Department of Economic Policy
Working Paper Series

WP No. 27

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Date: October 31, 2024

Published by:

University of Economics in Bratislava, Department of Economic Policy, Dolnozemská cesta 1, 852 35 Bratislava

Periodicity: irregular

ISSN 1339 - 0430

Unslicing the pie: AI innovation and the labor share in European regions

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Abstract

We study how the development of Artificial Intelligence (AI) influences the distribution of income between capital and labor and how this, in turn, exacerbates geographic income inequality. To investigate this issue, we first build a theoretical framework and then analyze data from European regions dating back to 2000. We find that for every doubling of regional AI innovation, there is a 0.7% to 1.6% decline in the labor share, which may have decreased by between 0.20 and 0.46 percentage points from a mean of 52% due solely to AI. This new technology is particularly detrimental to high-skill and medium-skill labor. The impact on income distribution is driven by worsening wage and employment conditions for high-skill labor, and by wage compression for medium- and low-skill labor. The effect of AI is not driven by other factors affecting regional development in Europe, nor by the concentration process in the AI market.

Keywords: Artificial Intelligence, patenting, labor share, European regions

JEL Classification: O31; O32; O34

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1 Introduction

In recent years, income inequality has emerged as a central topic in global economic discussions, drawing the interest of economists, policymakers, and the wider public. Many studies have shown that inequality can have adverse effects on human capital accumulation and economic growth (Galor and Zeira, 1993; Persson and Tabellini, 1994; Galor *et al.*, 2009). Moreover, it has significant social implications, reducing trust and creating fertile ground for discontent and the rise of populist movements (Piketty, 2014; Rodríguez-Pose *et al.*, 2023). The trend towards higher inequality is driven by various factors, including productive specialization, the transition towards service-based economies (tertiarization), the quality of governance, rent-seeking, lobbying by special interest groups, and rapid technological progress that benefits some more than others (Acemoglu and Autor, 2011; Chu and Peretto, 2023; Kerspien and Madsen, 2024). Collectively, these factors form a complex network of influences that shape the distribution of wealth and opportunity.

As far as wage inequality between low-skill workers and high-skill workers is concerned, Acemoglu (2002) has argued that technological progress was endogenously skill biased benefiting high-skill workers more than low-skill workers such that an increase in the relative number of high-skill workers led to an even higher skill premium (see also Goldin and Katz, 2009; Acemoglu and Autor, 2011, for discussions). In addition, advances in industrial robots as a low-skill labor replacing technology have put downward pressure on wages of low-skill workers, exacerbating the increase in wage inequality (Acemoglu and Restrepo, 2018; Cords and Prettner, 2022). When focusing on wealth inequality, lower capital taxation over time, increasing inheritances since the 1970s, and demographic aspects such as falling fertility that led to a concentration of inherited wealth have all been suggested as drivers (Piketty and Zucman, 2014; Alvaredo *et al.*, 2017). Finally, the decrease in labor income shares across the globe has mechanically increased income inequality because labor income is more equally distributed than capital income. For the decrease in the labor income share, various reasons have been suggested in the literature such as globalization, a declining bargaining power of labor unions, technological change that raises the productivity of capital that is a closer substitute for labor by more than the productivity of other types of capital, and demographic changes, which affect the relative return between labor and capital (Böckerman and Maliranta, 2012; Elsby *et al.*, 2013; Schmidt and Vosen, 2013; Karabarbounis and Neiman, 2014; Bengtsson and Waldenström, 2018; Bergholt *et al.*, 2022; Madsen *et al.*, 2024b).

With the recent advances in Artificial Intelligence (AI), another crucial force has entered center stage in determining inequality (Acemoglu, 2024; Autor, 2024; Bastani and Waldenström, 2024). AI, widely regarded as the leading disruptive force behind the Fourth Industrial Revolution, often delivers significant productivity benefits, though these are typically delayed (Brynjolfsson *et al.*, 2021; Igna and Venturini, 2023). This new wave of digital technologies is being adopted not only to boost worker productivity and firm efficiency but also to streamline production processes and reduce costs. Early evidence from the United States shows that AI can drive product innovation, leading to increases in firm sales, employment, and market valuations (Babina *et al.*, 2024; Alderucci *et al.*, 2020). Similar findings from Europe highlight AI's role in enhancing firm sales and productivity (Czarnitzki *et al.*, 2023; Marioni *et al.*, 2024), as well as its importance in shaping firms' new technological capabilities (Rammer *et al.*, 2022). While some argue that AI could reduce inequality (Bloom *et al.*, 2024b), others are more pessimistic (Acemoglu, 2023; Grant and Üngör, forthcoming), particularly due to AI's potential to reduce labor demand through automation, leading to a decoupling of productivity gains from labor market outcomes like employment and wages (Lane and Saint-Martin, 2021). In terms of inequality, Albanesi *et al.* (2023) analyze the impact of AI on labor markets in 16 European countries over the period 2011-2019, finding increased employment in AI-exposed, skill-intensive occupations. In addition, Bonfiglioli *et al.* (2023) analyze AI's impact on employment across US commuting zones from 2000-2020, showing that AI generally reduces overall employment and contributes to increased inequality across these zones. Moreover, the development and adoption of AI tend to be geographically concentrated, driven by factors such as the availability of specialized talent, investments in research and development, and the presence of high-quality digital infrastructure and competencies in digital fields (Xiao and Boschma, 2023). As a result, regional inequality, often overlooked in discussions of national income disparities, could be significantly impacted, with AI hubs advancing while other regions are left behind. This makes the regional effects of AI a critical issue that demands more attention and analysis.

