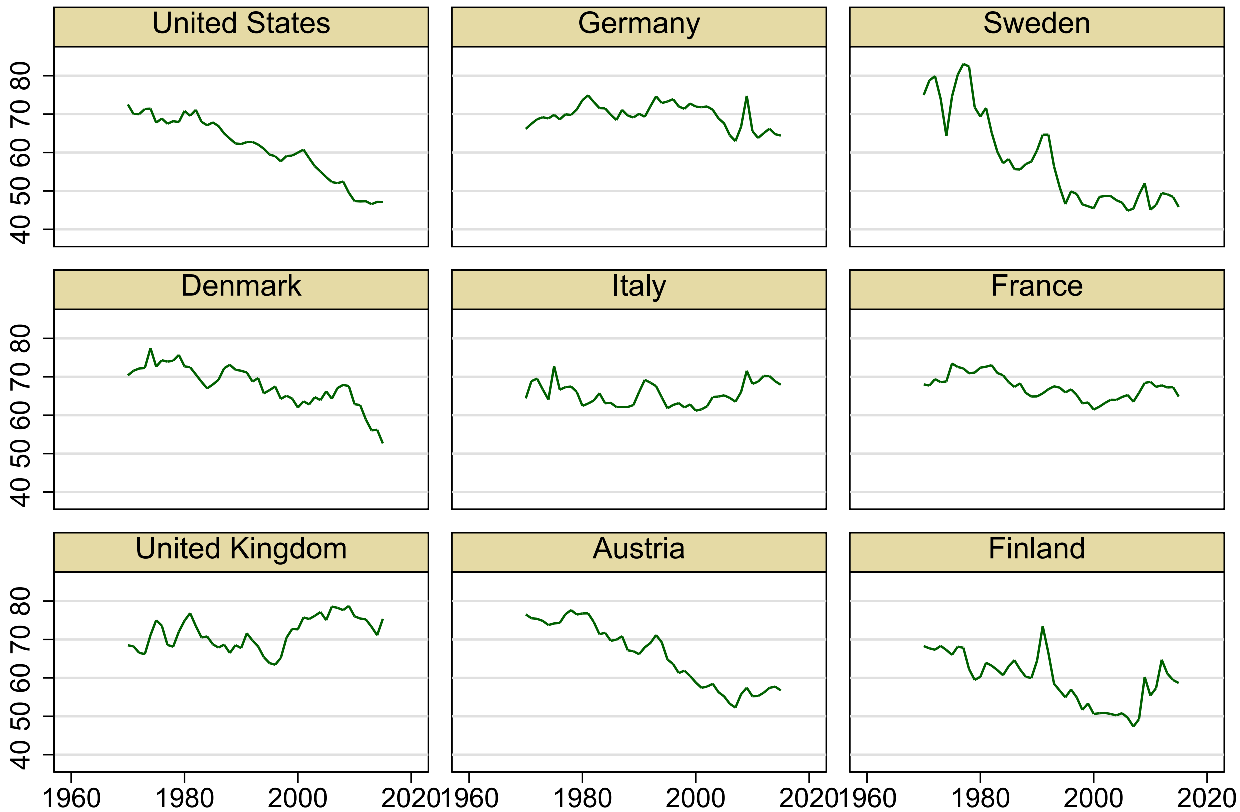
2 Model

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

Acemoglu and Restrepo (2020) define robots as "fully autonomous machines that do

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

Figure 1: Labor shares



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

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:

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

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

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

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

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

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

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

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

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

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

, 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:

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

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:

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

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, W, and ψ), we obtain the following estimating equation:

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

, where $W \equiv \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{\int_I^N W_j^{-\zeta}\gamma_j^{\zeta-1} dj}$ is the average wage, and assume $d\ln W = d\ln W_j$ 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, $d\ln W$, $d\ln R$, 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, $d\ln w$, 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 $d\ln w$ directly increase

[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 $\frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$ 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:

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

, 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 $S_I^L \equiv \frac{\left(\frac{W_I}{\gamma_N}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}$ represent the share of labor income conducting task N and I out of the total labor income, respectively.

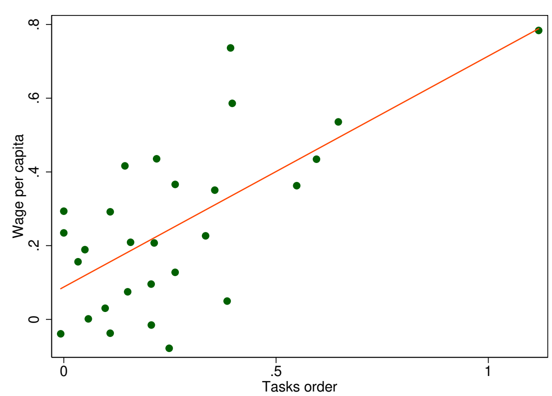
Labor Share by Task Determining the value of the elasticity of substitution between aggregated tasks and capital, as well as between tasks is crucial[7]. This understanding provides substantial insights into how the labor share changes due to the influence of robots or capital. In Equation (19), the sign of the term $S_N^L - S_I^L$ in the coefficient of dN

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

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.

