

Automation, Human Task Innovation, and Labor Share*

Deokjae Jeong[†]

Abstract

This study examines the impacts of robotic innovation (RI) and human innovation (HI) on labor share across nine EU countries. Using a general equilibrium model and shift-share instruments, this study addresses endogeneity concerns by utilizing US patents and a Cognitive Tasks Index. Findings show that until 2024, RI's negative impact on labor share is significant while HI's positive effect is minimal. This study estimates the elasticity of substitution between labor and non-robot capital at 0.516, and between labor and robots around unity. Notably, the analysis identifies increasing markup as the primary factor contributing to the decline in labor share.

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

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

1 Introduction

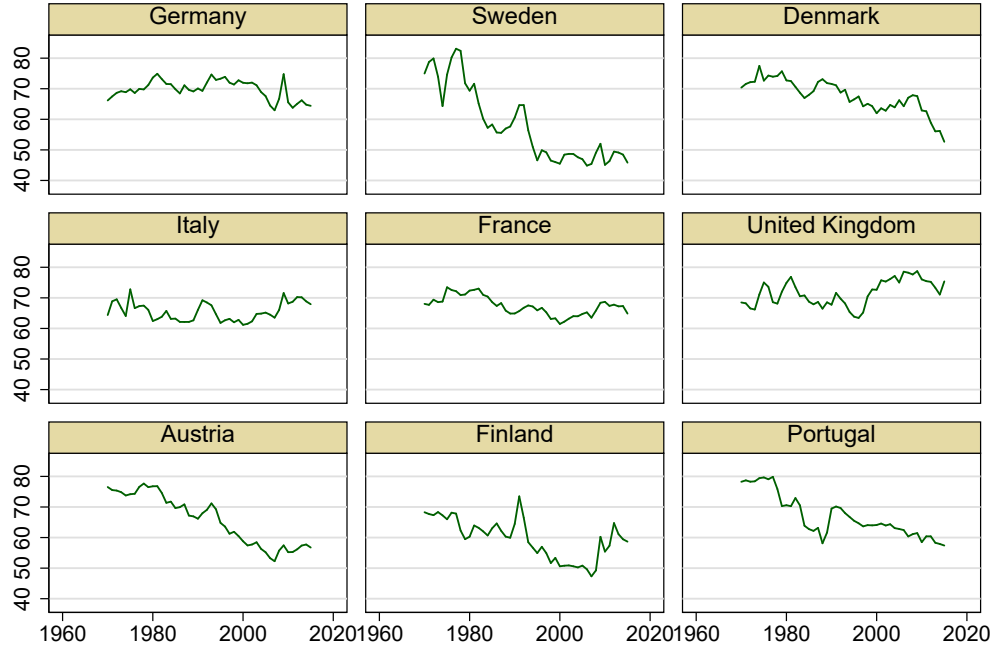
The global labor share has exhibited a declining trend since the early 1980s, with an average decrease of approximately five percentage points, as observed by [Karabarbounis and Neiman \(2014\)](#) and [Autor et al. \(2020\)](#). Figure 1, based on data compiled by [Gutiérrez and Piton \(2020\)](#), illustrates a comparison of labor shares in the manufacturing sectors of nine European Union countries analyzed in this study. While countries such as 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 investigating variations across countries and sectors to elucidate this decline.¹

This study examines the roles of robotic innovation (RI) and human innovation (HI) in influencing labor share across these nine European Union countries. The primary

*I extend my heartfelt thanks to Giovanni Peri, Òscar Jordà, Athanasios Geromichalos, Colin Cameron, and Takuya Ura for their ongoing guidance and invaluable support. I also thank participants at the WEAI 99th Annual Conference, the American Economic Association Annual Meeting in 2024, and the Annual All-California Labor Economics Conference.

[†]Replication data and code and the most recent version of paper:

Figure 1: Labor shares



research question addresses how RI and HI impact labor share in different countries and sectors. Two main hypotheses are proposed: first, that RI negatively impacts labor share due to the substitution of labor with automated processes; and second, that HI positively affects labor share by creating tasks beyond robotic capabilities.

To investigate these hypotheses, this study employs a general equilibrium model that uniquely incorporates both RI and HI. The model addresses endogeneity concerns through the use of novel shift-share instrumental variables. Data from the International Federation of Robotics, US patent records, and a Cognitive Tasks Index are analyzed to provide empirical evidence for the model’s predictions.

The precise cause of the declining labor share remains a subject of debate, with advancements in automation emerging as a potential key driver. The urgency of addressing this issue is intensified by the accelerated growth in automation and artificial intelligence technologies. For instance, Tesla’s aim to deploy “genuinely useful humanoid robots” in their factories by 2025 (Elon, 2024), and the recent debut of GPT-o3 and Deep Research, marking a significant advancement in AI reasoning capabilities, underscore the rapid evolution of robotic systems.

<https://github.com/jayjeo/public/blob/main/Laborshare/readme.md>

[†]Korea Customs and Trade Development Institute; ubuzuz@gmail.com; jayjeo.com

¹In this context, this 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.

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 my knowledge, [Autor et al. \(2024\)](#) represents the only study that empirically measures human innovations, utilizing the *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. This study’s 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, this study adopts 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 \(2018\)](#), this study incorporates both robotic innovation (RI) and human innovation (HI) into a general equilibrium model.² The 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 enables the analysis of how robot and non-robot capital differently affect the labor share in conjunction with two types of innovation.

This study addresses the endogeneity issues of RI and HI by proposing two shift-share variables. The first shift-share for RI utilizes the similarity between all U.S. patents and vocabularies closely related to automation and robotics. It employs the semantic understanding derived from recently developed sentence-to-sentence embedding technology. The second shift-share for HI utilizes the cognitive score developed

²Another study akin to this study 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. My 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.

by Jeong and Lee (2025). Cognition 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, this study argues that this serves as an appropriate proxy for HI. Through this approach, the study meticulously examines how RI and HI influence labor share across countries and sectors. This comprehensive analysis constitutes the primary contribution of this research to the literature.

Based on the theoretical framework, this study derives a regression equation. The empirical estimation reveals that RI has insignificant effects on labor share, whereas HI has dominantly positive effect on labor share. Other price factors —wage, robot price, and non-robot capital price— serve as control variables.

This study, while innovative, is subject to certain limitations. The primary concern pertains to the potential endogeneity of price factors. Although RI and HI are instrumented by two shift-share variables, other price factors inherently possess endogeneity issues. It is posited that these endogenous variables are orthogonal to the shift-share instrument, thereby not biasing the coefficients of interest.

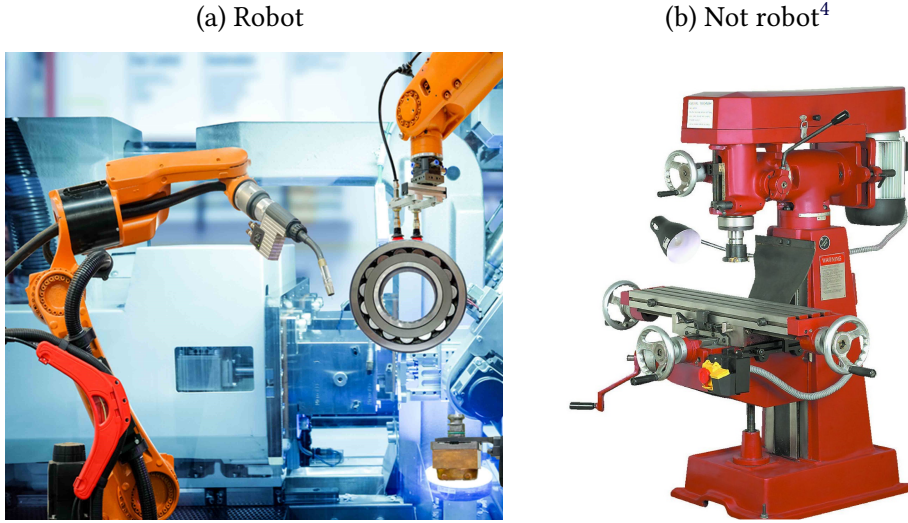
The major contributions of this research to the literature are twofold: First, while Autor et al. (2024) focused solely on the US case, this study examines the EU context. It is well-documented that the economic structures of the US and EU differ significantly. Hence, investigating the EU case is valuable.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

The subsequent sections of this paper are structured as follows: The following section provides key definitions used in this study. Section 3 presents the general equilibrium model, which forms the theoretical foundation of the analysis. Section 4 details the datasets and variables employed in the research. Section 5 shows summary statistics. Section 6 conducts the regression analysis, utilizing the model and data to examine the relationships between various factors and labor share. Section 7 performs accounting analysis to ascertain which mechanism predominantly explains labor share decline across different countries and industries. Finally, Section 8 provides concluding remarks and discusses the implications of the findings.

2 Definitions

This section provides definitions for ‘robot’, ‘robotic innovation (automation)’, and ‘human innovation’ that will be used throughout this paper. This paper adheres to the definition of a robot as specified by ISO standard 8373:2012, which describes it as an “automatically controlled, reprogrammable, multipurpose manipulator programmable

Figure 2: Examples of Robot



in three or more axes.”³ The International Federation of Robotics (IFR) also strictly adheres to this definition (Müller, 2022). This paper source 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.

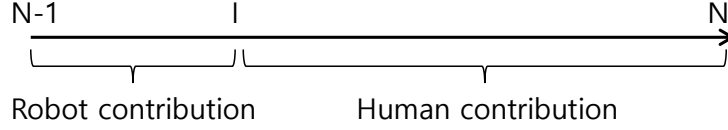
‘Automation’ (or ‘robotic innovation (RI)’ in alternative terminology) is defined as the enhancement of robots’ capabilities, enabling them to perform tasks previously beyond their scope. This paper proposes a definition of ‘human innovations’ (HI) as the expansion of tasks that human workers are expected to perform, specifically those beyond the current capabilities of robots. This concept is illustrated in a model shown in Figure 3.