Overall, the effects of AI on inequality are complex and multifaceted. Automation driven by AI can impact different types of labor in varied ways. For certain workers, AI may reduce demand, potentially lowering the labor share if the efficiency gains primarily benefit capital owners. In contrast, other workers may not experience the same degree of disruption. Additionally, rapid economic growth in regions with high patent activity could exacerbate regional disparities if the benefits are unevenly distributed. Given these potentially conflicting outcomes, a thorough investigation is required to understand how AI patents influence both the labor share and regional economic dynamics. This is the aim of our contribution, in which we first present a theoretical framework to analyze the effects of AI on different types of workers and the labor income share. We then empirically examine the theoretical implications using detailed data on regional patenting activity and labor income across regions.

Figure 1: Labor Income Share and AI Innovation in European Regions (2001-2017)

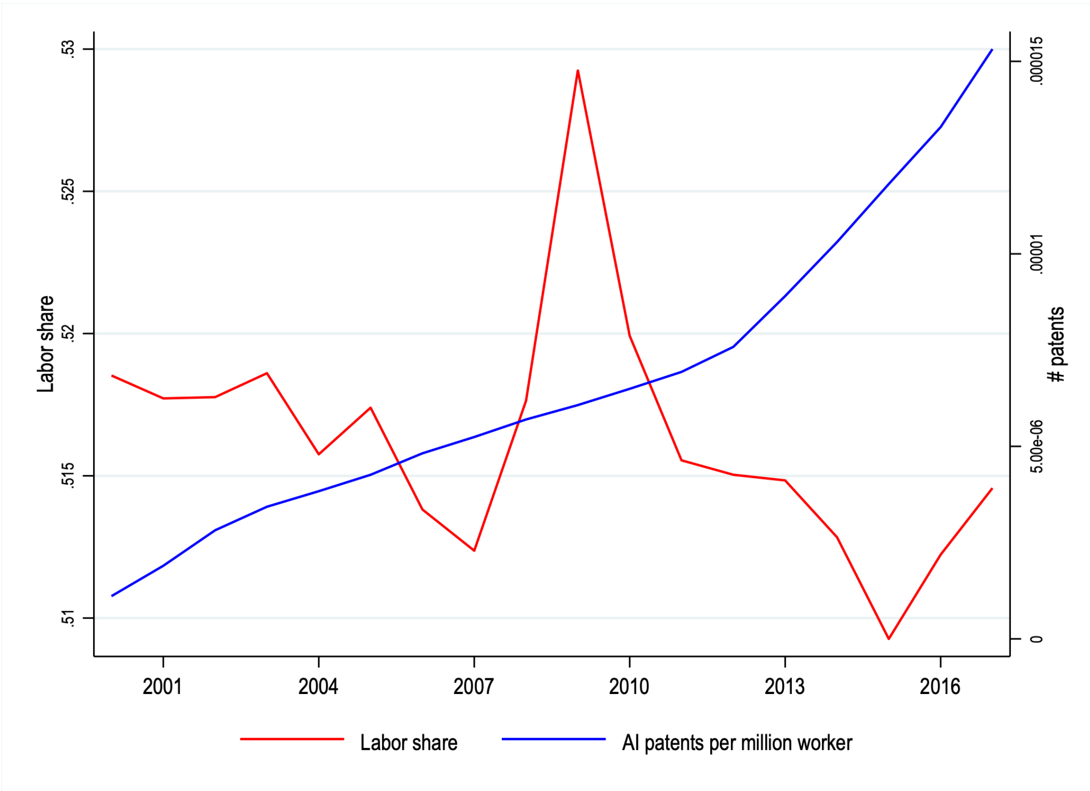


Figure 1 illustrates the trends in the labor income share and AI patenting across European regions from 2001 to 2017. Throughout this period, the number of AI patents per million workers experienced a significant and continuous rise. In contrast, the labor income share followed a declining trajectory, with a brief interruption marked by a temporary peak during the global economic and financial crisis of 2007-2009. Over the longer term, the figure suggests an inverse relationship between the growth of AI patenting and the labor income share.