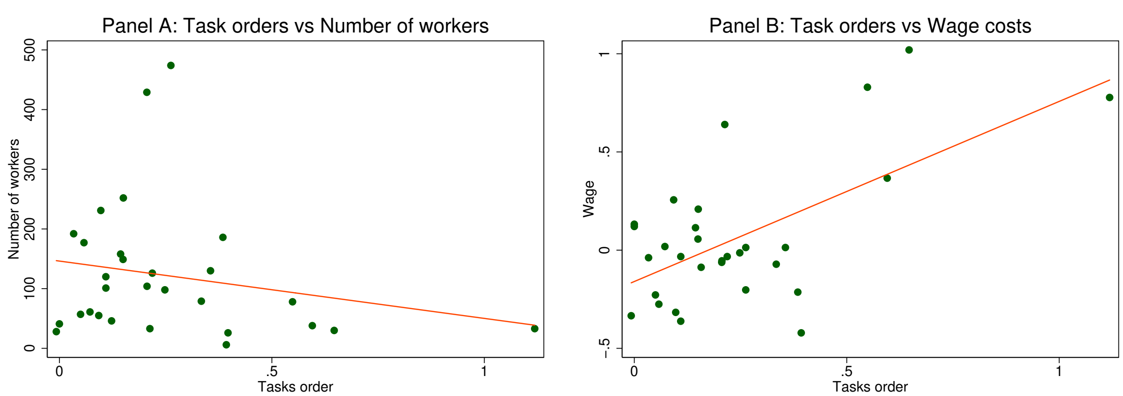
Wage per capita is heterogeneous by tasks throughout the model, as Figure 2 proves. We define 'high order of occupations' as occupations that demonstrate a higher growth rate of the number of tasks. In the figure, wages rise as the order of *occupations* ascends (We were unable to validate Figure 2 in 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)

Figure 3: Task orders



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 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 A. 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):

$$\begin{aligned} \text{APR}_{i,(t5,t1)} &= \frac{M_{i,t5} - M_{i,t1}}{L_{i,2005}} - \frac{Y_{i,t5} - Y_{i,t1}}{Y_{i,t1}} \frac{M_{i,t1}}{L_{i,2005}} && (20) \\ &= \Big(\frac{M_{i,t5} - M_{i,t1}}{M_{i,t1}} - \frac{Y_{i,t5} - Y_{i,t1}}{Y_{i,t1}} \Big) \frac{M_{i,t1}}{L_{i,2005}} && (21) \\ &= \big(g_M - g_Y \big) \frac{M_{i,t1}}{L_{i,2005}} && (22) \end{aligned}$$

, 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 GDP 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 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,

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

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 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'

[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 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 B. 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.

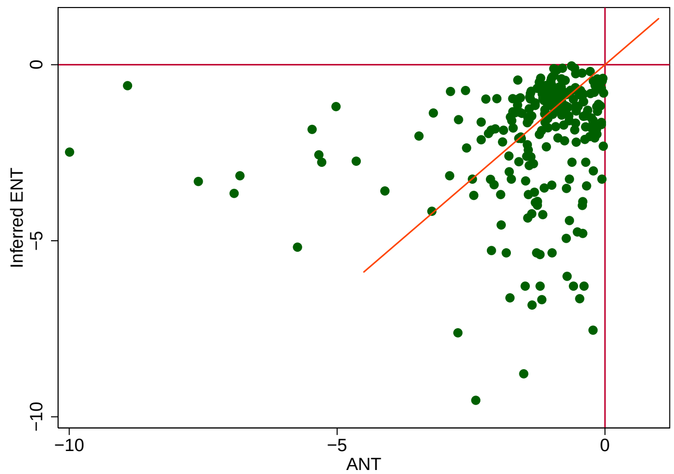
We compared ANT and the 'inferred value of ENT' in the USA. First, both have fixed differences at the industry level. Therefore, to make meaningful comparisons across industries, the industry-fixed effect must be removed. We regress each variable solely on industry dummies and take the residual. Secondly, as we are interested in long-term 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

[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)



(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 C. 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, Investment Price, 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 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.

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

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

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

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

4 Regressions

Based on the specification in Equation (19), we provide the consistent regression equation. In line with Equation (19), 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 outlined in Equation (19).

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

, 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 *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.