This paper adopts definitions of RI and HI similar to those in previous studies (Acemoglu and Restrepo, 2018, 2019). In this model, the variable I represents the extent of robotic innovation, while N signifies human innovation. The 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

³Acemoglu 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.”

⁴Vertical milling machine by [harborfreight](#)

Figure 3: Conceptual Diagram



tasks performed by robots and humans form what I 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. I have refined the model based on their static version, with my 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.

This paper’s 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, my 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 my model allows this paper 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 this paper’s model, firms face monopolistic competition, which allows them to generate positive profits. For simplicity, I assume that the production function is the same for all firms⁵. Also, for brevity, I omit the time subscript.

⁵Introducing heterogeneity in terms of Hicks-neutral productivity does not change the analysis.

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 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:

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

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

, 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:

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

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

, 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 this paper focuses on long-run change in labor share, it is reasonable to assume that factors are supplied elastically. For further simplicity, I assume that factors are supplied perfectly elastically at a given factor price at each period.

3.2 Labor Share

Let me move the detailed elaboration of the model to [Appendix A](#). Based on Equations (12) to (19) presented in this appendix, the labor share (S_L) is derived as follows:

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

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

, 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.

This paper transform Equation (5) by applying a natural logarithm and then calculate the total derivative with respect to the external variables of the model (I , N , average wage W , robot price ψ , non-robot capital price R , and labor productivity γ). This process results in Equation (6), which is the key equation I use in the regression analysis.

Let me explain the terms labeled ① to ⑤ in the equation. Readers will notice that ② shows up often in the expressions ③ to ⑦. This term combines two key parameters, ζ and σ , which are the elasticities of substitution. Meanwhile, ① and ④ are direct effects on the labor share, while ② \times ③ and ② \times ⑤ are indirect effects on the labor share. I 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 ③. This change is adjusted by the combination of elasticities, ②. Thus, when I changes, the labor share changes by ② \times ③ indirectly through the P_T channel.

From Equation (6), there are one important point: the sum of ④, ⑤, and ⑥ is zero. This relationship is particularly important for the data analysis, as I will use it in the estimations.

$$\begin{aligned}
d \ln S_L &= \underbrace{[-1]}_{\alpha_1} d \ln \text{Markup} \\
&+ \underbrace{\left[-\frac{\left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj} + \underbrace{\left(- (1-\zeta) + S_K^f(1-\sigma)\right)}_{\text{B}} \underbrace{\frac{1}{1-\zeta} \frac{\psi^{1-\zeta} - \left(\frac{W_I}{\gamma_I}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{C}} \right]}_{\alpha_2} dI \\
&+ \underbrace{\left[\frac{\left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj} + \underbrace{\left(- (1-\zeta) + S_K^f(1-\sigma)\right)}_{\text{B}} \underbrace{\frac{1}{1-\zeta} \frac{-\psi^{1-\zeta} + \left(\frac{W_N}{\gamma_N}\right)^{1-\zeta}}{P_T^{1-\zeta}}}_{\text{E}} \right]}_{\alpha_3} dN \\
&+ \underbrace{\left[(1-\zeta) + \left(- (1-\zeta) + S_K^f(1-\sigma)\right) S_L^T \right]}_{\alpha_4} d \ln W \\
&+ \underbrace{\left[\left(- (1-\zeta) + S_K^f(1-\sigma)\right) S_M^T \right]}_{\alpha_5} d \ln \psi \\
&- \underbrace{\left[S_K^f(1-\sigma) \right]}_{\alpha_6} d \ln R. \\
&- \underbrace{\left[(1-\zeta) + \left(- (1-\zeta) + S_K^f(1-\sigma)\right) S_L^T \right]}_{\alpha_7} d \ln \gamma
\end{aligned} \tag{6}$$

, where S_L represents labor share, I is RI, N is HI, ψ is robot price, R is non-robot capital price, and γ is labor productivity. $W \equiv \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{\int_I^N W_j^{-\zeta} \gamma_j^{\zeta-1} dj}$ 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 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:

$$S_M^T = \frac{(I - N + 1)\psi^{1-\zeta}}{P_T^{1-\zeta}}$$

$$S_L^T = \frac{\int_I^N \left(\frac{W_j}{\gamma_j}\right)^{1-\zeta} dj}{P_T^{1-\zeta}}$$

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

The next section discusses the datasets used in this paper and the construction of the variables.

4 Variable Generation

This section explicates the construction methodology for the explanatory variables. As established in Equation (6), the model-derived explanatory variables include automation (i.e., robotic innovation (RI)), human innovation (HI), labor price, robot price, and non-robot capital price.

First, HI is constructed using cognitive scores derived from O*NET data and the European Union Labor Force Survey (EU-LFS). To address endogeneity concerns in the cognitive score variable, I develop a shift-share instrument using the same cognitive score data. Second, RI is constructed using patent grants that demonstrate high similarity to automation. Given the endogeneity concerns associated with these patent grants, I develop an instrumental variable using a shift-share approach based on patent grants. The detailed construction procedures for all variables are elaborated in the following subsections.

4.1 Human Innovations

To represent changes in human innovation (dN) in the key equation, I employ cognitive scores developed by Jeong and Lee (2025). Their methodology utilizes O*NET data, which contains detailed textual task descriptions for various occupations (National Center for O*NET Development, 2023). They quantify the cognitive intensity of each task description using two Large Language Models (LLMs). A cognitive task involves activities that require mental processes, skills, and abilities. These include perception, thinking, reasoning, memory, learning, decision making, and other aspects of information processing. Examples of cognitive tasks are problem-solving, language

comprehension, attention, and pattern recognition. The researchers instructed the LLMs to evaluate how closely each task description aligns with this cognitive definition, thereby constructing cognitive scores for occupations classified under the detailed six-digit Standard Occupational Classification (SOC) system.

Cognitive score represents a conceptually distinct measure from routine score. A routine task involves activities that are predictable and can be automated, such as those performed by industrial robots on assembly lines or through computerization. This typically involves substituting human labor for routine information processing or repetitive tasks. While routine measures are closely associated with automation and robotics, cognitive scores specifically pertain to human thought processes involved in production.

I merge these occupation-specific cognitive scores with EU-LFS, which collects individual-level data. Subsequently, I aggregate (mean) this data to the country \times sector \times year level. The 5-year growth rate of this aggregated measure serves as the explanatory variable in the regression analysis.

However, this variable is potentially endogenous. To address this concern, I construct a shift-share instrument as follows: After merging the cognitive scores from O*NET with EU-LFS data, I aggregate (mean) the data to the country \times occupation \times year level. Denote this aggregated value as C . I obtain the country \times occupation values for the year 2004, then further aggregate (sum) these values to the country level, which serves as the denominator in the following equation. The share for each country is calculated as:

$$C_{c,o,t=2004} = \frac{C_{c,o,t=2004}}{\sum_{o=1}^O C_{c,o,t=2004}}.$$

For the shift component, after merging cognitive scores from O*NET with US Census data, I aggregate (mean) this data to the occupation \times year level. The shift is calculated as:

$$\text{shift}_{o,t} = \frac{C_{o,t5} - C_{o,t0}}{C_{o,t0}}.$$

Finally, the shift-share instrument is generated as:

$$\text{shiftshare}_{c,t} = \sum_{o=1}^O \text{share}_{c,o,t=2004} \times \text{shift}_{o,t}.$$

It is crucial to note that I calculated the mean rather than the sum of the scores. This approach ensures that the measure reflects the proportion of workers with higher cognitive capabilities, rather than being influenced by the absolute number of workers.

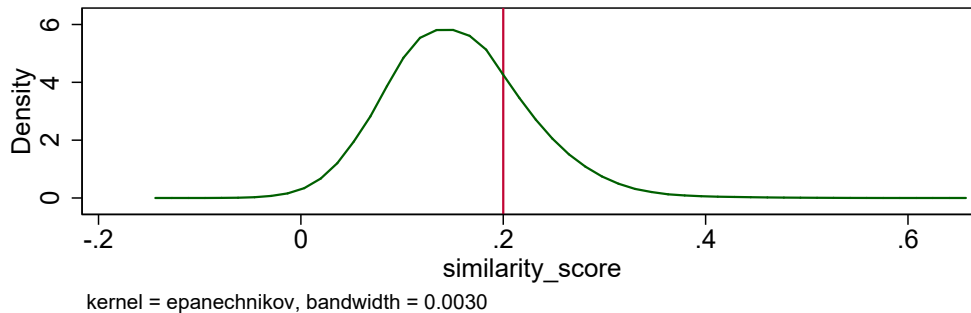
4.2 Robot Innovations

The United States Patent and Trademark Office (USPTO) provides comprehensive granted patents data. I compare each patent description with a curated list of vocabulary closely associated with robotics and automation technologies. The detailed vocabulary list is provided in the footnote.⁶

I analyze the detailed descriptions of all U.S. granted patents from 2004 to 2019, encompassing the entire timeframe of this study. These detailed descriptions provide comprehensive explanations beyond what is available in abstracts, International Patent Classification (IPC), or Cooperative Patent Classification (CPC) information. This methodological approach constitutes one of my contributions, as most existing studies rely exclusively on abstracts, IPC, or CPC information.

By comparing each patent description with these automation-related terms using ‘sentence-transformers/all-mpnet-base-v2’ developed by Microsoft, I derive similarity scores ranging from 0 to 1. I subsequently exclude values below 0.2, which I determined through manual inspection to be irrelevant to automation or robotics. Figure 4 shows the k-density of this similarity score across all patents.

