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

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Automation, Human Task Innovation, and Labor Share[*] [†]

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Abstract

This study examines the global decline in labor share since the 2005, focusing on the impacts of robotic and human innovation within a general equilibrium framework. Using novel shift-share variables —operational robot data, patent similarity to automation vocabularies, and cognitive task intensity scores— the research addresses endogeneity issues across countries and sectors. Findings reveal that while human innovation positively impacts labor share, robotic innovation exerts a predominantly negative influence, largely offsetting human innovation's effects.

JEL Codes: D24, E24, E25, J23, O33, O57

Keywords: Human task innovation, Robotic innovation, Automation, Labor share, Elasticity of substitution

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

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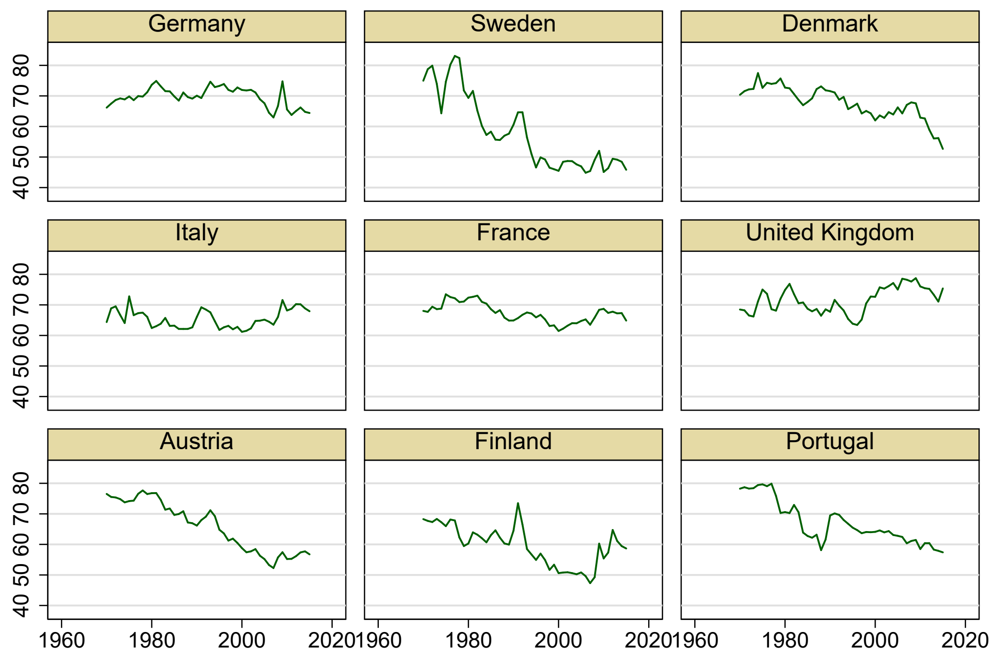
1 Introduction

The global labor share has exhibited a declining trend since the early 1980s, with an average decrease of approximately five percentage points, as observed by Karabarbounis and Neiman (2014) and Autor et al. (2020). Figure 1, based on data compiled by Gutiérrez and Piton (2020), illustrates a comparison of labor shares in the manufacturing sectors of nine European Union countries analyzed in our study. While countries such as the Sweden, Denmark, Portugal, and Austria have experienced substantial declines, others report comparatively modest decreases. This discrepancy highlights the considerable heterogeneity in global labor share trends, further emphasizing the importance of our investigation into variations across countries and sectors to elucidate this decline.[1]

Figure 1: Labor shares



Although the precise cause of this decline remains a subject of debate, advancements in automation have emerged as a potential key driver. The urgency of addressing the diminishing labor share is intensified by the accelerated growth in automation and artificial intelligence technologies. For example, Tesla aims to deploy "genuinely useful humanoid robots," known as Optimus, in their factories by 2025. Additionally, the

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

recent debut of GPT-o1 in September 2024, which marks a significant advancement in AI reasoning capabilities, further underscores the rapid evolution of AI systems.

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

Another factor potentially promoting labor share is 'human innovation' —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 'human innovation' outstrips the advancement of automation. To the best of our knowledge, Autor et al. (2024) represents the only study that empirically measures human innovations. They utilize *Census Alphabetical Index of Occupations and Industries* and patent information to produce a proxy for 'human innovation.'

However, few studies attempt to measure multiple factors within a unified framework (Bergholt et al., 2022). Bergholt 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." Similarly, 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.

Following the work of Autor et al. (2024) and Acemoglu and Restrepo (2018), we incorporate both robotic innovation (RI) and human innovation (HI) into a general equilibrium model.[2] Our study addresses the endogeneity issues of RI and HI by proposing three shift-share variables. The first shift-share for RI utilizes the number of operational robots provided by the International Federation of Robotics (IFR). The second shift-share for RI employs the semantic understanding derived from recently developed sentence-to-sentence embedding technology. We assess the similarity between all U.S. patents and vocabularies closely related to automation and robotics. The third shift-share for HI utilizes the cognitive score developed by Jeong and Lee (2025). Cognition

[2]Another study 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 model is built on Acemoglu and Restrepo (2022) but is distinct in that it separately introduces both robot and non-robot capital as inputs for production. This model setup is important because it enables us to analyze how robot and non-robot capital differently affect the labor share in conjunction with four types of technological innovation.

involves activities that require mental processes, skills, and abilities. These include perception, thinking, reasoning, memory, learning, decision-making, and other aspects of information processing. Therefore, we argue that this serves as an appropriate proxy for HI. Through this approach, we meticulously examine how RI and HI influence labor share across countries and sectors. This comprehensive analysis constitutes our primary contribution to the literature.

Based on our theoretical framework, we derive a reduced-form regression equation. Our empirical estimation reveals that RI negatively affects labor share, while HI positively affects it. The results indicate that the negative effects of RI overwhelmingly dominate the positive effects of HI. Other price factors —wage, robot price, and non-robot capital price— serve as control variables.

Our study, while innovative, is subject to certain limitations. The primary concern pertains to the potential endogeneity of price factors. Although RI and HI are exogenous variables, other price factors inherently possess endogeneity issues. We posit that these endogenous variables are orthogonal to our shift-share instrument, thereby not biasing the coefficients of interest.

We assert that our major contributions to the literature are twofold: First, while Autor et al. (2024) focused solely on the US case, we have examined the EU context. It is well-documented that the economic structures of the US and EU differ significantly. Hence, investigating the EU case is valuable. Second, our use of instruments for automation and human innovation is novel compared to Autor et al. (2024). Although many settings differ, our findings largely align with those of Autor et al. (2024).

In the following section, we provide key definitions used in this study. Section 3 presents our general equilibrium model, which forms the theoretical foundation of our analysis. Section 4 details the datasets and variables employed in our research. Section 5 conducts the regression analysis, utilizing our model and data to examine the relationships between various factors and labor share. Finally, Section 6 provides our concluding remarks.

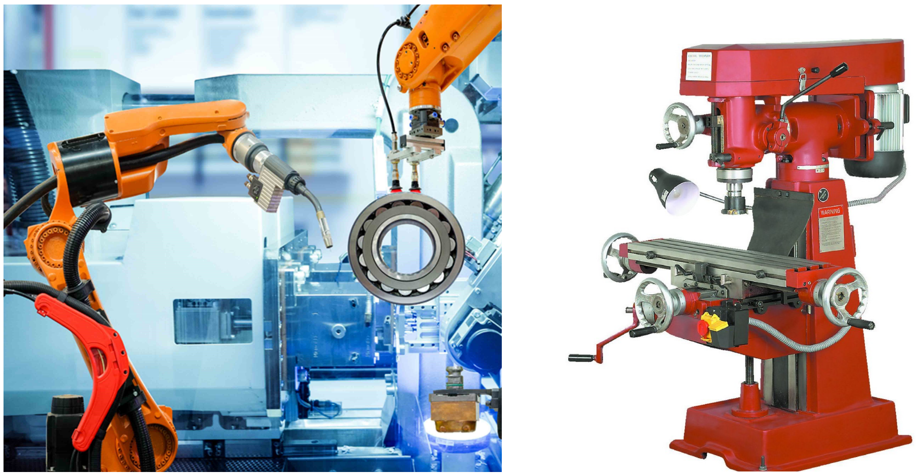
2 Definitions

This section provides definitions for 'robot', 'robotic innovation (automation)', and 'human innovations' that will be used throughout this paper. We adhere to the definition of a robot as specified by ISO standard 8373:2012, which describes it as an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes."[3] The International Federation of Robotics (IFR) also strictly

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

Figure 2: Examples of Robot

(a) Robot (b) Not robot[4]

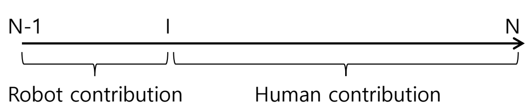


adheres to this definition (Müller, 2022). We source our robot data from the IFR.