Table 2: Regressions

	OLS	Quantile				
	(1)	(2)	(3)	(4)	(5)	(6)
	mean	q.1	q.3	q.5	q.7	q.9
APR	-0.070***	-0.076***	-0.071***	-0.057**	-0.071***	-0.072***
	(0.019)	(0.015)	(0.013)	(0.018)	(0.016)	(0.018)
ANT	0.079**	0.040**	0.036**	0.051**	0.044**	0.042*
	(0.029)	(0.015)	(0.013)	(0.018)	(0.015)	(0.017)
gr_capital price	-0.909**	-1.412***	-1.223***	-1.171***	-1.186***	-0.922***
	(0.346)	(0.121)	(0.106)	(0.145)	(0.124)	(0.143)
gr_labor price	0.815*	1.314***	1.182***	1.072***	1.061***	0.791***
	(0.341)	(0.120)	(0.105)	(0.144)	(0.123)	(0.142)
gr_robot price	-0.038**	-0.096***	-0.052***	-0.034*	-0.020	-0.017
	(0.014)	(0.013)	(0.011)	(0.016)	(0.013)	(0.015)
N	1040	1040	1040	1040	1040	1040
R^2	0.466					

Standard errors in parentheses

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

Table 2 is the regression result for Equation (26). Across all columns, the coefficients of APR are uniformly negative; The coefficients for ANT are consistently positive. The two opposite signs illustrate the ongoing tension between automation and the emergence of new tasks. The extent to which these elements contribute to the labor share will be examined in greater detail in the subsequent section.

As indicated by Equation (19), the signs of the coefficients for $d \ln R$ (capital price) and $d \ln W$ (labor price) are opposite. Specifically, the sign of the coefficient for $d \ln R$ is negative, which suggests that $\sigma < 1$. This indirectly confirms that capital and labor are complementary, a result that aligns with the findings reported by Glover and Short (2020). Conversely, this result contradicts the hypothesis of 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 Karabarbounis and Neiman (hereafter referred to as KN). The divergence stems from our model's distinction between robots and capital.

Specifically, in our model, σ represents the elasticity of substitution between 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.

Meanwhile, we infer from the sign of the coefficient for $d\ln\psi$ (robot price) and σ in Equation (19) that $\zeta < 1$. However, it's important to understand that $\zeta < 1$ doesn't imply a complementary relationship between robots and labor. Instead, ζ denotes the elasticity of substitution across different tasks, not between robots and labor; our model considers robots and labor as perfect substitutes within a task. Therefore, while robots and labor are interchangeable within a task, the indication of $\zeta < 1$ suggests complementarity between robots and labor across various tasks. Essentially, when the price of robots decreases—a trend observable in actual data—the labor share doesn't reduce correspondingly due to the counterbalancing effect of $\zeta < 1$ against the perfect substitutability.

The negative coefficient for the robot price in our regression model reveals interesting implications about the impact of robotic advancement. We can understand this advancement through two separate mechanisms: first, the enhancement of robots' capabilities, which allows them to perform tasks that were previously unachievable; and second, the reduction in robot prices without corresponding improvements in their capabilities. Our results propose that as robots become capable of performing new tasks, the labor share declines. Conversely, when robots become cheaper, the labor share increases.

Columns (2) to (6) in Table 2 represent quantile regressions. The coefficients across different quantiles retain the same sign as in the OLS regressions, and their magnitudes are similar. This suggests that the implications hold steady across different quantiles of labor share. 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. The comprehensive contents can be accessed in the Excel file provided in the associated footnote.[15] In this Excel file, Sheet 0 corresponds to Table 3, while Sheet 1 corresponds to Table 4. Sheet 0 displays the average values of variables from 2013 to 2019, whereas Sheets 1 and 2 exhibit the predicted changes in values (defined below). Sheet 1 organizes the rows by countries, and Sheet 2 sorts them by industries.