Figure 4: Kdensity of Similarity Score



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, I can infer the actual country of origin for each patent holder. Additionally, I can deduce the industrial sector of the patent. [Lybbert and Zolas \(2014\)](#) provides matching crosswalks between IPC codes and industrial sectors. Consequently, I construct a dataset comprising the patent descriptions, patent holder’s country, corresponding

⁶actuator, 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.

detailed industry in the manufacturing sector, and patent grant year. Subsequently, I aggregate the automation similarity scores by country \times sector \times year. Denote this aggregated value as P .

For the endogenous variable, I exclude patents whose holders are based in the United States, then calculate the 5-year growth rate of this P variable. This measurement incorporates variations across country, sector, and year dimensions, providing a comprehensive analytical framework for examining cross-national patent development patterns.

To address the endogeneity, I develop a shift-share instrument as follows. Let the country wide P , that is, summed across sectors, as P_{tot} . A share is defined as P/P_{tot} in the year 2004 for each sector (s) and country (c), excluding the USA. A shift represents the linear growth rate of P in the USA (the patent holders are from the USA). That is, $shift_{s,t} = (P_{s,t5} - P_{s,t0})/P_{s,t0}$. It exhibits sector and time variation. The shift-share is then constructed as follows:

$$shiftshare_{c,t} = \sum_{s=1}^S share_{c,s,t=2004} \times shift_{s,t}.$$

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, I 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 ‘text-embedding-3-large’ developed by OpenAI. To date, they represent one of the best-performing tools available (Harris et al., 2024).⁷

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). This study contributes to the

⁷While 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).

growing body of research applying advanced natural language processing techniques in economics by utilizing sentence embedding technology to analyzing labor share.

This study employs Microsoft’s ‘sentence-transformers/all-mpnet-base-v2’ to calculate similarity scores between patent descriptions and automation-related vocabulary. For illustrative purposes, I present two contrasting examples: one with a high similarity 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...

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...

4.3 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.⁸ An alternative method to obtain robot prices is by following the approach of Fernandez-Macias et al. (2021),

⁸They noted, “Due to the considerable effort involved and owing to compliance issues, the IFR no longer continues to construct the price indices.”

which involves the use of UN Comtrade data.⁹ I 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.¹⁰

4.4 Capital Price

In Figure 11, provided in Appendix I, I 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 variable is identical to that used by KN. Subsequently, I derive the non-robot capital price variable as detailed in Section 4.5. This non-robot capital price variable is then consistently utilized throughout Sections 6 and 7. Data indicate that the prices of non-robot capital have generally increased over the past 15 years, as illustrated in Figure 11 in Appendix I. This observation might initially appear contradictory to the claims of KN, who reported a rapid global decline in capital prices. However, Figure 11 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 this study’s analysis is more focused, presenting data at the country level for only 9 selected countries.

4.5 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.

⁹<https://comtradeplus.un.org/>

¹⁰The data generation process is as follows: UN Comtrade provides annual import and export values in dollar for ‘Machinery 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, this paper infer the robot prices by dividing the dollar values by their quantities.

For the capital price, gr_Price_K , this study strictly adhere to the approach outlined by Karabarbounis and Neiman (2014). For detailed explanations, please refer to Appendix C. The values for $Cost_K$ is acquired from KLEMS data. For further explanations regarding this, please refer to Appendix D.

$Cost_M$ can be estimated by sector and country through two approaches. The first approach employs the value obtained using the approach introduced in Section 6.3. This approach yields the ratio $\frac{Robot\ Cost}{Labor\ Cost} = 2.813\%$, and labor cost information is available from the KLEMS dataset. Consequently, I can calculate $Cost_M$ based on this information. However, this approach is contingent on labor cost values, raising concerns that the ratio $\frac{Robot\ Cost}{Labor\ Cost} = 2.813\%$ may vary significantly across sectors and countries. Therefore, I propose an alternative approach.

The alternative approach leverages information from the alternative method detailed in Appendix E.1. In this method, I 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 I possess detailed OMach cost data by sector and country, I can subsequently estimate $Cost_M$. This approach circumvents the need for labor cost data. By using this approach, I complete the derivation of the growth rate of non-robot capital price, which will be used in the regression analysis.

4.6 Labor Price

The wage variable is straightforwardly obtained from the KLEMS database.

5 Summary Statistics

This section presents a summary table for the main variables, along with country-level figures for the patent variable (automation similarity score, P) and the cognitive variable (C). As defined in Section 4, the 5-year growth rates of P and C serve as the endogenous variables in the regression analysis.

Table 5 provides a summary of the main variables from both KLEMS and OECD STAN databases. The similarity in values between these sources stems from their utilization of nearly identical underlying national-accounts series, with EU KLEMS explicitly importing and replicating the OECD-STAN series for output, value-added, and employment.

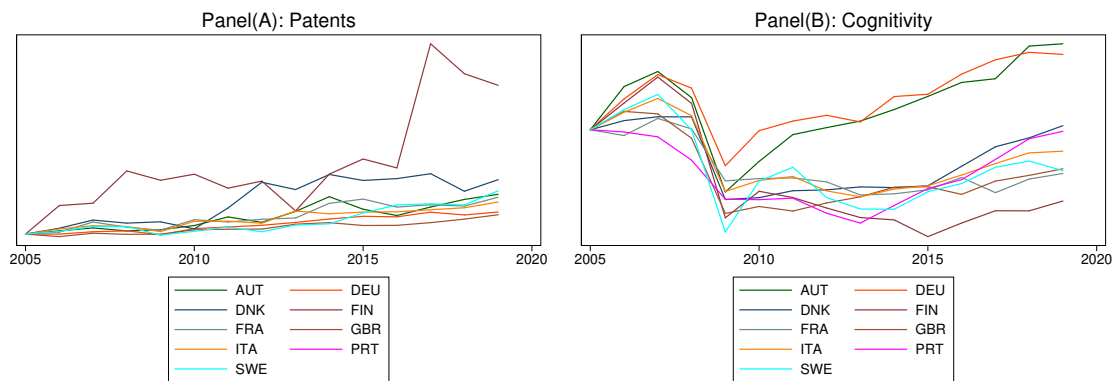
Figure 6 presents two panels of data visualization. Patent measures (P) display substantial increases, particularly pronounced in Finland. The cognitvity measures (C), however, exhibit a significant decline in 2009, followed by a gradual recovery phase. Despite this recovery trajectory, the magnitude of improvement in cognitvity measures remains insufficient to offset the initial decline, resulting in negative 5-year

growth rates across several instances in the dataset. This contrasting pattern between patent and cognitivity metrics suggests differential dynamics in technological innovation versus human cognitive task development.

Figure 5: Summary of KLEMS and OECD

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

Figure 6



6 Regressions

6.1 Regression Equations

Based on the specification in Equation (6) shown in Section 3.2, Equation (7) provide consistent regression equations as below:

$$\begin{aligned} \text{gr_}(\text{laborshare})_{cst} = & \alpha_1 \text{gr_markup}_{cst} + \alpha_2 \text{gr_patent}_{cst} + \alpha_3 \text{gr_cognitive}_{ct} \\ & + \alpha_4 \text{gr_labor price}_{cst} + \alpha_5 \text{gr_robot price}_{cst} \\ & + \alpha_6 \text{gr_non-robot capital price}_{cst} \\ & + \lambda_c + \lambda_s + \lambda_t + \lambda_{cs} + \varepsilon_{cst}. \end{aligned} \quad (7)$$

gr denotes variables expressed as a 5-year growth rate spanning from 2005 to 2019. The subscripts *c*, *s*, and *t* represent country, industry sector, and year respectively.

6.2 Regression Results

Table 1 presents regression results. To improve readability, both the coefficients and standard errors have been multiplied by 100. Upon examination of Equation (6), it is evident that the sum of the coefficients for $d \ln W$, $d \ln \psi$, and $d \ln R$ is equal to zero (i.e., $\alpha_4 + \alpha_5 + \alpha_6 = 0$). Therefore, all columns in Table 1 incorporate this constraint, with *gr_patent* and *gr_cognitive* being instrumented by patent shiftshare and cognitive shiftshare in both Column (2) and (3). For example, in Column (3), the first-stage F statistic is 22.132, substantially exceeding the conventional threshold of 10, which serves as a rule of thumb for instrument relevance. Column (3) specification serves as the baseline model throughout this paper. To address potential serial correlation issues, Column (2) employs standard errors wild bootstrapped 1000 times, whereas Columns (1) and (3) utilize clustering by country and industry.

To mitigate issues arising from serial correlation in panel data, researchers often employ cluster-robust standard errors or bootstrap methods. However, when the number of clusters is small or the within-cluster sample sizes are limited, standard inference techniques may yield unreliable results. In their seminal work, [Cameron et al. \(2008\)](#) advocate for the use of the wild cluster bootstrap method under such circumstances. This approach enhances inference accuracy by accommodating within-cluster correlation and heteroskedasticity, even in scenarios with a limited number of clusters. Their simulation studies demonstrate that the wild cluster bootstrap provides more reliable p-values and confidence intervals compared to conventional methods, thereby offering a robust solution for inference in clustered data settings with potential serial correlation. The wild bootstrap results in Column (2) indicate a p-value of 0.035 with a 95% confidence interval ranging from -0.911 to -0.832.