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

We define ‘automation’ (or ‘robotic innovation (RI)’ in alternative terminology) as the enhancement of robots’ capabilities, enabling them to perform tasks previously beyond their scope. We propose a definition of ‘human innovations’ (HI) as the expansion of tasks that human workers are expected to perform, specifically those beyond the current capabilities of robots. This concept is framed within a model where ‘I’ represents robot innovation in production, while ‘N’ denotes human innovation.

Figure 3: Conceptual Diagram



We adopt definitions of RI and HI similar to those in previous studies (Acemoglu and Restrepo, 2018, 2019). In our model (illustrated in Figure 3), the variable I represents the extent of robotic innovation, while N signifies human innovation. The

[4]Vertical milling machine by harborfreight

segment from $N-1$ to I indicates the tasks performed by robots, and the segment from I to N represents tasks carried out by humans. If robotic innovation (I) grows faster than human innovation (N), robots will contribute more to production than humans. Together, the tasks performed by robots and humans form what we call 'aggregated tasks' (T), which, when combined with non-robot capital (R), result in the final output (Y).

3 Model

Acemoglu and Restrepo (2018) propose a formal model that illustrates how RI and HI influence labor share. We have refined our model based on their static version, with our key contribution being the distinction between robots and other capital equipment —a delineation absent in their model. Subsequent research by Acemoglu and Restrepo (2020) found that advancements in robotics negatively impact wages and employment, while other forms of capital positively affect these variables. This distinction underscores that 'robots' and 'non-robot capital' can have divergent implications for labor demand.

Our model offers several advantages over existing literature, such as Berg et al. (2018) and DeCanio (2016), which also introduced robots as a distinct factor from traditional capital. Primarily, our model comprehensively incorporates multiple technological changes affecting labor share, most notably RI and HI, along with productivity enhancements in the manufacturing of both robotic and non-robotic capital, as well as wage dynamics. Second, the regression equation derived from our model allows us to estimate both the elasticity of substitution between labor and robot capital and the elasticity of substitution between labor and non-robot capital within a single framework. These advantages enable a more nuanced and thorough analysis of the interplay between different technological changes and their effects on labor share.

3.1 Firms

In our 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[5]. 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 human innovations (HI), 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

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

automation (RI) 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 non-robot 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.

3.2 Labor Share

Let us move the detailed elaboration of our model to Appendix A. Based on Equations (11) to (18) presented in this appendix, the labor share is derived as follows:

$$S_L = \frac{\eta - 1}{\eta} \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{P_T^{1-\zeta}} \frac{P_T^{1-\sigma}}{P_T^{1-\sigma} + R^{1-\sigma}} \tag{5}$$

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

, where γ_j represents the productivity of labor for task j. The productivity, γ_j, increases with a higher task index, j. W_j, ψ, and R represent wage for labor conducting task j, robot price, and non-robot capital price, respectively. P_T is the price for the aggregated tasks, T, which is intuitively determined by the sum of the robots' contribution multiplied by the robot price and the humans' contribution multiplied by the wage rate.

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:

$$S_L^f \equiv \frac{\eta}{\eta-1} S_L = \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{P_T^{1-\zeta}} \frac{P_T^{1-\sigma}}{P_T^{1-\sigma} + R^{1-\sigma}} \tag{6}$$

It is worth noting that our dependent variable is S_L^f, which, to be precise, is not the labor share (S_L). Labor share is defined as Labor Costs/(Labor Costs + Robot Costs + Non-robot Capital Costs+Profits). In contrast, S_L^f is defined as Labor Costs/(Labor Costs+ Robot Costs + Non-robot Capital Costs).

We transform Equation (6) by applying a natural logarithm and then calculate the total derivative with respect to the external variables of our model (I, N, average wage $\mathbb{W}$, robot price ψ, non-robot capital price R, and labor productivity γ). This process results in Equation (7), which is the key equation we use in our regression analysis.

Even though it's not essential for our data analysis, we explain the terms labeled Ⓐ to Ⓔ in our equation. Readers will notice that Ⓑ shows up often in the expressions α_1 to α_6. This term combines two key parameters, ζ and σ, which are the elasticities of substitution. Meanwhile, Ⓐ and Ⓓ are direct effects on the labor share, while Ⓑ $\times$ Ⓒ and Ⓑ $\times$ Ⓔ are indirect effects on the labor share. We classify effects that operate via the variable P_T as 'indirect effects,' while those that affect the outcome without involving P_T are called 'direct effects.' For example, when I changes, it affects P_T, which in turn changes Ⓒ. This change is adjusted by the combination of elasticities, Ⓑ. Thus, when I changes, the labor share changes by Ⓑ $\times$ Ⓒ indirectly through the P_T channel.

From Equation (7), we notice two important points. First, when we add the terms α_3 and α_6, they sum to zero. Second, the sum of α_3, α_4, and α_5 is also zero. This second relationship is particularly important for our data analysis, as we'll use it in our estimations. Because we couldn't find a dependable way to measure labor productivity (γ), we include it within the fixed effects in our regression model.

$$
\begin{aligned}
d\ln S_L^f = {} & \\
& \underbrace{\left[\underbrace{-\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}}_{\text{Ⓐ}} + \underbrace{\left(-(1-\zeta) + S_K^f(1-\sigma)\right)}_{\text{Ⓑ}} \underbrace{\frac{1}{1-\zeta} \frac{\psi^{1-\zeta} - \left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{Ⓒ}} \right] dI}_{\alpha_1} \\
& + \underbrace{\left[\underbrace{\frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}}_{\text{Ⓓ}} + \underbrace{\left(-(1-\zeta) + S_K^f(1-\sigma)\right)}_{\text{Ⓑ}} \underbrace{\frac{1}{1-\zeta} \frac{-\psi^{1-\zeta} + \left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{Ⓔ}} \right] dN}_{\alpha_2} \\
& + \underbrace{\left[(1-\zeta) + \left(-(1-\zeta) + S_K^f(1-\sigma)\right) S_L^T \right]}_{\alpha_3} d\ln \mathbb{W} \\
& + \underbrace{\left[\left(-(1-\zeta) + S_K^f(1-\sigma)\right) S_M^T \right]}_{\alpha_4} d\ln \psi \\
& \underbrace{- \left[S_K^f(1-\sigma) \right]}_{\alpha_5} d\ln R. \\
& - \underbrace{\left[(1-\zeta) + \left(-(1-\zeta) + S_K^f(1-\sigma)\right) S_L^T \right]}_{\alpha_6} d\ln \gamma
\end{aligned} \tag{7}
$$

, where S_L^f represents labor share times markup, I is RI, N is HI, ψ is robot price, R is non-robot capital price, and γ is labor productivity. $\mathbb{W} \equiv \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{\int_I^N W_j^{-\zeta} \gamma_j^{\zeta-1} dj}$ is the average wage, and assume $d\ln \mathbb{W} = d\ln W_j$ for all j. Additionally, $d\ln\gamma$ represents the change in labor productivity. It is also assumed that $d\ln\gamma = d\ln\gamma_j$ for all j. S_K^f is the capital cost over total cost. By definition, $S_L^f + S_K^f = 1$.