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

Table 3: Summary of Variables by Observations

location	sector	APR	ANT	gr_R	gr_W	gr_robotprice
AUT	10-12 Food products	0.141	0.640	0.003	0.059	-0.069
AUT	13-15 Textiles, wearing apparel	0.008	0.640	0.075	0.226	-0.007
AUT	16-18 Wood and paper products	0.073	0.640	0.164	0.294	0.040
AUT	19 Coke and refined petroleum	-1.983	0.640	4.253	4.237	-2.801
AUT	20-21 Chemicals	0.004	0.640	0.150	0.301	0.019
AUT	22-23 Rubber and plastics	1.249	0.640	0.044	0.150	-0.041
AUT	24-25 Basic metals	1.281	0.640	-0.060	0.059	-0.097
AUT	26-27 Electrical and optical	0.477	0.640	0.124	0.196	0.016
AUT	28 Machinery and equipment	0.418	0.640	0.007	0.143	-0.049
AUT	29-30 Car and Transport equipment	2.430	0.640	0.125	0.252	0.011
AUT	31-33 Other manufacturing	0.358	0.640	-0.030	0.166	-0.071
DEU	10-12 Food products	0.190	0.661	-0.006	0.078	-0.083
DEU	13-15 Textiles, wearing apparel	0.013	0.661	-0.034	0.119	-0.074
DEU	16-18 Wood and paper products	-0.229	0.661	0.093	0.158	-0.004
DEU	19 Coke and refined petroleum	0.203	0.661	-0.598	-0.560	-0.425
DEU	20-21 Chemicals	0.005	0.661	0.010	0.100	-0.084
DEU	22-23 Rubber and plastics	0.977	0.661	0.021	0.106	-0.058
DEU	24-25 Basic metals	0.637	0.661	0.071	0.154	-0.038
DEU	26-27 Electrical and optical	-0.076	0.661	0.181	0.266	0.016
DEU	28 Machinery and equipment	0.629	0.661	-0.108	-0.017	-0.140
DEU	29-30 Car and Transport equipment	-2.081	0.661	0.011	0.130	-0.077
DEU	31-33 Other manufacturing	-0.144	0.661	-0.111	-0.043	-0.134
FRA	10-12 Food products	0.367	0.644	0.036	0.167	-0.034
FRA	13-15 Textiles, wearing apparel	-0.005	0.644	0.055	0.151	-0.016
FRA	16-18 Wood and paper products	0.081	0.644	0.253	0.354	0.099
FRA	19 Coke and refined petroleum	0.077	0.644	0.562	0.621	0.103
FRA	20-21 Chemicals	0.008	0.644	0.142	0.308	0.031
FRA	22-23 Rubber and plastics	0.419	0.644	0.103	0.211	0.009
FRA	24-25 Basic metals	0.165	0.644	0.151	0.264	0.038
FRA	26-27 Electrical and optical	0.040	0.644	0.349	0.449	0.153
FRA	28 Machinery and equipment	0.347	0.644	-0.049	0.104	-0.069
FRA	29-30 Car and Transport equipment	-0.955	0.644	-0.166	0.076	-0.129
FRA	31-33 Other manufacturing	0.151	0.644	-0.156	0.008	-0.128
ITA	10-12 Food products	1.013	0.572	0.054	0.120	-0.101
ITA	13-15 Textiles, wearing apparel	-0.008	0.572	0.131	0.148	-0.101
ITA	16-18 Wood and paper products	0.117	0.572	0.081	0.129	-0.079
ITA	19 Coke and refined petroleum	0.415	0.572	-0.427	-0.393	-0.342
ITA	20-21 Chemicals	0.017	0.572	0.004	0.060	-0.121
ITA	22-23 Rubber and plastics	0.689	0.572	0.043	0.124	-0.103
ITA	24-25 Basic metals	0.658	0.572	0.085	0.181	-0.079
ITA	26-27 Electrical and optical	0.096	0.572	-0.163	-0.032	-0.193
ITA	28 Machinery and equipment	0.568	0.572	-0.033	0.088	-0.131
ITA	29-30 Car and Transport equipment	-1.891	0.572	-0.011	0.094	-0.121
ITA	31-33 Other manufacturing	0.027	0.572	-0.055	0.023	-0.149
USA	10-12 Food products	0.049	1.172	-0.175	-0.106	-0.164
USA	13-15 Textiles, wearing apparel	0.001	1.601	-0.086	0.048	-0.094
USA	16-18 Wood and paper products	0.003	0.727	-0.058	0.033	-0.084
USA	19 Coke and refined petroleum	0.026	1.107	0.062	0.170	-0.096
USA	20-21 Chemicals	0.000	0.891	0.000	0.000	0.000
USA	22-23 Rubber and plastics	0.053	0.943	-0.086	-0.000	-0.115
USA	24-25 Basic metals	0.063	0.600	0.035	0.114	-0.052
USA	26-27 Electrical and optical	0.148	1.303	0.428	0.662	0.164
USA	28 Machinery and equipment	0.020	1.598	-0.112	0.009	-0.125
USA	29-30 Car and Transport equipment	0.382	3.714	-0.022	0.016	-0.082
USA	31-33 Other manufacturing	0.064	1.717	-0.052	0.157	-0.070