Table 1: Regressions

	OLS Cluster	IV Wild Bootstrap	IV Cluster
	(1)	(2)	(3)
α_1 : gr_markup	-87.288*** (2.850)	-86.103*** (1.469)	-86.103*** (2.688)
α_2 : gr_patent (RI)	0.012 (0.054)	-1.379** (0.671)	-1.379** (0.698)
α_3 : gr_cognitive (HI)	0.241 (0.286)	0.607 (0.705)	0.607 (0.935)
α_4 : gr_labor price	11.915*** (3.587)	11.940*** (1.559)	11.940*** (3.743)
α_5 : gr_robot price	-1.958* (1.139)	-1.394 (1.147)	-1.394 (1.485)
α_6 : gr_non robot capital price	-9.957*** (3.496)	-10.546*** (1.681)	-10.546*** (3.638)
N	783	783	783
R^2	0.941	0.907	0.907

The coefficients and the standard errors have been multiplied by 100 for better readability. Fixed effects are not reported.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

From Equation (6), it is evident that the regression coefficient for gr_markup should theoretically equal -1 . Consistently, the estimated coefficients approximate -0.86 across all columns, which closely approaches the theoretical value of -1 . This convergence demonstrates the robustness of this paper’s empirical methodology.

Recall that this 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. Robot price and non-robot capital price present fewer endogeneity concerns due to their indirect relationship with labor share. In alignment with this perspective, Karabarbounis and Neiman (2014) similarly employed capital price as a regressor for labor share without instrumental variables. Conversely, labor price poses more significant endogeneity challenges, as it directly correlates with labor share through employment. To address this concern, I implemented the constraint $\alpha_4 + \alpha_5 + \alpha_6 = 0$.

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. To mitigate this, this study uses two instruments.

In the baseline model (Column 3), the coefficient for Robotic Innovation (RI) demonstrates a statistically significant negative effect, whereas Human Innovation (HI) ex-

hibits a positive but statistically insignificant impact. This indicates that robot innovation substantially decreases labor share, while the effect of human innovation lacks statistical robustness.

The significant negative RI coefficient aligns with a task-substitution mechanism: as robotics technologies mature and diffuse, they replace routine and some non-routine labor tasks, reducing income flowing to labor. This coefficient captures the rapid acceleration in industrial robotics after the mid-2000s, reflecting the transition where robots became effective substitutes for human labor.

Importantly, while HI shows a positive association with labor share, it has decreased during the study period (2005~2019). This decline in human innovation, combined with its positive relationship to labor share, contributes to the overall decline in labor share. The declining trend in HI suggests diminishing creation of tasks beyond robotic capabilities, further tilting the balance toward automation and potentially explaining part of the observed labor share decline across the studied economies.

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

6.4 Estimation of σ and ζ

By utilizing Equation (6) along with the regression results, σ and ζ can be estimated. 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.

The literature on the elasticity of substitution between labor and ‘overall’ capital is extensive. However, relatively less attention has been given to ζ , which is the elasticity of substitution between tasks in the model but can also be interpreted as the elasticity of substitution between human workers and robots at an aggregate level.¹¹

¹¹In Acemoglu and Restrepo (2019), the model does not distinguish between robot and non-robot

Furthermore, to my knowledge, no previous studies have attempted to estimate both the elasticity of substitution between labor and non-robot capital and between labor and robot capital within a single framework. One contribution of this section is to provide such estimates.

Detailed methodology for estimating these two elasticities, σ and ζ , is provided in Appendix F. First, I calculate $\sigma = 0.539$, with a 95% confidence interval for σ of $(0.284, 0.795)$. σ differs from the elasticity of substitution between labor and non-robot-capital, but as mentioned, σ serves as a close proxy of this elasticity. In Appendix G, I provide a formal estimation of the elasticity of substitution between labor and non-robot capital using the estimation of σ . This definition closely aligns with the definitions used by Karabarbounis and Neiman (2014) and Glover and Short (2020), and my estimate ranges between 0.539 and 0.667. Thus, this result contributes to literature by providing additional empirical evidence that the elasticity of substitution between labor and non-robot capital is less than one, indicating a gross complementary relationship between the two. This is supported by most literature, as suggested by Chirinko (2008), Grossman and Oberfield (2022), and Glover and Short (2020).

I also estimate $\zeta = 0.736$, with a 95% confidence interval ranging from -0.200 to 1.673. This estimate is somewhat lower than the findings of DeCanio (2016), who reported a ζ value of approximately 1.9. Given that the confidence interval spans values both above and below unity, it remains statistically ambiguous whether ζ exceeds or falls short of one. Consequently, for subsequent analyses, I adopt the working assumption that ζ approximates unity.

Lastly, I estimate the term $-(1 - \zeta) + S_K^f(1 - \sigma)$, which is determined by the values of ζ and σ . This expression appears frequently in Equation (6) and plays a crucial role in understanding how price factors influence labor share. The point estimate is -0.155, with a 95% confidence interval spanning from -1.094 to 0.783. Since this confidence interval encompasses both negative and positive values, it remains statistically indeterminate whether this term is positive or negative. Consequently, for subsequent analyses, I proceed with the assumption that this term approximates zero.

6.5 Direct and Indirect Effects

As previously noted, the coefficient for Robotic Innovation (RI) demonstrates a significant negative effect, whereas Human Innovation (HI) lacks statistical significance. We can comprehend this result through the conceptual framework of direct and indirect effects: effects that do not route through P_T are defined as the direct effects, are classified as direct effects, while those that operate via P_T are categorized as indirect effects. This

capital, using only overall capital. Consequently, their measure of the elasticity of substitution between tasks is interpreted as the elasticity between human workers and overall capital at an aggregate level.

conceptual distinction was elaborated in Section 3. In Equation (6), ① and ② are direct effects. In contrast, ③×④ and ③×⑤ are indirect effects.

Crucially, ③, $-(1 - \zeta) + S_K^f(1 - \sigma)$, is statistically indistinguishable from zero. Consequently, both indirect effects become statistically insignificant. It is noteworthy that ④ is negative under Assumption 1, regardless of the sign of ζ . This indicates that the price of the aggregated task, denoted by P_T , falls when robots take over tasks previously performed by humans. This change in P_T is then scaled by the factor $-(1 - \zeta) + S_K^f(1 - \sigma)$, which represents the partial derivative of labor share with respect to the aggregated task price. Therefore, the sign of the indirect effect on labor share hinges critically on the sign of $-(1 - \zeta) + S_K^f(1 - \sigma)$, which I have estimated to be zero. Given that the indirect effect for RI (automation) is insignificant and the overall effect of RI is negatively significant, I can surmise that the term ① must be significantly negative.

The following subsections address the less critical topics of price determinant decomposition and elasticity of substitution. I classify these as secondary considerations primarily due to the endogeneity challenges inherent in the price factors.

6.6 Effects of Price Factors on Labor Share

6.6.1 Labor Price

The regression findings provide important insights into the relationship between factor prices and labor share. This paper’s 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 the 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

$\alpha_4 > 0$ is fundamentally $\sigma < 1$, from a technical perspective.

$$\begin{aligned}
\alpha_4 &= (1 - \zeta) + \left(-(1 - \zeta) + S_K^f(1 - \sigma) \right) S_L^T \\
&= (1 - \zeta)(1 - S_L^T) + S_K^f(1 - \sigma)S_L^T \\
&= (1 - \zeta)(S_M^T) + S_K^f(1 - \sigma)S_L^T \\
&= 0.007 + S_K^f(1 - \sigma)S_L^T \\
&\approx S_K^f(1 - \sigma)S_L^T = 0.105 > 0.
\end{aligned}$$

6.6.2 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 $\alpha_6 < 0$ is essentially that $\sigma < 1$.

$$\alpha_6 = - \left[S_K^f(1 - \sigma) \right] < 0 \quad (8)$$

6.6.3 Robot Price

Meanwhile, the regression results indicate a statistically insignificant association between robot price and labor share. This lack of significance primarily stems from the condition $-(1 - \zeta) + S_K^f(1 - \sigma) \approx 0$, as demonstrated in Section 6.4.

$$\alpha_4 = \left(-(1 - \zeta) + S_K^f(1 - \sigma) \right) S_M^T \approx 0 \quad (9)$$

This finding suggests that changes in robot prices exert minimal influence on labor share. Looking forward, I anticipate that the share of robot costs in production (S_M^T) will increase. Nevertheless, the coefficient for robot price is unlikely to gain significance since $-(1 - \zeta) + S_K^f(1 - \sigma)$ approximates zero. Consequently, even in future scenarios, labor share will likely remain largely unaffected by robot prices. This finding contrasts with the conclusion that robotic innovation (quality improvement) negatively affects labor share. It is essential to distinguish between these two distinct effects: quality improvement and price reduction. The former relates to technological advancement in robotic capabilities, while the latter concerns the economic accessibility of existing technology.