S_M^T (S_L^T) represents the share of robot cost (labor cost) in the total combined task cost, which comprises both labor and robot costs. By definition, $S_M^T + S_L^T$ equals one. In detail, these are described mathematically as follows:

$$S_M^T = \frac{(I - N + 1)\psi^{1-\zeta}}{P_T^{1-\zeta}}$$
$$S_L^T = \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{P_T^{1-\zeta}}$$
$$\text{, where } P_T^{1-\zeta} = (I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj.$$

We acknowledge that price factors $-R$ (non-robot capital price), $\mathbb{W}$ (labor price), and ψ (robot price)— are not purely exogenous. We do not employ instrumental variables or other techniques to mitigate endogeneity. This limitation represents the most significant weakness of this paper. In the next section, we discuss the datasets used in this paper and the construction of the variables.

4 Data Collection and Variable Generation

To address endogeneity concerns in measuring HI and RI, we propose three shift-share instrumental variables (IVs). For RI, we utilize operational robot data from the International Federation of Robotics (IFR) or the patent similarity to automation vocabularies. For HI, we employ the Cognitive Task Intensity (CTI) developed by Jeong and Lee (2025). These instrumental variables are then directly employed in reduced-form regressions, as will be demonstrated in the Regression section.

A crucial assumption underlying the three shift-share approaches is that the shift component depends on changes in the USA. Undoubtedly, there exists the possibility of mutual influence between the U.S. economy and the economies of the countries in our sample. This interdependence could potentially violate the exogeneity assumption, resulting in biased estimates. Nevertheless, this approach represents the most viable option available, as exemplified by Autor et al. (2013), who stated: "we instrument for growth in Chinese imports to the United States using the contemporaneous composition and growth of Chinese imports in eight other developed countries."

The three shift-share variables exhibit solely country-level variation, lacking both sectoral and year dimensions. This absence of sectoral variation poses a significant challenge in capturing the nuanced differences in human innovation across industries, potentially diminishing the robustness and granularity of the analysis. While we acknowledge this limitation, we contend that this approach represents the most viable option available within the constraints of our study.

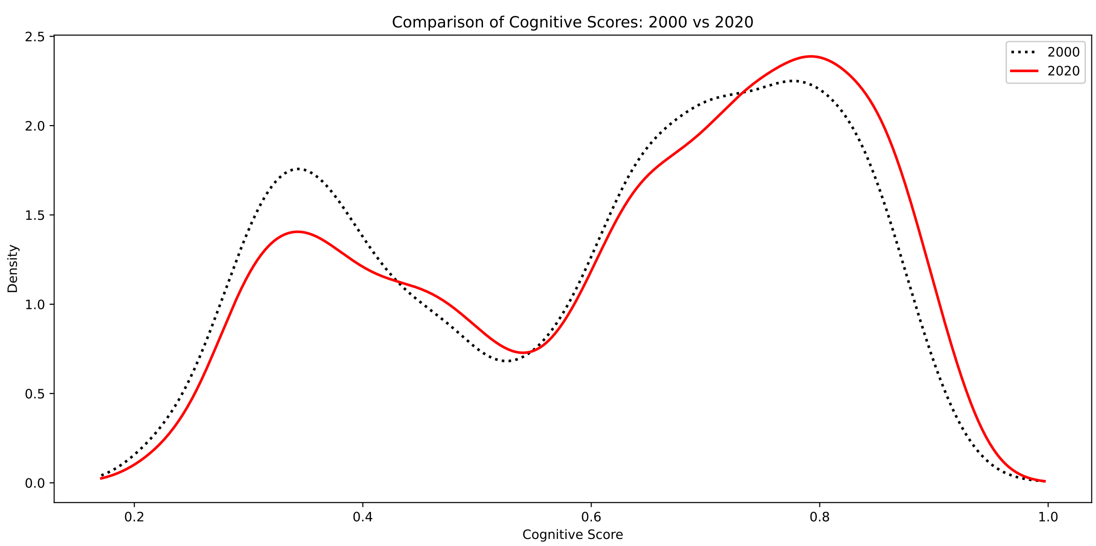
4.1 Human Innovations

To represent changes in human innovation (dN) in our key equation, we use a shift-share instrument for HI. Specifically, we use cognitive scores for different occupations provided by Jeong and Lee (2025), which are categorized using the detailed six-digit Standard Occupational Classification (SOC) system. To calculate cognitive intensity, they utilize GPT-4 and OPUS-3, which were the most advanced large language models until OpenAI introduced GPT-o1 in September 2024. They use the task descriptions provided by the Occupational Information Network (O*NET) (National Center for O*NET Development, 2023) and ask GPT-4 and OPUS-3 to determine the cognitive intensity.

Cognitive scores quantify the cognitive demands of occupations; however, they may not directly reflect innovative activities or the creation of novel tasks that surpass robotic capabilities. Readers might question whether cognitive intensity genuinely represents human innovation, as innovation encompasses more than mere cognitive skill levels. Nevertheless, as elucidated in the Introduction section, cognitive tasks encompass activities that necessitate mental processes, skills, and abilities. These include perception, thinking, reasoning, memory, learning, decision-making, and other facets of information processing. Consequently, we posit that cognitive intensity serves as the most suitable available proxy for human innovation (HI).

Cognitive score represents a distinctly different concept from routine score. While routine is closely associated with automation and robotics, cognitive score pertains to the human thought processes involved in production. Figure 4 illustrates the changes in cognitive intensity in the United States from 2000 to 2020.

Figure 4: Cognitive Intensity between 2000 and 2020 in the USA



We merge[6] these cognitive scores that vary by occupation code into the European Union Labor Force Survey (EU-LFS), which is an individual-level dataset, akin to the Current Population Survey (CPS) in the USA. Let C represent the weighted mean of the cognitive scores by industrial sector, occupation, country, and year.[7] It is crucial to note that we calculated the mean rather than the sum of the scores. This approach ensures that C reflects the proportion of workers who are more cognitive than others, rather than being influenced by the absolute number of workers. C_share is the C in 2005 for each country (c) and occupation (o), excluding the USA. Unfortunately, sector variation is not possible because EU-LFS does not provide detailed manufacturing sector information. Let C_shift be the USA's linear growth rate of C.[8] That is, C_shift $= (C_{2019} - C_{2005})/C_{2005}$. Then we make the shift-share IV by the following equation:

$$\text{C\_Shiftshare}_c = \sum_{o=1}^{O} \text{C\_Share}_{c,o,2005} \times \text{C\_Shift}_o$$

4.2 Robot Innovations using IFR Data

The International Federation of Robotics (IFR) provides data on the number of automated robots (both flow and stock) at the country-industry-year level. Let the stock value of these robots be denoted as M. Let the country wide M, that is, summed across sectors, as M_{tot}. We normalize M because it varies significantly based on the absolute size of the clusters. M_share is defined as M/M_{tot} in the year 2005 for each sector (s) and country (c), excluding the USA. M_shift represents the USA's linear growth rate of M. That is, M_shift $= (M_{2019} - M_{2005})/M_{2005}$. It exhibits sector variation. The shift-share IV for RI is then constructed as follows:

$$\text{M\_Shiftshare}_c = \sum_{s=1}^{S} \text{M\_Share}_{c,s,2005} \times \text{M\_Shift}_s$$

4.3 Robot Innovations using Patent Data

Alternative to M_Shiftshare that uses IFR data, we additionally present regression results using a shift-share constructed from patent data. We compare each patent descrip-

[6]EU-LFS uses ISCO for occupational taxonomy, and ISCO (4-digits) matches with SOC (6-digits). This granular level of crosswalk matching is made possible by the recent work of Frugoli and ESCO (2022). The excel file for the crosswalk between ISCO and SOC is in this link. This is publicly released by O*NET and ESCO.

[7]The weights represent the respondents' sampling weights in the survey.