Table 4: Predicted Impact on Labor share

location	sector	gr_S_L^f	chg_sum	chg_productivity	chg_APR	chg_ANT	chg_gr_R	chg_gr_W	chg_gr_robotprice	chg_APR+chg_ANT
AUT	10-12 Food products	0.166	0.828	0.265	-0.063	0.319	-0.016	0.306	0.017	0.256
AUT	13-15 Textiles, wearing apparel	-1.128	-0.466	-1.521	-0.004	0.319	-0.429	1.167	0.002	0.315
AUT	16-18 Wood and paper products	1.248	1.910	1.063	-0.033	0.319	-0.947	1.517	-0.010	0.286
AUT	19 Coke and refined petroleum	-1.792	-1.130	-0.396	0.883	0.319	-24.500	21.886	0.677	1.202
AUT	20-21 Chemicals	-0.031	0.630	-0.375	-0.002	0.319	-0.862	1.554	-0.005	0.317
AUT	22-23 Rubber and plastics	-0.621	0.041	-0.252	-0.556	0.319	-0.256	0.776	0.010	-0.237
AUT	24-25 Basic metals	-0.224	0.438	0.017	-0.570	0.319	0.345	0.304	0.023	-0.252
AUT	26-27 Electrical and optical	-4.566	-3.904	-4.305	-0.213	0.319	-0.714	1.012	-0.004	0.106
AUT	28 Machinery and equipment	-1.683	-1.021	-1.863	-0.186	0.319	-0.042	0.739	0.012	0.133
AUT	29-30 Car and Transport equipment	-1.903	-1.241	-1.060	-1.082	0.319	-0.719	1.304	-0.003	-0.763
AUT	31-33 Other manufacturing	0.330	0.991	-0.211	-0.159	0.319	0.171	0.855	0.017	0.160
DEU	10-12 Food products	1.142	1.803	1.101	-0.085	0.329	0.033	0.405	0.020	0.244
DEU	13-15 Textiles, wearing apparel	1.783	2.445	1.294	-0.006	0.329	0.196	0.613	0.018	0.323
DEU	16-18 Wood and paper products	1.557	2.218	1.504	0.102	0.329	-0.536	0.817	0.001	0.431
DEU	19 Coke and refined petroleum	2.443	3.105	2.212	-0.091	0.329	3.443	-2.892	0.103	0.238
DEU	20-21 Chemicals	3.212	3.873	3.063	-0.002	0.329	-0.056	0.519	0.020	0.327
DEU	22-23 Rubber and plastics	1.867	2.528	2.192	-0.435	0.329	-0.122	0.550	0.014	-0.106
DEU	24-25 Basic metals	0.885	1.547	1.108	-0.284	0.329	-0.409	0.794	0.009	0.045
DEU	26-27 Electrical and optical	2.285	2.946	2.256	0.034	0.329	-1.045	1.376	-0.004	0.363
DEU	28 Machinery and equipment	1.136	1.798	1.176	-0.280	0.329	0.625	-0.086	0.034	0.049
DEU	29-30 Car and Transport equipment	-0.933	-0.271	-2.154	0.927	0.329	-0.065	0.674	0.019	1.256
DEU	31-33 Other manufacturing	0.120	0.781	-0.060	0.064	0.329	0.638	-0.223	0.032	0.393
FRA	10-12 Food products	1.535	2.196	1.374	-0.163	0.321	-0.207	0.864	0.008	0.158
FRA	13-15 Textiles, wearing apparel	-0.314	0.347	-0.444	0.002	0.321	-0.314	0.779	0.004	0.323
FRA	16-18 Wood and paper products	-0.068	0.593	-0.036	-0.036	0.321	-1.458	1.826	-0.024	0.285
FRA	19 Coke and refined petroleum	-4.977	-4.315	-4.550	-0.034	0.321	-3.236	3.210	-0.025	0.287
FRA	20-21 Chemicals	-1.506	-0.844	-1.926	-0.004	0.321	-0.818	1.590	-0.008	0.317
FRA	22-23 Rubber and plastics	-1.202	-0.541	-1.170	-0.187	0.321	-0.593	1.090	-0.002	0.134
FRA	24-25 Basic metals	-0.046	0.616	-0.115	-0.074	0.321	-0.871	1.364	-0.009	0.247
FRA	26-27 Electrical and optical	-0.546	0.116	-0.461	-0.018	0.321	-2.009	2.320	-0.037	0.303
FRA	28 Machinery and equipment	-0.800	-0.138	-1.140	-0.154	0.321	0.280	0.538	0.017	0.167
FRA	29-30 Car and Transport equipment	0.892	1.554	-0.572	0.425	0.321	0.956	0.392	0.031	0.746
FRA	31-33 Other manufacturing	-0.184	0.478	-0.746	-0.067	0.321	0.900	0.040	0.031	0.254
ITA	10-12 Food products	1.206	1.867	1.704	-0.451	0.285	-0.313	0.618	0.024	-0.166
ITA	13-15 Textiles, wearing apparel	-0.769	-0.107	-0.433	0.004	0.285	-0.752	0.765	0.024	0.289
ITA	16-18 Wood and paper products	-1.256	-0.595	-1.048	-0.052	0.285	-0.464	0.665	0.019	0.233
ITA	19 Coke and refined petroleum	-9.542	-8.880	-9.496	-0.185	0.285	2.462	-2.029	0.083	0.100
ITA	20-21 Chemicals	-0.340	0.322	-0.276	-0.007	0.285	-0.021	0.312	0.029	0.278
ITA	22-23 Rubber and plastics	-2.177	-1.515	-1.912	-0.307	0.285	-0.248	0.642	0.025	-0.022
ITA	24-25 Basic metals	0.267	0.928	0.473	-0.293	0.285	-0.491	0.935	0.019	-0.008
ITA	26-27 Electrical and optical	-1.115	-0.453	-1.519	-0.043	0.285	0.940	-0.163	0.047	0.242
ITA	28 Machinery and equipment	0.459	1.121	0.413	-0.253	0.285	0.191	0.453	0.032	0.032
ITA	29-30 Car and Transport equipment	-4.747	-4.085	-5.790	0.842	0.285	0.065	0.485	0.029	1.127
ITA	31-33 Other manufacturing	1.376	2.037	1.293	-0.012	0.285	0.318	0.118	0.036	0.273
USA	10-12 Food products	0.720	1.382	0.322	-0.022	0.584	1.008	-0.550	0.040	0.562
USA	13-15 Textiles, wearing apparel	0.051	0.713	-0.851	-0.000	0.797	0.494	0.250	0.023	0.797
USA	16-18 Wood and paper products	-0.372	0.290	-0.594	-0.001	0.362	0.332	0.170	0.020	0.361
USA	19 Coke and refined petroleum	-2.880	-2.218	-3.301	-0.011	0.551	-0.358	0.878	0.023	0.540
USA	20-21 Chemicals	0.000	-3.059	-3.503	0.000	0.444	0.000	0.000	0.000	0.444
USA	22-23 Rubber and plastics	0.255	0.916	-0.048	-0.024	0.470	0.493	-0.002	0.028	0.446
USA	24-25 Basic metals	-0.258	0.404	-0.266	-0.028	0.299	-0.201	0.587	0.013	0.271
USA	26-27 Electrical and optical	-0.258	0.403	-1.095	-0.066	0.649	-2.465	3.419	-0.040	0.583
USA	28 Machinery and equipment	-0.093	0.568	-0.942	-0.009	0.796	0.644	0.049	0.030	0.787
USA	29-30 Car and Transport equipment	-1.293	-0.631	-2.541	-0.170	1.850	0.127	0.083	0.020	1.679
USA	31-33 Other manufacturing	0.234	0.896	-1.060	-0.028	0.855	0.302	0.810	0.017	0.827