7 Accounting

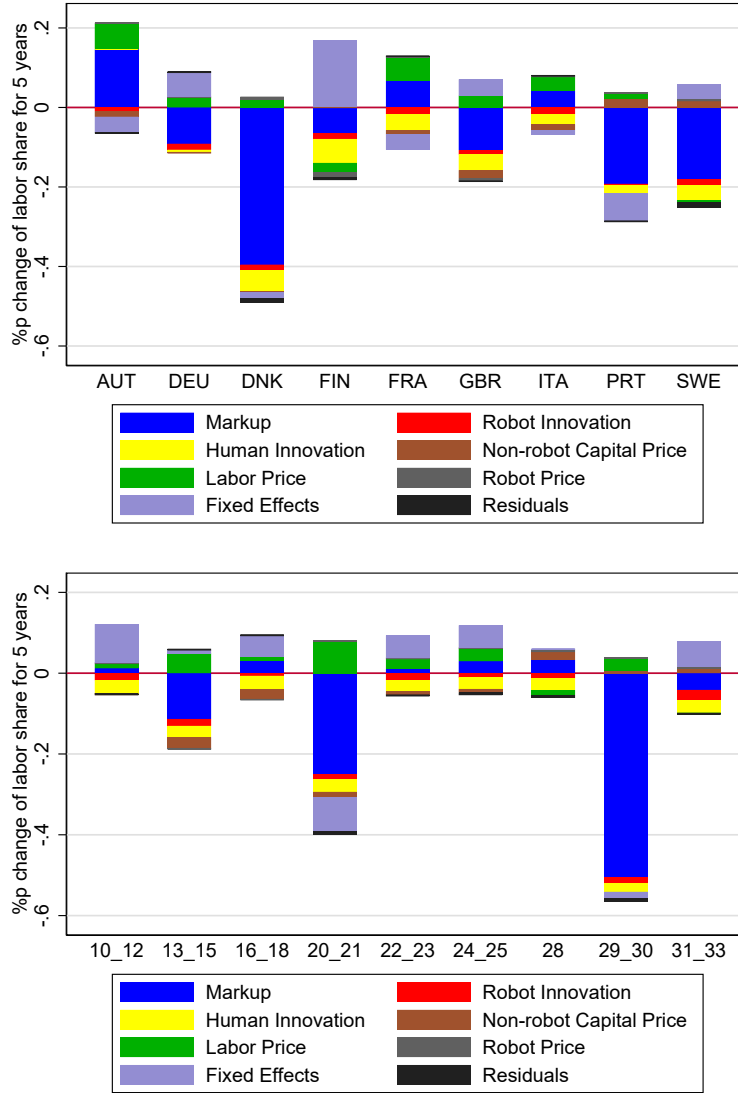
This study examines the factors influencing labor share, focusing on automation (robotic innovation, RI) and human innovation (HI). The analysis reveals that while automation has a significant impact on labor share, human innovation exerts a negligible positive impact. Section 5 demonstrated that human innovation stagnated between 2000 and 2020. Consequently, this stagnation contributed to the observed decline in labor share. In contrast, robot innovation has rapidly evolved, with significant impact. Thus, this robotic innovation will negatively affect labor share. This key finding constitutes the core contribution of this paper. This section elaborates on the direction and magnitude of RI and HI effects on labor share, providing comprehensive empirical support for these conclusions.

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

According to Figure 7, markup emerges as the predominant factor affecting labor share. This is natural, as my model already anticipated a fixed -1 relationship to labor share. Moreover, markup dominantly increased in recent years. The influence of markups varies across countries; Denmark, for instance, demonstrates positive markup growth, consequently producing a negative effect on labor share growth. Conversely, almost all countries exhibit negative effects of RI on labor share, which contributes to the overall decline in labor share. The impact of HI on labor share also appears non-negligible. Labor price consistently shows positive growth, thus generating a positive contribution to labor share. Contrary to the assertion by Karabarbounis and Neiman (2014) that recent labor share decline can be primarily attributed to falling capital prices, this paper's analysis indicates that capital price exerts only a marginal influence on labor share dynamics.

The second panel of Figure 7 compares labor share responses across manufacturing branches. Markups are associated with the steepest labor-share declines in divisions 20–21 (Chemicals and pharmaceutical products) and 29–30 (Motor-vehicle and other transport-equipment manufacturing). These results imply that firms in the chemical and automotive clusters capture a disproportionately large share of value added as extra profits rather than wages.

Figure 7: Accounting



8 Concluding Remarks

This study 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. The primary research question addressed how RI and HI influence labor share across different EU countries and sectors. By integrating both RI and HI into the model and addressing endogeneity concerns through the use of shift-share instrumental variables, this study has provided empirical evidence on how

these factors influence labor share across countries and sectors.

This study's empirical analysis reveals that robotic innovation exhibits a statistically significant negative effect on labor share, while human innovation shows a positive but statistically insignificant impact. These findings substantiate the hypothesis that automation can supplant labor in production processes through task substitution.

The significant negative coefficient for RI reflects the accelerated diffusion of industrial robotics technologies post-2005, when automated systems became increasingly effective substitutes for human labor. This technological transition has redirected income flows away from labor toward capital, contributing to the observed decline in labor share.

Notably, while HI demonstrates a positive association with labor share, the data indicate that human innovation has experienced a decline during the 2005-2019 study period. This diminishment in tasks beyond robotic capabilities, combined with its positive relationship to labor share, provides a compelling explanation for the observed labor share decline across the studied economies.

This research contributes to the existing literature in two significant ways. First, while previous studies such as [Autor et al. \(2024\)](#) focused solely on the US context, this study examines the EU setting. Given the well-documented differences in economic structures between the US and EU, investigating the EU case provides valuable insights. Second, the use of novel instruments for automation and human innovation distinguishes this study from prior research.

While this study provides significant insights, it is important to acknowledge its limitations. Primarily, I recognize that the price factors in the model are not exogenous. This endogeneity could potentially introduce biases if these endogenous covariates are strongly correlated with the two shift-share instruments. 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 the findings. Such regional specificity necessitates caution when extrapolating these results to economies outside the studied European framework.

Future research avenues could include extending the 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.

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:

$$U = \left(\int_0^1 Y(i)^{\frac{\eta-1}{\eta}} di \right)^{\frac{\eta}{\eta-1}} \quad (10)$$

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

The representative consumer's budget constraint is as follows:

$$\int_0^1 P(i)Y(i)di = \int_0^1 \left(\int_{N-1}^N W_j l_j(i) dj + \int_{N-1}^N \psi m_j(i) dj + RK_i + \Pi_i \right) di \quad (11)$$

, 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. This paper sets an assumption related to robot and labor productivity for simple algebra in deriving the equilibrium in the model.

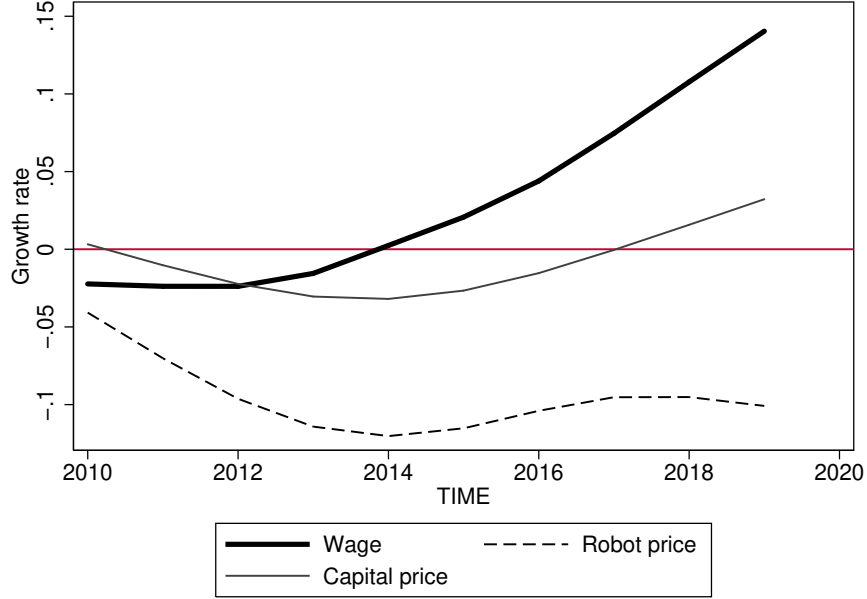
Assumption 1. $\psi < \frac{W_I}{\gamma_I}$

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 8 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:

$$l_j(i) = 0, \text{ if } j \leq I \quad (12)$$

Figure 8: Prices in a 5-year growth rate



$$l_j(i) = \gamma_j^{\zeta-1} \left(\frac{W_j}{P_T} \right)^{-\zeta} T(i), \text{ if } j > I \quad (13)$$

$$m_j(i) = \left(\frac{\psi}{P_T} \right)^{-\zeta} T(i), \text{ if } j \leq I \quad (14)$$

$$m_j(i) = 0, \text{ if } j > I \quad (15)$$

$$T(i) = \left(\frac{P_T}{MC(i)} \right)^{-\sigma} Y(i) \quad (16)$$

$$K(i) = \left(\frac{R}{MC(i)} \right)^{-\sigma} Y(i) \quad (17)$$

$$P_T = \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{W_j}{\gamma_j} \right)^{1-\zeta} dj \right]^{\frac{1}{1-\zeta}} \quad (18)$$

$$MC(i) = [P_T^{1-\sigma} + R^{1-\sigma}]^{\frac{1}{1-\sigma}} \quad (19)$$

$$W_j l_j(i) = \left(\frac{W_j}{\gamma_j} \right)^{1-\zeta} \cdot P_T^\zeta \cdot T_i \quad (20)$$

, 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 (21):

$$U = \left(\int_0^1 Y(k)^{\frac{\eta-1}{\eta}} dk \right)^{\frac{\eta}{\eta-1}}. \quad (21)$$

There are infinite number of identical firms i with production functions in Equation (24) and (25):

$$t_j(i) = m_j(i) + \gamma_j l_j(i) \text{ if } j \leq I \quad (22)$$

$$t_j(i) = \gamma_j l_j(i) \text{ if } j > I \quad (23)$$

$$T(i) = \left(\int_{N-1}^N t_j(i)^{\frac{\zeta-1}{\zeta}} dj \right)^{\frac{\zeta}{\zeta-1}} \quad (24)$$

$$Y(i) = \left(T(i)^{\frac{\sigma-1}{\sigma}} + K(i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \quad (25)$$

By Assumption 1, Equation (22) simplifies to Equation (26). 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.

$$t_j(i) = m_j(i) \text{ if } j \leq I \quad (26)$$

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

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

$$\min \text{cost}(i) \text{ for } T(i) \text{ s.t. Equation(26), (23), and (24)}$$