[8]In this study, we merge the cognitive scores with the US Census (Ruggles et al., 2020). Our matching procedure to the US Census uses SOC as it is. The US Census provides both SOC and OCC for occupational taxonomy, enabling us to directly use SOC to match with the US Census data.

tion with a curated list of vocabulary closely associated with robotics and automation technologies. The detailed vocabulary list is provided in the footnote.[9]

We utilize the detailed descriptions of all U.S. granted patents from 2004 to 2019, which encompasses the entire span of our study. These detailed descriptions extend beyond abstracts, International Patent Classification (IPC), or Cooperative Patent Classification (CPC) information, providing comprehensive explanations of the patents. This approach constitutes one of our contributions, as most existing studies rely solely on abstracts, IPC, or CPC information.

By comparing each patent description with these automation-related terms, we derive a similarity score ranging from 0 to 1. We then exclude values below 0.3, which we manually determine to become irrelevant to automation or robotics. Subsequently, we aggregate the scores by country, industry, and year. We denote this aggregated value as P.

Let the country wide P, that is, summed across sectors, as P_{tot}. We normalize P because it varies significantly based on the absolute size of the clusters. P_share is defined as P/P_{tot} in the year 2005 for each sector (s) and country (c), excluding the USA. P_shift represents the USA's linear growth rate of P. That is, P_shift $= (P_{2019} - P_{2005})/P_{2005}$. It exhibits sector variation. The shift-share IV for RI is then constructed as follows:

$$\text{P\_Shiftshare}_c = \sum_{s=1}^{S} \text{P\_Share}_{c,s,2005} \times \text{P\_Shift}_s$$

Although U.S. patent data do not directly provide the country information of patent holders, they include company names and city locations. By leveraging the Google Maps API, we can infer the actual country of origin for each patent holder. Additionally, we can deduce the industrial sector of the patent. Lybbert et al. (2014) provide matching crosswalks between IPC codes and industrial sectors. Consequently, we construct a dataset comprising Patent ID, patent descriptions, patent holder's country, corresponding detailed industry in the manufacturing sector, and patent grant year.

Recent advancements in semantic embedding technology have led to significant improvements in natural language understanding. This technology enables the comprehension of semantic content within sentences. Unlike other studies, we utilized the most recently developed text-to-vector embedding software. One such software is 'sentence-transformers/all-mpnet-base-v2' developed by Microsoft, and the other is

[9]actuator, artificial intelligence, automation, autonomous, biomimetics, computer vision, cybernetics, human-machine interface (HMI), humanoid robots, industrial automation, industrial robot, kinematics, machine learning, machine perception, machine vision, motion control, Natural Language Processing (NLP), neural networks, object recognition, odometry, programmable, programmable logic controller, robot, Robot Operating System (ROS), robotic, robotic arm, robotic exoskeleton, robotic process automation (RPA), sensor fusion, servo motor, visual servoing, workflow automation.

‘text-embedding-3-large’ developed by OpenAI. To date, they represent one of the best-performing tools available (Harris et al., 2024).[10]

Both of these embedding software tools are unique in their ability to understand not only word-to-word similarity but also sentence-to-sentence similarity. If two sentences have completely different meanings, even if they use similar words, sentence embedding models will recognize them as different. In contrast, word embedding models will perceive the sentences as similar (Ul Haq et al., 2024; Zhang et al., 2024; Mandelbaum and Shalev, 2016; Li et al., 2015).

Baer and Purves (2023) demonstrates that the ‘sentence-transformers/all-mpnet-base-v2’ approach significantly outperforms TF-IDF in identifying similar documents, as judged by human annotators. Existing studies have predominantly relied on word embeddings. For instance, studies have utilized TF-IDF (Autor et al., 2024; Kogan et al., 2021; Webb, 2019) and BERT (Frugoli and ESCO, 2022). To the best of our knowledge, we are the first to apply sentence embedding technology in the field of economics.

We used Microsoft’s ‘sentence-transformers/all-mpnet-base-v2’, and calculated the similarity scores. For the sake of brevity, we present two examples: one with a high score and another with a low score.

Patent Number: 10209063
Applicant: X Development LLC
City: Mountain View
Similarity Score: 0.61 (high)
Patent Description: (1) Robots may be programmed to perform a variety of tasks such as, for example, autonomous or semi-autonomous navigation, manipulating objects (e.g., repositioning an object, altering an object, and/or picking up an object and moving it to a different location), transporting objects (without necessarily manipulating those objects), monitoring environmental conditions, functioning as “video conferencing on wheels”, and so forth. ...(Omitted to save space)... (3) The present disclosure is generally directed to using sensor-based observations from multiple agents (e.g., mobile robots and/or fixed sensors) in an environment to estimate the pose of an object in the environment at a target time and to estimate an uncertainty measure for that pose. The object for which the pose and uncertainty measure are estimated may be a non-agent object such as a pallet, a box, a product, etc. or may itself be an agent (e.g., a mobile robot). As used herein, “pose” of an object may reference a position of the object only (e.g., a multidimensional coordinate), or may reference both the position of the object and an orientation of the object (e.g., a pose in the SE(3) configuration space).

[10] While both OpenAI’s ‘text-embedding-3-large’ and Microsoft’s ‘sentence-transformers/all-mpnet-base-v2’ are among the best-performing tools available, they are not the only top performers. Other models like NVIDIA’s ‘NV-Embed’ and Salesforce’s ‘SFR-Embedding’ also demonstrate exceptional performance (Lee et al., 2024; Meng et al., 2024).

Patent Number: 10137757
Applicant: BEHR GmbH & Co. KG
City: Stuttgart
Similarity Score: 0.22 (low)
Patent Description: The invention relates to an air conditioning system for heating and air conditioning a motor vehicle, comprising a first heat exchanger and a second heat exchanger, the air conditioning system having a first flow channel and a second flow channel and flow being able to pass around both heat exchangers along the second flow channel and around only the first heat exchanger along the first flow channel. ...(Omitted to save space)... It is therefore the object of the present invention to provide an air conditioning system which reduces or completely prevents the unwanted residual heating of the air inside the air conditioning system. The structure of the air conditioning system is also especially simple and is optimized as compared to the solutions in the prior art.

4.4 Robot Price

Unfortunately, the International Federation of Robotics (IFR) no longer provides information on the prices of robots. IFR provided robot prices in the form of an average unit price until 2009, and as a price index until 2005. Klump et al. (2021) and Jurkat et al. (2022) provide in-depth information on this topic.[11] 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, which 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.[13]

4.5 Capital Price

In Figure 7, provided in Appendix G, we replicate the derivation of capital price following the approach used by Karabarbounis and Neiman (2014) (hereafter referred to as KN), utilizing the KLEMS data version. This ensures that the 'overall' capital price

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

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

[13] The data generation process is as follows: UN Comtrade provides annual import and export values in dollar for 'Machinaery and mechanical appliances; industrial robot, n.e.c. or included. (HS847950)' They also provide the quantity of these values for both imports and exports. Hence, we infer the robot prices by dividing the dollar values by their quantities.

variable is identical to that used by KN. Subsequently, we derive the non-robot capital price variable as detailed in Section 4.6. This non-robot capital price variable is then consistently utilized throughout Sections 5 and ??. Our data indicate that the prices of non-robot capital have generally increased over the past 15 years, as illustrated in Figure 7 in Appendix G. This observation might initially appear contradictory to the claims of KN, who reported a rapid global decline in capital prices (see Figure 7 of their paper). However, our Figure 7 is consistent with their findings, considering that capital prices began to rise from around year 2000. Furthermore, their figure aggregates data from all countries worldwide, whereas our analysis is more focused, presenting data at the country level for only 9 selected countries.

4.6 Non-robot Capital Price

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

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

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

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

, where α is $\frac{\text{Cost}_M}{\text{Cost}_K}$. This completes the derivation of the growth rate of price for the non-robot capital.