S_L^f is defined in Equation (19) in the Model section. Meanwhile, the predicted change in values represents the multiplication of coefficients and variables. For instance, chg_ANT indicates the change in predicted ANT between 2012 and 2017 That is to say,

$$\text{chg\_ANT} = \text{Coefficient of ANT} \times \text{Average of ANT}.$$

In essence, chg_ANT explains how much of labor share (S_L^f) has changed from 2012 to 2017 due to the emergence of new tasks.

The variable 'chg_productivity' is calculated in a similar manner. The difference here is that it employs dummy variables for the fixed effects. Under the assumption that our model is the true model, we interpret that the fixed effects include unobserved productivity.

Finally, chg_sum is the sum of chg_productivity, chg_APR, chg_ANT, chg_gr_R, chg_gr_w, and chg_gr_robotprice. This summation represents the total explanatory power of the predicted regression. Indeed, gr_S_L^f and chg_sum have a correlation of 0.994. R and W represent capital price and wage, respectively.

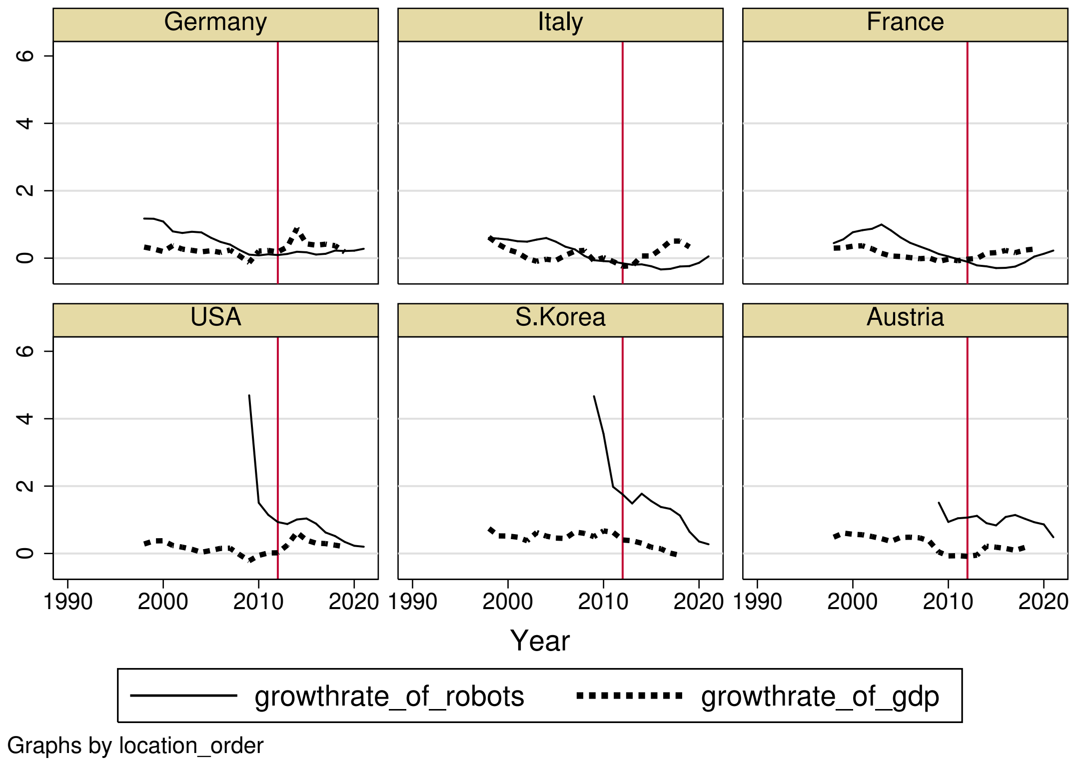
The table reveals patterns that are not readily discernible through regression results. The color gradient from red to green signifies the relative size of the values within each column (i.e., colors are independent across columns).