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

\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 :

$$\Rightarrow P_T = \left[(I - N + 1)\psi^{1-\zeta} + \int_I^N \left(\frac{w_j}{\gamma_j} \right)^{1-\zeta} dj \right]^{\frac{1}{1-\zeta}} \quad (27)$$

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

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

$$\begin{aligned}
& \min \text{cost}(i) \text{ for } Y(i) \text{ s.t. Equation(25)} \\
& \Leftrightarrow \min P_T \cdot T(i) + R \cdot K(i) \text{ s.t. Equation(25)} \\
& \Rightarrow \text{This finds optimal inputs for } T(i)^* \text{ and } K(i)^* \text{ to produce } Y(i) \\
& \Rightarrow \text{Specifically, the minimization solution is the minimum cost for producing } Y(i) \\
& \Rightarrow \begin{cases} T(i)^* = Y(i)P_T^{-\sigma} \\ K(i)^* = Y(i)R^{-\sigma} \\ \text{Cost for } Y(i) = Y(i) [P_T^{1-\sigma} + R^{1-\sigma}]^{\frac{1}{1-\sigma}} \\ \quad = Y(i) \times \text{AC} \\ \quad = Y(i) \end{cases}
\end{aligned}$$

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

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

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

$$\begin{aligned}
& \min \text{cost for consumption s.t. Equation(21)} \\
& \Leftrightarrow \min \int_0^1 P(i)Y(i)di \text{ s.t. Equation(21)} \\
& \Rightarrow \text{Specifically, this yields a demand function for } Y(i) \\
& \Leftrightarrow Y(i) = \left(\frac{P(i)}{\mathbb{P}} \right)^{-\eta}, \text{ where } \mathbb{P} \equiv \left[\int_0^1 P(i)^{1-\eta} di \right]^{\frac{1}{1-\eta}}
\end{aligned}$$

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 $T(i)$.

$$\begin{aligned} l_j(i)^* &= \left(\frac{W_j(i)}{\gamma_j P_T} \right)^{-\zeta} \gamma_j^{-1} T(i) \\ \Rightarrow W_j(i) l_j(i)^* &= \left(\frac{W_j(i)}{\gamma_j} \right)^{1-\zeta} P_T^\zeta T(i) \end{aligned} \quad (28)$$

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.

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

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 .

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

C Appendix: Capital Price

In this paper, I utilize the replicated values for capital price from [Karabarbounis and Neiman \(2014\)](#) (hereinafter KN). To calculate this, the investment price is initially required, which the KLEMS data provides, including industry variations.

It's important to note that I don't directly observe the capital price, which represents the *usage* cost of one unit of capital. I 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 \(1963\)](#), I can calculate the capital price as follows:

$$R_t = \xi_{t-1}(1 + i_t) - \xi_t(1 - \delta_t) \quad (29)$$

$$R_t = \xi_t \left(\frac{1}{\beta} - 1 + \delta \right) \quad (30)$$

In this Equation (29), 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 (29) into the form presented in Equation (30), [Karabarbounis and Neiman \(2014\)](#) follows a specific process. This involves the assumption of a constant interest rate, i , and approximating $1 + i$ as $\frac{1}{\beta}$. Equation (30), 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, I strictly adhere to the approach by KN.¹²

D Appendix: KLEMS Data and Capital Cost

D.1 KLEMS Data

Aside from the IFR dataset, the O*NET dataset, and Robot Price, I will use data from KLEMS.¹³ 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 my analysis, I use the national accounts when using KLEMS.

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, I could deduce the other because Value-added is calculated as $WL + RK + \text{Profit}$. 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

¹²It 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, my 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 my analysis, as I focus on the growth rate of the capital price, which effectively cancels out the impact of β .

¹³KLEMS: EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs.

cost, not the rental cost. To convert the purchase cost into rental cost, the real interest rate and depreciation rate as shown in Equation (29) are required. Notably, the depreciation rate requires numerous assumptions, and I 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, I 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 my analysis, I 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 10 in Appendix I). 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, I assume that the markups in KLEMS and STAN are identical, denoted by $\frac{\text{Value-added}}{WL+RK}$. Based on this assumption, I can recover RK for KLEMS as below:

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

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_5 , with the term $S_M^T = 2.81\%$ included, which I estimated in Section 6.3. 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.

$$\alpha_5 = \left(-(1 - \zeta) + S_K^f(1 - \sigma) \right) S_M^T$$

E Appendix: Estimation of 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 . This paper supplements 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 costs¹⁴, 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, I have accounted for this information accordingly.

E.1 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 I 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,¹⁵ and separately calculating the total export values of HS Code 8479 (which pertains to robots),¹⁶ I 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%.¹⁷

¹⁴33.04% = 35.73% × (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. \(2021\)](#).

¹⁵HS Classification 84 excluding 8401, 8402, 8403, 8404, 8405, 8429, 8440, 8443, 8470, 8471, and 8472.

¹⁶Machinery and mechanical appliances; having individual functions, n.e.c. in this chapter.

¹⁷2.104% = $\frac{2.149}{2.149+100}$

F Appendix: Estimation of σ and ζ

Given that $S_K^f > 0$ and the coefficient for $d \ln R$ is negative, I can infer that $\sigma < 1$. Further, by substituting the value $S_K^f = 0.235$ that I obtained from the data, I calculate $\sigma = 0.539$, as illustrated in Equation (31). I conduct a Wald test on the null hypothesis that $\sigma = 0$ and find that it can be rejected at the 0.05 significance level. The confidence interval for σ is (0.284, 0.795). Consequently, I can conclude with confidence that σ lies within the range of 0 to 1.

$$\begin{aligned} - \underbrace{S_K^f}_{0.235} (1 - \sigma) &= \underbrace{\alpha_6}_{-0.10546} \\ \Rightarrow \sigma &= 1 + \frac{\alpha_6}{S_K^f} \end{aligned} \quad \text{(Sigma)}$$

The derivation of the value for ζ proceeds as follows. From Equation (6), utilizing coefficients α_4 and α_6 , we can arrive at Equation (Zeta).

$$\zeta = 1 - \frac{\alpha_3 + \alpha_5 S_L^T}{1 - S_L^T} \quad \text{(Zeta)}$$

As demonstrated earlier in Section 6.3, I estimate S_L^T to be 0.972. Upon substituting $S_L^T = 0.972$ into Equation (Zeta), I obtain an estimate for ζ of 0.736. I then conduct a Wald test at the 0.05 significance level. Specifically, the confidence interval is from -0.200 to 1.673. Consequently, I can conclude with confidence that ζ lies within the range of this interval.

G Appendix: Estimation of the Elasticity of Substitution between Labor and Non-robot Capital

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

Hence, in this subsection, I introduce the elasticity of substitution between labor and non-robot capital, denoted by μ , a measure that closely aligns with the findings of

both KN and Glover and Short (2020). The solution for μ is given in Equation (32), and its derivation can be found in Appendix H.

$$\begin{aligned} \mu &\equiv \frac{d\left(\frac{L}{K}\right) \frac{R}{W}}{d\left(\frac{R}{W}\right) \frac{L}{K}}, \text{ where} \\ d\left(\frac{L}{K}\right) &= \left(\frac{W_1}{R_1}\right)^{-\sigma} \left[\frac{S_M^T}{1 - S_M^T} \left(\frac{W_0}{W_1}\right)^{1-\zeta} + 1 \right]^{\frac{\zeta-\sigma}{1-\zeta}} - \left(\frac{W_0}{R_0}\right)^{-\sigma} \left[\frac{S_M^T}{1 - S_M^T} + 1 \right]^{\frac{\zeta-\sigma}{1-\zeta}} \\ \frac{L}{K} &= \left(\frac{W_0}{R_0}\right)^{-\sigma} \left[\frac{S_M^T}{1 - S_M^T} + 1 \right]^{\frac{\zeta-\sigma}{1-\zeta}} \\ \Rightarrow \mu &= \sigma \text{ if } S_M^T = 0. \end{aligned} \tag{32}$$

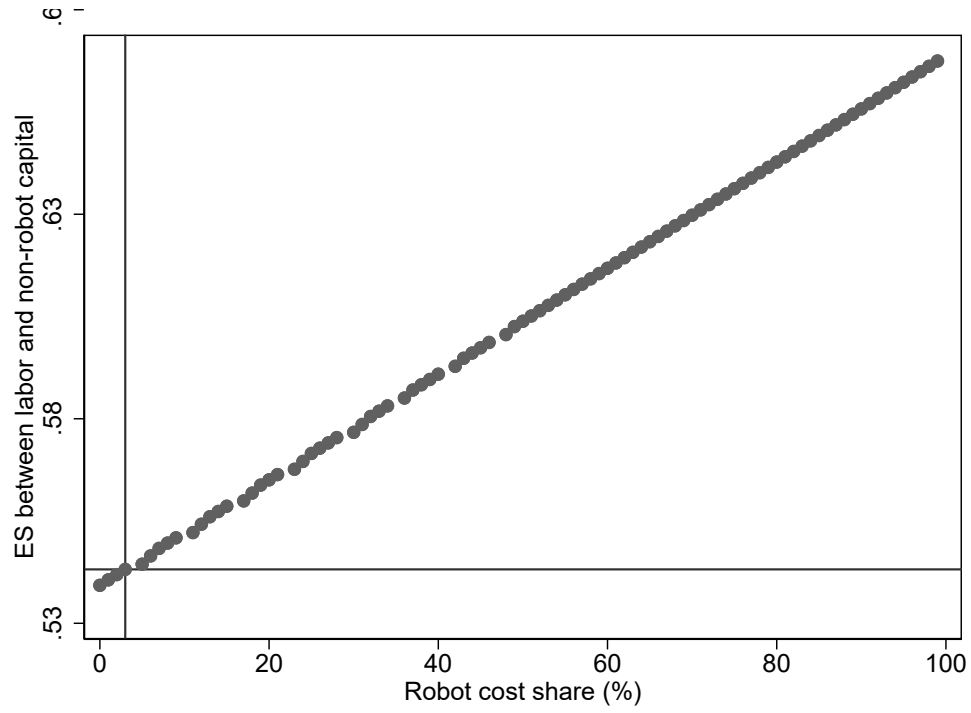
Differentiating Equation (32) is infeasible. However, we can employ numerical approximation to estimate μ . I use actual W and R values from the dataset (all possible combinations of these), along with $\sigma = 0.539$. I introduce small random variations to each W and R and consider scenarios where $|\Delta \frac{R}{W}|$ is approximately 0.01. These values are then plugged into Equation (32) to obtain an approximated μ .