For the capital price, gr_Price_K, we strictly adhere to the approach outlined by Karabarbounis and Neiman (2014) throughout this paper. For detailed explanations, please refer to Appendix C. We have values for Cost_K from KLEMS data. For further explanations regarding this, please refer to Appendix D.

We can estimate Cost_M by sector and country through two approaches. The first approach employs the value obtained using the approach introduced in Section E.1. This approach yields the ratio $\frac{\text{Robot Cost}}{\text{Labor Cost}} = 2.813\%$, and labor cost information is available from the KLEMS dataset. Consequently, we can calculate Cost_M based on this information. However, this approach is contingent on labor cost values, raising concerns that the ratio $\frac{\text{Robot Cost}}{\text{Labor Cost}} = 2.813\%$ may vary significantly across sectors and countries. Therefore, we propose an alternative approach.

The alternative approach leverages information from the alternative method detailed in Appendix E.2. In this method, we have determined the cost ratio between OMach and robots to be $13.595 : 2.149$, where 'OMach' refers to the machinery and equipment in the KLEMS. Given that we possess detailed OMach cost data by sector and country, we can subsequently estimate Cost_M. This approach circumvents the need for labor cost data. By using this approach, we complete our derivation of the growth rate of non-robot capital price, which will be used in our regression analysis.

5 Regressions

5.1 Regression Equations

Based on the specification in Equation (7) shown in Section 3.2, we provide consistent regression equations as below:

$$\begin{aligned} \text{gr\_(laborshare} \times \text{markup)}_{cst} = & \alpha_1 \text{RI}_c + \alpha_2 \text{HI}_c \\ & + \alpha_3 \text{gr\_labor price}_{cst} + \alpha_4 \text{gr\_robot price}_{cst} \\ & + \alpha_5 \text{gr\_non-robot capital price}_{cst} \\ & + \alpha_6 \text{gr\_labor productivity}_{cst} \\ & + \lambda_c + \lambda_s + \lambda_t + \lambda_{cs} + \varepsilon_{cst}. \end{aligned} \tag{8}$$

gr indicates the variables are in a 10-year growth rate, and c, s, and t correspond to country, industry sector, and year, respectively. We exclude the notation of *gr* from RI and HI, as by definition, they already represent a linear growth rate from 2005 to 2019.

5.2 Regression Results

We present reduced-form regresion results in Table 1. Standard errors are clustered by country and industry to account for serial correlation. To improve readability, both the coefficients and standard errors have been multiplied by 100.

Upon examination of Equation (7), it is evident that the sum of the coefficients for $d \ln \mathbb{W}$, $d \ln \psi$, and $d \ln R$ is equal to zero (i.e., $\alpha_3 + \alpha_4 + \alpha_5 = 0$). Moreover, the sum of the coefficients for $d \ln \mathbb{W}$ and $d \ln \gamma$ is also equal to zero (i.e., $\alpha_3 + \alpha_6 = 0$). In the regression table, Columns (1) and (3) do not incorporate these constraints, whereas Columns (2) and (4) impose them. The baseline models employed throughout this study are represented by Columns (2) and (4), which include these restrictions.

Recall that our paper's main focus is how RI and HI influence labor share. All other price factors are endogenous, thus their coefficients are of less importance. One might argue that including endogenous price factors constitutes a 'bad control' in Angrist and Pischke (2008)'s terminology. Bad control occurs when a control variable is correlated with both the dependent and explanatory variables. In our case, we use

Table 1: Regressions

Constraints	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
α_1: Robot_shiftshare (RI)	-11.184	-24.823***		
	(7.887)	(4.787)		
α_1: Patent_shiftshare (RI)			-3.073	-6.820***
			(2.167)	(1.315)
α_2: Cognitive_shiftshare (HI)	27.929**	40.712***	17.559*	17.697*
	(10.869)	(12.853)	(9.344)	(9.852)
α_3: gr_labor price	36.488***	6.763	36.488***	6.763
	(12.219)	(6.855)	(12.219)	(6.855)
α_4: gr_robot price	2.799	0.662	2.799	0.662
	(2.223)	(2.572)	(2.223)	(2.572)
α_5: gr_non robot capital price	-13.850**	-7.425	-13.850**	-7.425
	(5.484)	(6.232)	(5.484)	(6.232)
α_6: gr_labor productivity	-20.413*	-6.763	-20.413*	-6.763
	(10.497)	(6.855)	(10.497)	(6.855)
N	386	386	386	386
R^2	0.824	0.797	0.824	0.797

The coefficients and the standard errors have been multiplied by 100 for better readability.
Standard errors in parenthesis are clustered by country.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

shift-share instruments, which we assert are confidently free from any association with endogenous price factors. Thus, our coefficients of interest, those of RI and HI, are not affected by these covariates.

By estimating the elasticity of substitution between labor and robots (ζ), as well as between labor and overall capital (σ), we can observe many interesting mechanisms. However, we acknowledge that these elasticities are derived from endogenous factors, which reduces our confidence in their estimates. Therefore, we postpone the discussion of this matter to Appendix F.

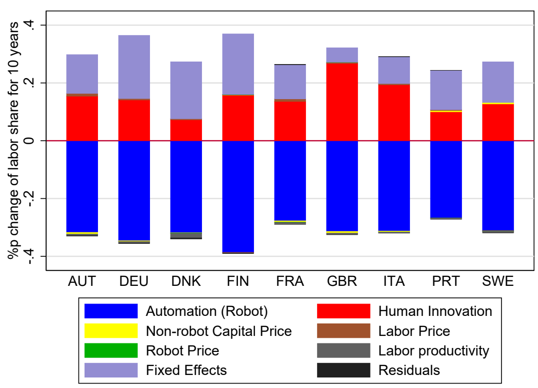
5.3 Accounting

This study examines the factors influencing labor share, focusing on automation (robotic innovation, RI) and human innovation (HI). Our analysis reveals that while automation negatively impacts labor share, human innovation exerts a positive influence. We argue that, up to 2024, HI has counterbalanced the downward pressure on labor share caused by RI. This key finding forms the core contribution of our paper. The following section details the direction and magnitude of RI and HI effects on labor share, providing empirical support for our conclusions.

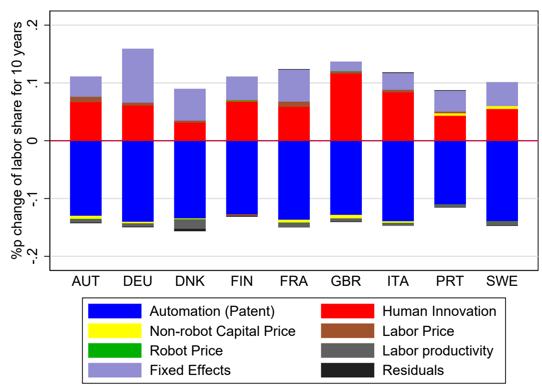
For the sake of concision, the figures that we will discuss below will concentrate exclusively on country-level variations (or sector-level variations). Accordingly, the values presented in our figures are derived from aggregated level data. During the aggregation process, average variables are consolidated by weighting the corresponding value-added.

Figure 5: Accounting

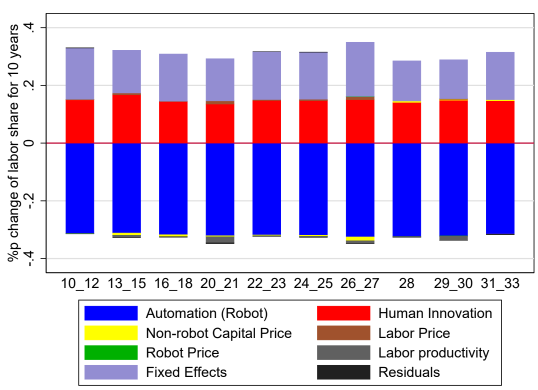
(a) Using Robots for RI



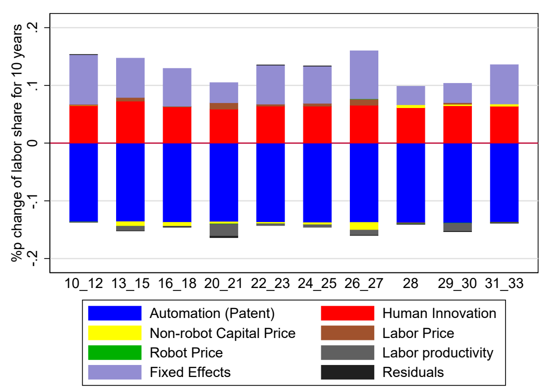
(b) Using Patent for RI



(c) Using Robots for RI



(d) Using Patent for RI



We additionally provide Figure Panel (c) and (d) of Figure 5 that have sector variation. The implication is not much different: the positive effect of HI surpasses the negative effect of RI.