In the analysis of chg_APR, the patterns distinctly vary by country and industry. For example, results for the 'Car and Transport Equipment' sector demonstrate notable variation across different countries. Austria and the USA demonstrate a negative sign, indicating a deeper penetration of robots (APR) —faster growth of machines compared to GDP in this particular industry. In contrast, countries like Germany, France, and Italy present a positive sign, indicating lighter penetration of robots —a slower pace of machine growth compared to GDP in the same industry. Figure 5 further elucidates this trend, revealing that the USA, South Korea, and Austria exhibit a more accelerated growth of robots compared to their GDP.

When we shift our focus to chg_ANT, a distinct pattern emerges. ANT surpasses APR in most instances, barring a few industries in Austria and Italy. This indicates that the advent of new tasks has a more substantial influence on labor share compared to automation. It's particularly noteworthy that the USA exhibits a considerably larger ANT than APR, signifying that innovation in terms of new task creation is particularly robust in this country.

The results for chg_gr_R (capital price) are mixed, showing both positive and negative signs across different countries and industries. This suggests that the impact of

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



ordinary capital —things like buildings, equipment, and non-robot machinery— on labor share appears to be more complex. This distinction underscores the need to consider different types of capital separately when examining their effects on labor share.

In contrast, chg_gr_W (wage) and chg_gr_robot price display consistent patterns. The positive sign for chg_gr_W and chg_gr_robot price suggests that increases in wages and decreases in robot prices contribute to an uptick in labor share. The magnitude of chg_gr_robot price is relatively small, which aligns with our model in Equation (19). In this equation, S_M^f is generally small across most countries and industries, as the actual data demonstrates, which results in a small value of chg_gr_robot price.

Among all countries, France stands out as an anomaly with regard to gr_robot price (positive sign), as reported in the UN Comtrade data used for this analysis. As a result, France records the smallest chg_gr_robot price (negative sign).

Importantly, our accounting analysis indicates that the emergence of labor has had a positive impact on labor share, despite the negative effects brought about by the rise of automation. This suggests that there's a tug-of-war between robots and the emergence of new tasks, with the balance of power varying across countries and industries.

Although the accounting analysis discussed in this section doesn't involve complex reasoning, this straightforward method efficiently uncovers a number of important patterns. For additional insights, please refer to the accompanying Excel file.

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 paper uniquely contributes to the existing literature by incorporating accounting exercises after the regression analysis. This approach allows us to observe the effects of heterogeneity in labor share changes. Our findings indicate that the 'Car and Transport Equipment' sector's performance is country-dependent. For instance, the USA and Austria experiences a quicker machine growth rate than its GDP, resulting in a negative influence from the Adjusted Penetration of Robots (APR). On the other hand, Germany, France, and Italy show a positive APR trend, denoting slower machine growth compared to GDP. This discrepancy is due to the USA and Austria's faster robotization pace versus its GDP growth, whereas robotization in Germany, France, and Italy has decelerated since 2012. Furthermore, we noted that the emergence of new tasks has eclipsed the impact of automation on labor share, particularly in the USA, where task innovation is presumably robust.

Meanwhile, 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."