Panel (a) of Figure 9 displays the approximation results. When S_M^T is zero, I find that $\mu = \sigma = 0.539$. This stage indicates a complete absence of robot tasks, with all tasks being performed by labor. When $S_M^T = 2.813\%$, which corresponds to my estimate presented in Section 6.3, I obtain $\mu = 0.543$. Even when I assume $S_M^T = 100\%$, $\mu = 0.667$ does not exceed one. Consequently, I argue that in the context of the KN model, the elasticity of substitution between labor and non-robot capital closely approximates σ . The analysis suggests that μ ranges between 0.539 and 0.667, supporting the idea of a gross complementary relationship between the two. In the future, as automated robots assume a greater share of tasks, the elasticity of substitution between labor and non-robot capital may gradually approach one. However, my analysis indicates that even with complete task automation (i.e., when the robot share approaches 100%), the elasticity remains below unity. This finding reinforces the persistent complementary relationship between labor and non-robot capital, suggesting that the gross complementarity between these factors may be a fundamental characteristic of production structures rather than merely a transient phenomenon of current technological capabilities.

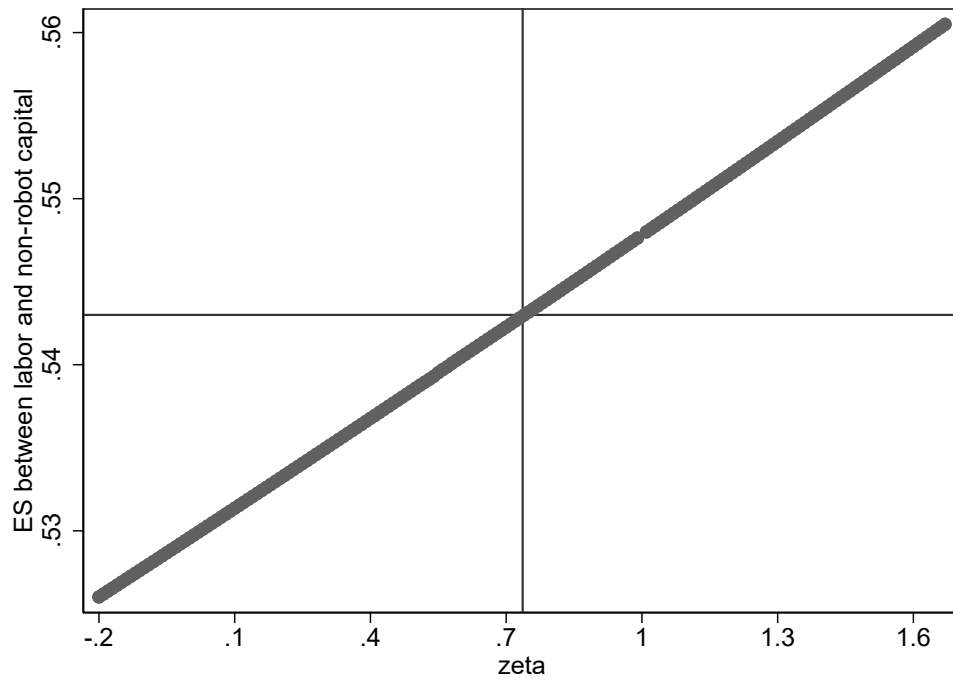
The above estimation of μ is contingent upon the value of $\zeta = 0.736$, which is my point estimate as derived in Section 6.4. However, the confidence interval for ζ varies: it spans from -0.200 to 1.673. To demonstrate the robustness of the μ estimate, I examine its sensitivity across a wide range of ζ values. This analysis is presented in Panel (b) of Figure 9. Within the ζ range of -0.200 to 1.673, μ varies between 0.526 and 0.560, confirming the robustness of the previous μ estimation.

Figure 9: Elasticity of Substitution between Labor and Non-robot Capital

(a) Fixing ζ to be 0.736; Moving S_M^T



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



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

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

In contrast, [Glover and Short \(2020\)](#) reached a different conclusion, that of gross complements, by using cross-country variation with instrumental variables. They argue that correcting for bias is critical when estimating the correlation between the capital price and labor share. My study supports [Glover and Short \(2020\)](#).

H Appendix: Derivation of μ

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

$$\mu \equiv \frac{d\left(\frac{L}{K}\right) \frac{R}{W}}{d\left(\frac{R}{W}\right) \frac{L}{K}}. \quad (33)$$

To proceed, I must express L and K in terms of W and R , respectively. Equation (28), derived in Appendix B.6, provides the formulation for L as follows:

$$\begin{aligned} l_j(i)^* &= \left(\frac{W_j(i)}{\gamma_j P_T} \right)^{-\zeta} \gamma_j^{-1} T(i) \\ \Rightarrow L &= \int_I^N l_j(i)^* dj \\ &= \int_I^N \left(\frac{W_j(i)}{\gamma_j P_T} \right)^{-\zeta} \gamma_j^{-1} T(i) dj. \end{aligned} \quad (34)$$

I introduce a parameter β_j to serve as a weight for the wage distribution corresponding to each worker, indexed by j . Utilizing β_j enables me to establish a representative

measure for wages, \mathbb{W} .

$$W_j \equiv \beta_j \mathbb{W} \quad (35)$$

Consequently, Equation (34) can be restructured to yield Equation (36). To streamline the notation, I define $A = \int_I^N \gamma_j^{\zeta-1} \beta_j^{-\zeta} dj$.

$$L = \int_I^N \gamma_j^{\zeta-1} \beta_j^{-\zeta} dj \cdot T(i) \left(\frac{\mathbb{W}}{P_T} \right)^{-\zeta} \quad (36)$$

$$= A \cdot T(i) \left(\frac{\mathbb{W}}{P_T} \right)^{-\zeta} \quad (37)$$

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

$$T(i) = Y(i) P_T^{-\sigma}$$

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

By substituting $T(i)$ and P_T into Equation (37),

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

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

$$(I - N + 1) \psi^{1-\zeta} \equiv S_M^T$$

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

Therefore, L can be reformulated as follows:

$$\begin{aligned} L &= A \cdot Y(i) \left[S_M^T + S_L^T \right]^{\frac{\zeta-\sigma}{1-\zeta}} \mathbb{W}^{-\zeta} \\ &= A \cdot Y(i) \left[\frac{S_M^T}{S_L^T} + 1 \right]^{\frac{\zeta-\sigma}{1-\zeta}} \mathbb{W}^{-\zeta} \end{aligned} \quad (38)$$

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

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

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

$$\frac{d(\frac{L}{K})}{\frac{L}{K}} = \frac{\left(\frac{W_1}{R_1}\right)^{-\sigma} \left[\frac{S_M^T}{1 - S_M^T} \left(\frac{W_0}{W_1}\right)^{1 - \zeta} + 1 \right]^{\frac{\zeta - \sigma}{1 - \zeta}} - \left(\frac{W_0}{R_0}\right)^{-\sigma} \left[\frac{S_M^T}{1 - S_M^T} + 1 \right]^{\frac{\zeta - \sigma}{1 - \zeta}}}{\left(\frac{W_0}{R_0}\right)^{-\sigma} \left[\frac{S_M^T}{1 - S_M^T} + 1 \right]^{\frac{\zeta - \sigma}{1 - \zeta}}}$$