Table 2: Industry Codes and Their Corresponding Sectors

Code Range	Sector Description
10-12	Food products, beverages and tobacco
13-15	Textiles, wearing apparel, leather and related products
16-18	Wood and paper products; printing and reproduction of recorded media
20-21	Chemicals and chemical products
22-23	Rubber and plastics products, and other non-metallic mineral products
24-25	Basic metals and fabricated metal products
26-27	Electrical and optical equipment
28	Machinery and equipment n.e.c.
29-30	Transport equipment
31-33	Other manufacturing; repair and installation

6 Concluding Remarks

This study has sought to deepen the understanding of the declining global labor share by examining the roles of robotic innovation (RI) and human innovation (HI) within a unified general equilibrium framework. By integrating both RI and HI into our model and addressing endogeneity concerns through the use of novel shift-share instrumental variables, we have provided empirical evidence on how these factors influence labor share across countries and sectors.

Our empirical findings demonstrate that RI negatively impacts labor share, corroborating the hypothesis that automation can supplant labor in production processes. Conversely, HI exhibits a positive effect on labor share, indicating that human innovation —encompassing tasks beyond robotic capabilities— reinforces labor's role in the economy. These results indicate that, up to 2024, the impact of automation on labor share has been counterbalanced by human innovation. However, as robotic and AI innovation develops exponentially, future research may yield different outcomes.

While our study provides significant insights, it is important to acknowledge its limitations. Primarily, we recognize that the price factors in our model are not exogenous. This endogeneity could potentially introduce biases if these endogenous covariates are strongly correlated with our shift-share instrument. However, we argue that this correlation is minimal, mitigating concerns about substantial bias in our results. Second, this study's focus on nine European Union countries may constrain the generalizability of its results to other contexts. The inherent differences in economic structures, labor market dynamics, and patterns of technological adoption across diverse national settings could potentially limit the broader applicability of our findings. Such regional specificity necessitates caution when extrapolating these results to economies outside the studied European framework.

Future research avenues could include extending our analysis by incorporating more granular data at the sectoral or firm level, such as BvD Orbis Historical data.

This would allow for the development of shift-share instruments with richer industrial sector variations. Moreover, investigating the dynamic interactions between RI and HI over time could provide deeper insights into the long-term trends affecting labor share. Additionally, measuring coefficients that vary by each country could offer a more detailed understanding of how different economies are impacted by automation and human innovation.

We are on the cusp of a rapid development stage in artificial intelligence and humanoid robotics. This advancement is poised to transform society at an unprecedented rate, potentially surpassing the impact of personal computers and the internet. The current state of progress may be approaching an inflection point towards artificial general intelligence (AGI) or nearing its realization. Consequently, future research encompassing subsequent years may significantly alter the implications and results of this study.

In conclusion, our findings suggest that while automation has exerted downward pressure on labor share, human innovation has served as a countervailing force. Policymakers aiming to address the decline in labor share may benefit from fostering environments that encourage human innovation, such as investing in education and training programs that enhance cognitive skills and promote creative problem-solving. By doing so, it may be possible to enhance the complementary relationship between labor and technology, ensuring that workers remain integral to the production process even as automation advances.

A Appendix: Model

A.1 Households

The representative consumer consumes an aggregated continuum of final goods, with the mass of final goods assumed to be one 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:

$$U = \left(\int_0^1 Y(i)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}} \tag{9}$$

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

The representative consumer's budget constraint is as follows:

$$\int_0^1 P(i)Y(i)di = \int_0^1 \left(\int_{N-1}^{N} W_j l_j(i)dj + \int_{N-1}^{N} \psi m_j(i)dj + RK_i + \Pi_i \right) di \tag{10}$$

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

A.2 Labor Share

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

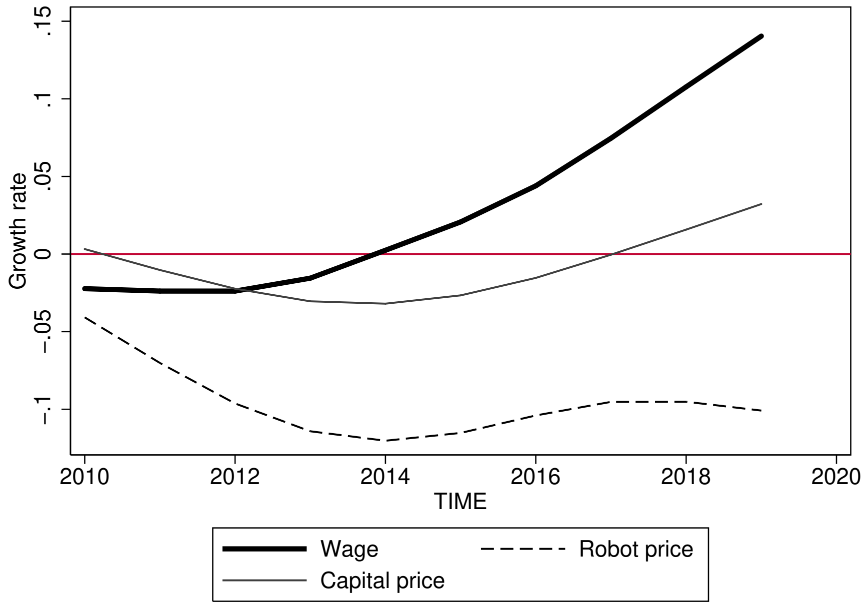
Assumption 1. $\psi < \frac{W_I}{\gamma_I}$

The above assumption implies that it is efficient to use a robot for task j below I. In other words, whenever firms have the technological capability to substitute labor with a robot, they would be inclined to do so. This is a reasonable assumption, especially considering that robot prices have significantly declined, while wages have seen a steady increase. Figure 6 illustrates these trends by depicting the 5-year growth rates of the respective prices.

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

$$l_j(i) = 0, \quad \text{if } j \leq I \tag{11}$$

Figure 6: Prices in a 5-year growth rate



$$l_j(i) = \gamma_j^{\zeta-1}\left(\frac{W_j}{P_T}\right)^{-\zeta} T(i), \ \text{ if } j > I \tag{12}$$

$$m_j(i) = \left(\frac{\psi}{P_T}\right)^{-\zeta} T(i), \ \text{ if } j \leq I \tag{13}$$

$$m_j(i) = 0, \ \text{ if } j > I \tag{14}$$

$$T(i) = \left(\frac{P_T}{MC(i)}\right)^{-\sigma} Y(i) \tag{15}$$

$$K(i) = \left(\frac{R}{MC(i)}\right)^{-\sigma} Y(i) \tag{16}$$

$$P_T = \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj\right]^{\frac{1}{1-\zeta}} \tag{17}$$

$$MC(i) = \left[P_T^{1-\sigma} + R^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{18}$$

$$W_j l_j(i) = \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} \cdot P_T^{\zeta} \cdot T_i \tag{19}$$

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

B Appendix: Detailed Model Derivations

B.1 Environment

There is a representative household with utility function in Equation (20):

$$U = \left(\int_0^1 Y(k)^{\frac{\eta-1}{\eta}} dk\right)^{\frac{\eta}{\eta-1}}. \tag{20}$$