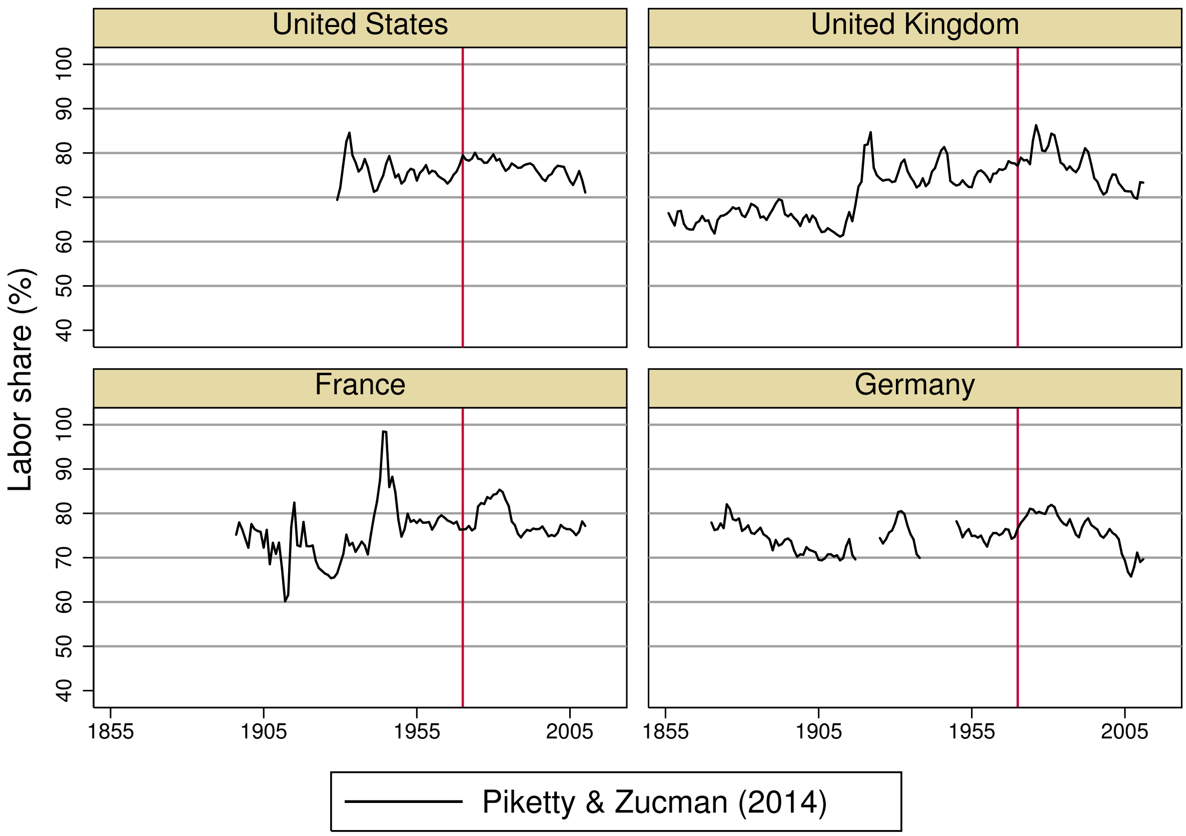
In contrast to their study that employs time series techniques, we utilize a general equilibrium model based on Acemoglu and Restrepo (2018). Our contribution to this model involves differentiating between robots and capital. In their model, only robots are considered, with capital not taken into account.

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); and Zhang (2023)) by indirectly providing evidence that the elasticity is less than one, indicating a 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?[16] 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 3 and 4, where the impact of ANT (New Tasks), as well as the predicted value for ANT on labor share, are particularly substantial in the USA.

[16] 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 6.

Figure 6: Historical Labor Share



A Appendix: Acemoglu and Restrepo (2019)

Let me first introduce their notations in Table 5.

Table 5

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

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);

$$
\begin{aligned}
&\ln\left(\frac{W_t L_t}{N_t}\right) - \ln\left(\frac{W_{t0} L_{t0}}{N_{t0}}\right) && \text{(AR1)}\\
&= \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right) && \text{(AR2)}\\
&+ \ln\left(\sum_i \chi_{it} s^L_{it}\right) - \ln\left(\sum_i \chi_{it0} s^L_{it0}\right)\\
&= \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right)\\
&+ \ln\left(\sum_i \chi_{it} s^L_{it}\right) - \ln\left(\sum_i \chi_{it0} s^L_{it}\right)\\
&+ \ln\left(\sum_i \chi_{it0} s^L_{it}\right) - \ln\left(\sum_i \chi_{it0} s^L_{it0}\right)\\
&\approx \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right)\\
&+ \sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0} s^L_{jt}} (\chi_{it} - \chi_{it0})\\
&+ \ln\left(\sum_i \chi_{it0} s^L_{it}\right) - \ln\left(\sum_i \chi_{it0} s^L_{it0}\right)\\
&\approx \ln\left(\frac{Y_t}{N_t}\right) - \ln\left(\frac{Y_{t0}}{N_{t0}}\right) && \text{(AR3)}\\
&+ \sum_i \frac{s^L_{it}}{\sum_j \chi_{jt0} s^L_{jt}} (\chi_{it} - \chi_{it0})\\
&+ \sum_i \ell_{it0} (\ln s^L_{it} - \ln s^L_{it0}) && \text{(AR4)}
\end{aligned}
$$

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

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

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

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

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

B 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, which results in some loss during the match. In contrast, we use SOC as it is, eliminating any loss. 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'. However, they use OCC, which generates extra loss because OCC has changed its version frequently, and the matching success rate for crosswalks of different versions of OCC is not high. This crosswalk conversion is necessary for them because the OCC of 'Task score' is in the 2018 version, while the OCC of the US Census is in the 1990 version. Although SOC also involves the same crosswalk conversion process—because SOC varies its version by year—the loss is relatively low due to the more accurate matching for crosswalks of different versions of SOC.

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).[17] 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.

C Appendix: Why AR's comparison was insignificant

We suspect 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 A 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

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

industry, and we focus on just one year. Suppose the 'change in task contents' in the automotive industry is given as Table 6. 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' 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 6, 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 6: 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

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