I Appendix: Tables and Figures

Figure 10: Values by Country, Sector, and Year

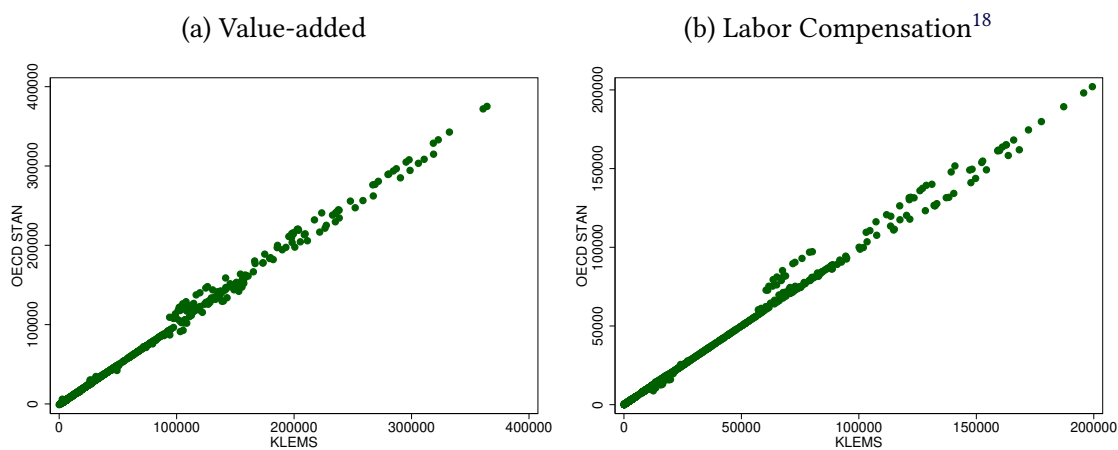
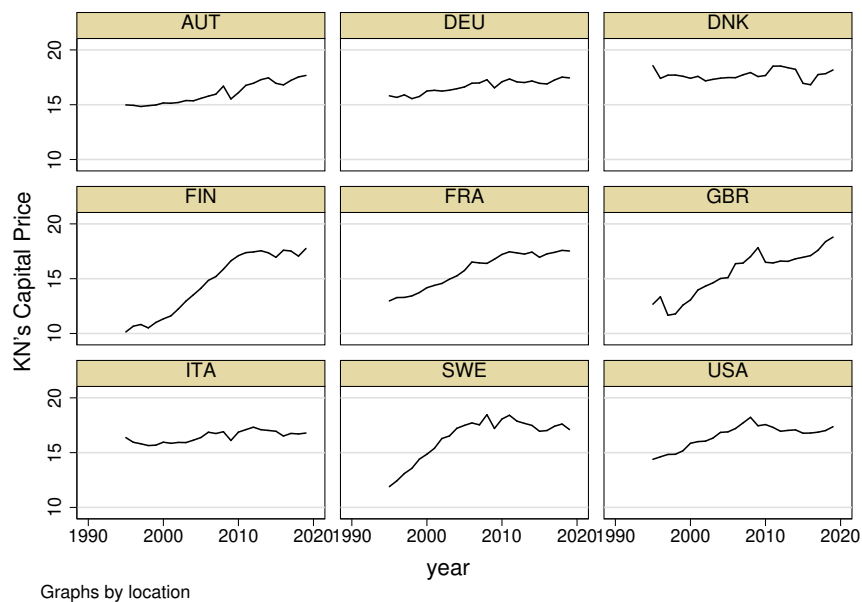


Figure 11: KN's Capital Prices



References

- Acemoglu, D., C. Lelarge, and P. Restrepo (2020). Competing with robots: Firm-level evidence from France. In *AEA Papers and Proceedings*, Volume 110, pp. 383–388. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.
- Acemoglu, D. and P. Restrepo (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American economic review* 108(6), 1488–1542.
- Acemoglu, D. and P. Restrepo (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives* 33(2), 3–30.
- Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128(6), 2188–2244.
- Acemoglu, D. and P. Restrepo (2022). Tasks, automation, and the rise in US wage inequality. *Econometrica* 90(5), 1973–2016.
- Angrist, J. D. and J. S. Pischke (2008). *Mostly Harmless Econometrics: An Empiricist’s Companion*.
- Autor, D., C. Chin, A. Salomons, and B. Seegmiller (2024). New frontiers: The origins and content of new work, 1940–2018. *The Quarterly Journal of Economics*, qjae008.
- Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics* 135(2), 645–709.
- Autor, D. H. (2015, June). Why are there still so many jobs? the history and future of workplace automation. In *Journal of Economic Perspectives*, Volume 29, pp. 3–30. American Economic Association.
- Baer, M. F. and R. S. Purves (2023, March). Identifying Landscape Relevant Natural Language using Actively Crowdsourced Landscape Descriptions and Sentence-Transformers. *KI - Künstliche Intelligenz* 37(1), 55–67.
- Berg, A., E. F. Buffie, and L.-F. Zanna (2018). Should we fear the robot revolution?(The correct answer is yes). *Journal of Monetary Economics* 97, 117–148.
- Bergholt, D., F. Furlanetto, and N. Maffei-Faccioli (2022). The decline of the labor share: New empirical evidence. *American Economic Journal: Macroeconomics* 14(3), 163–98.
- Cameron, A. C., J. B. Gelbach, and D. L. Miller (2008). Bootstrap-based improvements for inference with clustered errors. *The review of economics and statistics* 90(3), 414–427.
- Chirinko, R. S. (2008). σ : The long and short of it. *Journal of Macroeconomics* 30(2), 671–686.
- Dauth, W., S. Findeisen, J. Suedekum, and N. Woessner (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association* 19(6), 3104–3153.
- De Vries, G. J., E. Gentile, S. Miroudot, and K. M. Wacker (2020). The rise of robots and the fall of routine jobs. *Labour Economics* 66, 101885.
- DeCanio, S. J. (2016). Robots and humans—complements or substitutes? *Journal of Macroeconomics* 49, 280–291.

- Elon, M. (2024). Tesla will have genuinely useful humanoid robots in low production for Tesla internal use next year and, hopefully, high production for other companies in 2026.
- Fernandez-Macias, E., D. Klenert, and J.-I. Anton (2021). Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe. *Structural Change and Economic Dynamics* 58, 76–89.
- Frugoli, P. and ESCO (2022). The crosswalk between ESCO and O*NET (Technical Report).
- Glover, A. and J. Short (2020). Can capital deepening explain the global decline in labor’s share? *Review of Economic Dynamics* 35, 35–53.
- Gouma, R. and M. Timmer (2013). World KLEMS Growth and Productivity Accounts Japan: Sources and notes. *Groningen Growth and Development Centre* 8.
- Graetz, G. and G. Michaels (2018). Robots at work. *Review of Economics and Statistics* 100(5), 753–768.
- Gregory, T., A. Salomons, and U. Zierahn (2016). Racing with or against the machine? Evidence from Europe. *Evidence from Europe (July 15, 2016)*. ZEW-Centre for European Economic Research Discussion Paper (16-053).
- Grossman, G. M. and E. Oberfield (2022). The elusive explanation for the declining labor share. *Annual Review of Economics* 14, 93–124.
- Gutiérrez, G. and S. Piton (2020). Revisiting the global decline of the (non-housing) labor share. *American Economic Review: Insights* 2(3), 321–338.
- Harris, N., A. Butani, and S. Hashmy (2024, April). Enhancing Embedding Performance through Large Language Model-based Text Enrichment and Rewriting.
- Hubmer, J. and P. Restrepo (2021). Not a typical firm: The joint dynamics of firms, labor shares, and capital–labor substitution. Technical report, National Bureau of Economic Research.
- Humlum, A. (2019). Robot adoption and labor market dynamics. *Princeton University*.
- Jeong, D. and T. Lee (2025). Measuring Routine and Cognitive Task Indices Using Large Language Models to Analyze Occupational Change in the United States. *Labour Economics (under review)*.
- Jorgenson, D. W. (1963). Capital theory and investment behavior. *The American Economic Review* 53(2), 247–259.
- Jurkat, A., R. Klump, and F. Schneider (2022). Tracking the Rise of Robots: The IFR Database. 242(5-6), 669–689.
- Karabarbounis, L. and B. Neiman (2014). The global decline of the labor share. *The Quarterly journal of economics* 129(1), 61–103.
- Klump, R., A. Jurkat, and F. Schneider (2021). Tracking the rise of robots: A survey of the IFR database and its applications.
- Kogan, L., D. Papanikolaou, L. D. Schmidt, and B. Seegmiller (2021). *Technology-Skill Complementarity and Labor Displacement: Evidence from Linking Two Centuries of Patents with Occupations*. National Bureau of Economic Research.

- Lee, C., R. Roy, M. Xu, J. Raiman, M. Shoeybi, B. Catanzaro, and W. Ping (2024, May). NV-Embed: Improved Techniques for Training LLMs as Generalist Embedding Models.
- Li, S., J. Zhu, and C. Miao (2015, August). A Generative Word Embedding Model and its Low Rank Positive Semidefinite Solution.
- Lybbert, T. J. and N. J. Zolas (2014). Getting patents and economic data to speak to each other: An ‘algorithmic links with probabilities’ approach for joint analyses of patenting and economic activity. *Research Policy* 43(3), 530–542.
- Mandelbaum, A. and A. Shalev (2016, October). Word Embeddings and Their Use In Sentence Classification Tasks.
- Martinez, J. (2018). Automation, growth and factor shares. In *2018 Meeting Papers*, Volume 736. Society for Economic Dynamics.
- Meng, R., Y. Liu, S. R. Joty, C. Xiong, Y. Zhou, and S. Yavuz (2024). SFR-embedding-mistral: Enhance text retrieval with transfer learning. *Salesforce AI Research Blog* 3.
- Müller, C. (2022). World Robotics 2022 - Industrial Robots.
- National Center for O*NET Development (2023). O*NET Resource Center.
- Oberfield, E. and D. Raval (2021). Micro data and macro technology. *Econometrica* 89(2), 703–732.
- Piketty, T. and G. Zucman (2014). Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly journal of economics* 129(3), 1255–1310.
- Stehrer, R., A. Bykova, K. Jäger, O. Reiter, and M. Schwarzhappel (2019). Industry level growth and productivity data with special focus on intangible assets. *Vienna Institute for International Economic Studies Statistical Report* 8.
- Ul Haq, I., M. Pifarré, and E. Fraca (2024, January). Novelty Evaluation using Sentence Embedding Models in Open-ended Cocreative Problem-solving. *International Journal of Artificial Intelligence in Education*.
- Webb, M. (2019). The impact of artificial intelligence on the labor market. *Available at SSRN* 3482150.
- Zhang, B., K. Chang, and C. Li (2024, May). Simple Techniques for Enhancing Sentence Embeddings in Generative Language Models.
- Zhang, P. (2023). Endogenous capital-augmenting R&D, intersectoral labor reallocation, and the movement of the labor share. *Journal of Economics*, 1–36.
- Zhao, X., C. Wu, and D. Liu (2021). Comparative Analysis of the Life-Cycle Cost of Robot Substitution: A Case of Automobile Welding Production in China. *Symmetry* 13(2), 226.