There are infinite number of identical firms i with production functions in Equation (23) and (24):

$$t_j(i) = m_j(i) + \gamma_j l_j(i) \ \text{ if } j \leq I \tag{21}$$
$$t_j(i) = \gamma_j l_j(i) \ \text{ if } j > I \tag{22}$$
$$T(i) = \left(\int_{N-1}^{N} t_j(i)^{\frac{\zeta-1}{\zeta}} dj\right)^{\frac{\zeta}{\zeta-1}} \tag{23}$$
$$Y(i) = \left(T(i)^{\frac{\sigma-1}{\sigma}} + K(i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{24}$$

By Assumption 1, Equation (21) simplifies to Equation (25). 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.

$$t_j(i) = m_j(i) \ \text{ if } j \leq I \tag{25}$$

B.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.

$$\min \text{cost(i) for } T(i) \text{ s.t. Equation(25), (22), and (23)}$$

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

$\Rightarrow$ 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 :

$$\Rightarrow P_T = \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{w_j}{\gamma_j}\right)^{1-\zeta} dj\right]^{\frac{1}{1-\zeta}} \tag{26}$$

B.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 $Y(i)$.

$$
\begin{aligned}
&\min \text{cost(i) for } Y(i) \text{ s.t. Equation(24)} \\
\Leftrightarrow &\min P_T \cdot T(i) + R \cdot K(i) \text{ s.t. Equation(24)} \\
\Rightarrow &\text{This finds optimal inputs for T(i)* and K(i)* to produce Y(i)} \\
\Rightarrow &\text{Specifically, the minimization solution is the minimum cost for producing } Y(i) \\
\Rightarrow &\begin{cases}
T(i)^* = Y(i) P_T^{-\sigma} \\
K(i)^* = Y(i) R^{-\sigma} \\
\text{Cost for } Y(i) = Y(i) \left[P_T^{1-\sigma} + R^{1-\sigma} \right]^{\frac{1}{1-\sigma}} \\
\qquad = Y(i) \times \text{AC} \\
\qquad = Y(i)
\end{cases}
\end{aligned}
$$

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.

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

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

$$
\begin{aligned}
&\min \text{cost for consumption s.t. Equation(20)} \\
\Leftrightarrow &\min \int_0^1 P(i) Y(i) di \text{ s.t. Equation(20)} \\
\Rightarrow &\text{Specifically, this yields a demand function for } Y(i) \\
\Leftrightarrow &Y(i) = \left(\frac{P(i)}{\mathbb{P}} \right)^{-\eta}, \text{ where } \mathbb{P} \equiv \left[\int_0^1 P(i)^{1-\eta} di \right]^{\frac{1}{1-\eta}}
\end{aligned}
$$

B.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.

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

B.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 $T(i)$.

$$l_j(i)^* = \left(\frac{W_j(i)}{\gamma_j P_T}\right)^{-\zeta} \gamma_j^{-1} T(i) \tag{27}$$

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

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:

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

B.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 $S_L^f(i)$.

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

C Appendix: Capital Price

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

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

$$R_t = \xi_{t-1}(1 + i_t) - \xi_t(1 - \delta_t) \tag{28}$$

$$R_t = \xi_t \left(\frac{1}{\beta} - 1 + \delta \right) \tag{29}$$

In this Equation (28), R represents the capital price, ξ is the investment price, i is the interest rate, and δ is the depreciation rate. All values are expressed in real terms. This equation signifies that investors are indifferent between paying a *usage* cost for capital (R_t) and *purchasing* capital, paying interest, and then selling the depreciated capital at a later date.

To simplify Equation (28) into the form presented in Equation (29), we follow a specific process. This involves the assumption of a constant interest rate, i, and approximating $1 + i$ as $\frac{1}{\beta}$. Equation (29), as employed by KN in their KLEMS version of the capital price variable, assumes a depreciation rate of 10%. This rate aligns closely with the 10.8% rate assumed by Stehrer et al. (2019), an official KLEMS document. Throughout this paper, we strictly adhere to the approach by KN.[14]

D Appendix: KLEMS Data and Capital Cost

D.1 KLEMS Data

Aside from the IFR dataset, the O*NET dataset, and Robot Price, we will use data from KLEMS.[15] 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).

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.

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

[15]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 3 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 3: 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

D.2 Capital Cost

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

In particular, the KLEMS dataset lacks RK. It does include I_GFCF (Investment in Gross Fixed Capital Formation) and K_GFCF (Capital Stock of Gross Fixed Capital Formation), but these do not provide the necessary RK information. I_GFCF represents the net investment in fixed assets —a flow metric indicating capital goods investment. K_GFCF, on the other hand, denotes the total value of all fixed assets available for production —a stock variable. Consequently, although RK can be estimated based on K_GFCF, this method lacks precision. This is because K_GFCF represents the purchase cost, not the rental cost. To convert the purchase cost into rental cost, the real interest rate and depreciation rate as shown in Equation (28) are required. Notably, the depreciation rate requires numerous assumptions, and we lack this information.

A pertinent question arises: why not use OECD STAN initially, instead of KLEMS? The response lies in the fact that OECD STAN does not contain R (capital price) data.

Therefore, we resort to using R obtained from KLEMS. However, integrating this with other data from OECD STAN, particularly wage variables, poses complications. Furthermore, STAN does not provide industry-specific Producer Price Index (PPI). To enhance the accuracy of our analysis, we prefer to use industry-specific PPI, specifically the VA_PI variable from KLEMS.

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

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

In assessing the congruence between the regression results and the model's predictions, two findings are noteworthy. First, the model delineates the coefficient for robot price as α_4, with the term $S_M^T = 2.81\%$ included, which we estimated in Section E.1. The model thus anticipates this coefficient to be of an insignificantly small value. In line with this prediction, the regression coefficient for robot price is not statistically significant, and the point estimate lacks precision.

$$\alpha_4 = \left(-(1-\zeta) + S_K^f(1-\sigma)\right) S_M^T$$

Second, the regresion results maintain consistency in direction, regardless of whether the restrictions are applied. Utilizing the regression without the restrictions (as shown in Column (1) and (3)), we test the null hypothesis that the restriction is non-binding. The hypotheses is rejected at the 0.05 significance level. This suggests some misalignment between the data and the model's predictions.

E Appendix: Estimation of S_M^T

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

For a detailed explanation of how we estimated S_M^T, please refer to Appendix E.1. By synthesizing all available information, we estimate S_M^T to be 2.813% for the total manufacturing sectors. An alternative method detailed in Appendix E.2 estimates the S_M^T value at 2.104%. However, we consider the method outlined in this section to be more accurate and reliable, leading us to conclude that the S_M^T value is 2.813%.

E.1 Detailed Explanation for S_M^T

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

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

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

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

E.2 An Alternative Approach to Estimating the S_M^T

Let's assume labor cost to be 100 without loss of generality. According to KLEMS data, the rental cost for OMach is recorded as 13.595. But it's important to note that OMach encompasses not just robots but also a range of other items, including equipment, machinery, engines, and turbines (Stehrer et al., 2019; Gouma and Timmer, 2013). Therefore, the challenge is to determine the share of robots within the broader category of OMach. The most reliable approach we can consider involves utilizing UN Comtrade data, which offers information about import and export values by detailed commodity categories. By calculating the total export values of commodities corresponding to OMach,[17] and separately calculating the total export values of HS Code 8479 (which

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

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

pertains to robots),[18] we find that the ratio between these values is 13.595 : 0.71. In brief, the ratio between labor cost, OMach cost, and robot cost is 100 : 13.595 : 0.71.

The equipment cost for robots is estimated to be around 33.04% of the total robot costs (Zhao et al., 2021), and the UN Comtrade estimate of 0.71 corresponds to the equipment cost. Therefore, the total cost of the robot amounts to $0.71/0.33 = 2.149$. Hence, S_M^T is estimated to be 2.104%.[19]

F Appendix: Estimation of σ and ζ and Their Implications for Factor Prices

By utilizing Equation (7) along with the regression results in Column (2) of Table 1, we estimate the values of σ and ζ. σ represents the elasticity of substitution between the aggregate task and non-robot capital. Notably, labor costs account for 97.2% of the aggregate task cost, while non-robot capital accounts for 91.1% of the 'overall' capital cost. Thus, σ serves as a close proxy for the elasticity of substitution between labor and overall capital. Our results for σ are as follows:

- Given that $S_K^f > 0$ and the coefficient for $d \ln R$ is negative, we can infer that $\sigma < 1$.
- We derive σ using the following equation:

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

- We conduct a Wald test on the null hypothesis that $\sigma = 0$ and find that it can be rejected at the 0.10 significance level.
- We calculate $\sigma = 0.685$, with a 90% confidence interval of $(0.248, 1.121)$.

There is high interest in this elasticity of substitution, as seen in studies such as Karabarbounis and Neiman (2014), Glover and Short (2020), Chirinko (2008), and Grossman and Oberfield (2022). Unfortunately, since our confidence interval for σ exceeds 1, we cannot assert whether it indicates a gross complement or substitute relationship. For simplicity, we will proceed using the point estimate in our further analysis.

For ζ, our findings are:

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

[19] $2.104\% = \frac{2.149}{2.149+100}$

- We estimate $\zeta = 1.161$, which is similar to, but lower than, the findings of DeCanio (2016), suggesting a ζ of approximately 1.9.

- We derive ζ using the following equation:

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

- We estimate S_L^T to be 0.972, which we substitute into Equation (Zeta) to obtain our ζ estimate.

- The 90% confidence interval for ζ ranges from -0.356 to 2.678.

- We conduct a Wald test on the null hypothesis that $\zeta = 0$ and find it cannot be rejected at the 0.10 significance level.

Consequently, we cannot draw any definitive conclusions about whether ζ indicates a gross complement or substitute relationship. For further analysis, we will use the point estimate of $\zeta = 1.161$.

Finally, we note that the equivalent values for ζ and σ based on the regression results of the constrained model utilizing Patent-shiftshare, as displayed in Column (4) of Table 1, are identical to our findings for Robot-shiftshare.

F.1 Effects of Price Factors on Labor Share

F.1.1 Labor Price

The regression findings provide important insights into the relationship between factor prices and labor share. Our analysis reveals a positive correlation between the labor price (wage) and labor share. This relationship can be understood through the concept of gross complementarity between labor and non-robot capital, as indicated by $\sigma < 1$ in our model.

The mechanism underlying this relationship can be explained as follows: When the wage increases, the usage of labor does not decrease proportionally to the price increase. This disproportionate response leads to an overall increase in the cost attributed to labor. Consequently, a larger portion of the cost is allocated to labor, resulting in a rise in labor share.

Technically speaking, the robot cost share, denoted by S_M^T, is a very small value, specifically 0.028. This indicates that when wages change, substitution between labor and robots does not have a significant effect, and substitution between labor and non-robot capital plays a more important role. In essence, the condition that determines $\alpha_3 > 0$ is fundamentally $\sigma < 1$, from a technical perspective.

$$
\begin{aligned}
\alpha_3 =& (1-\zeta) + \left(-(1-\zeta) + S_K^f(1-\sigma)\right) S_L^T \\
=& (1-\zeta)(1-S_L^T) + S_K^f(1-\sigma)S_L^T \\
=& (1-\zeta)(S_M^T) + S_K^f(1-\sigma)S_L^T \\
=& -0.005 + S_K^f(1-\sigma)S_L^T \\
\approx& \; S_K^f(1-\sigma)S_L^T = 0.072 > 0.
\end{aligned}
$$

F.1.2 Non-robot Capital Price

The underlying principle is analogous to the labor price scenario. An increase in the price of non-robotic capital does not elicit a proportional decrease in its utilization. This disproportionate response engenders an overall increase in the costs associated with non-robotic capital, consequently leading to a reduction in the relative costs attributed to labor. As a result, a diminished proportion of total costs is allocated to labor, precipitating a decline in the labor share. From a technical perspective, the fundamental reason for $\alpha_5 < 0$ is essentially that $\sigma < 1$.

$$\alpha_5 = -\left[S_K^f(1-\sigma)\right] < 0 \tag{30}$$

F.1.3 Robot Price

The regression results indicate a positive, albeit small, association between robot price and labor share. This insignificance is attributed to the low share of the robot cost ($S_M^T = 2.8\%$). This means that even if robot prices change, their impact on labor share will inevitably be small.

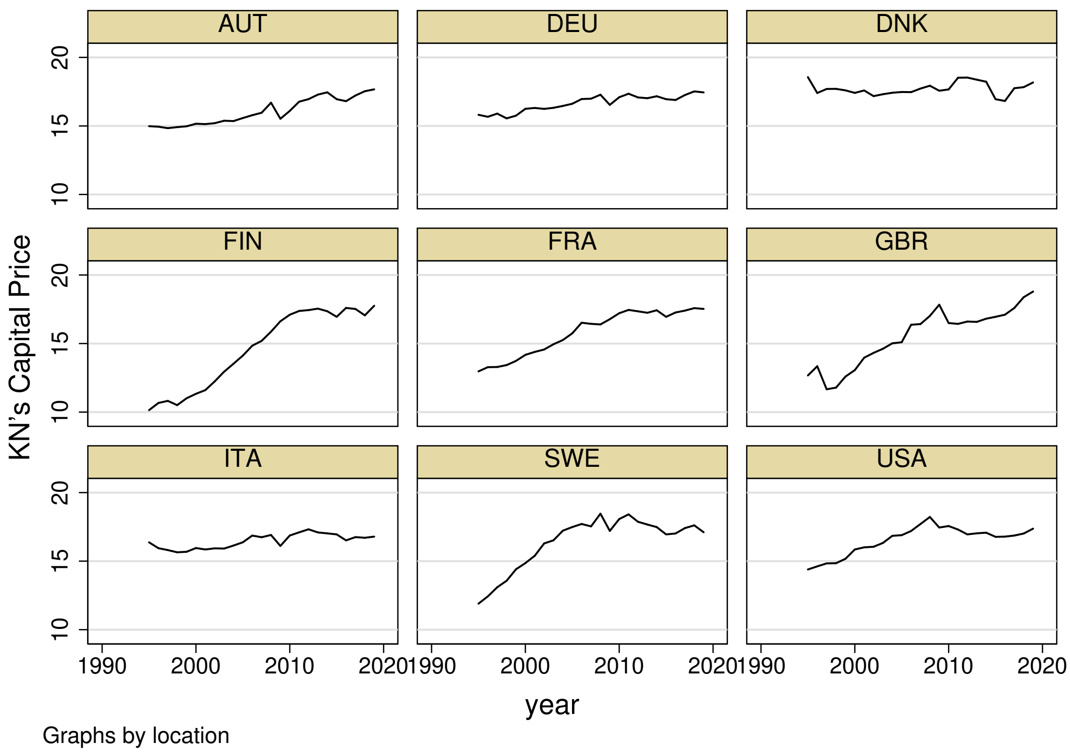
$$\alpha_4 = \left(-(1-\zeta) + S_K^f(1-\sigma)\right) S_M^T > 0 \tag{31}$$

In the future, we anticipate that the coefficient for robot price will become more significant, yielding a stronger association as the proportion of robots in society increases. This expectation is attributable to the term S_M^T, which represents the share of robot costs and is projected to be larger in the future.

Our analysis of the robot price factor reveals a positive correlation with labor share. We demonstrated, ζ has a 90% confidence interval of (-0.356, 2.678), yielding inconclusive results. Furthermore, the term $\left(-(1-\zeta) + S_K^f(1-\sigma)\right)$ has confidence interval of (-1.273, 1.744) with a point estimate of 0.235. Consequently, interpreting this positive coefficient the above term lacks statistical significance.

G Appendix: Tables and Figures

Figure 7: KN's Capital Prices



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