Against this backdrop, we examine the relationship between technological innovation and labor market outcomes to assess how AI development influences income distribution across regions. First, we introduce a theoretical framework for evaluating the effects of AI innovation on the regional labor income share. We then utilize data from European regions since 2000 to analyze the variation in labor income relative to regional GDP, using this as an indicator of inequality trends. Specifically, we investigate whether regions specializing in AI innovation experience greater inequality and identify which skill group of workers is most affected by this trend.

We adopt two approaches of analyses. First, we implement a dynamic regression that considers various economic factors that may drive the dynamics of regional labor share, including alternative sources of technological development, accumulation of tangible and intangible assets, productivity upgrades, structural changes, demographic shifts, market concentration, and more. We also address a number of econometric issues that can affect estimation results, such as spatial dependence, the count nature of patent data, dynamic adjustment, and simultaneous feedback. To confirm that the estimated effect of AI innovation on regional labor share is causal, we additionally employ a Difference-in-Differences (DiD) regression framework. Specifically, we assess the significance of the change in the labor share following the introduction of new technologies, applying the Local Projections (LP) approach (LP-DiD, Dube *et al.*, 2023). Using the year of the first AI patent as the "event," we compare changes in the labor share in AI-innovating regions with those in a control group of regions that never introduced AI patents during the sample period, finding evidence that the investigated relationship is causal.

Our analysis reveals a significant pattern of effects: with each doubling of regional AI innovation, there is an associated decrease in labor share of between 0.7% and 1.6%. The impact is even larger—around 2.5%—when considering the years following the Great Recession (see also Eden and Gaggl, 2018; Prettner and Strulik, 2020; Guimarães and Mazeda Gil, 2022). Overall, our estimates suggest that the labor share may have decreased by between 0.20 and 0.46 percentage points from a mean of 52% due to AI development. Importantly, we document that AI innovation has heterogeneous effects across different worker skill levels, as measured by education. While AI negatively impacts the income share of all worker categories, this effect is more pronounced for high- and medium-skill workers compared to low-skill workers.

Regarding mechanisms, our estimates suggest that AI innovations are unrelated to the employment share of high- and medium-skill workers, but positively related to that of low-skill workers. This implies that the reduction in the labor share for high- and medium-skill workers is mainly driven by wage compression, while for low-skill workers, employment expansion enabled by AI partially offsets the associated wage reduction. For high- and medium-skill workers, AI's effect appears to stem mainly from its substitutability/complementarity with other production inputs, rather than changes in labor demand induced by the concentration of new technology production in a handful of firms and areas. For low-skill workers, however, the effect of AI on the labor share—and the underlying drivers—remain uncertain.

The rest of the paper is structured as follows: Section 2 provides an overview of the various contributions to the literature, explaining how our paper relates to existing research. Section 3 outlines the analytical framework and the associated prediction that we test empirically. Section 4 presents the econometric model, while Section 5 describes the dataset used in the analysis. Section 6 contains the results of the baseline specification and several robustness checks, and it explores the effect of AI innovation across various skill levels. Finally, Section 7 provides the conclusions.

2 Contribution to the literature

With our paper, we contribute to the growing literature exploring i) the drivers behind the emergence of AI technologies; ii) the effects of AI development on productivity, employment, and wages; and iii) the consequences of AI for the evolution of regional inequality.

Research into the drivers of AI production and related innovations underscores the technical competencies in the field of ICT and earlier digital technologies (Xiao and Boschma, 2023) and (Igna and Venturini, 2023). Technical skills useful for developing AI can be broadly categorized into three main areas: the development and advancement of AI, its applications, and robotics (Samek *et al.*, 2021). AI technologies are increasingly recognized for their potential to boost firm productivity by enhancing efficiency, automating prediction-based tasks, and generating substantial economic returns. Advances in AI, particularly in machine learning and deep learning, enable firms to optimize production processes and decision-making systems.[1] However, the productivity gains from AI technologies might not be immediate. The so-called "modern productivity paradox" suggests that despite advanced technology, productivity improvements can be delayed due to adjustment costs, complementary innovations, and necessary organizational changes (Brynjolfsson *et al.*, 2019).

[1] For example, AI can serve as a command center in manufacturing, analyzing data to fine-tune equipment performance and optimize input usage (Agrawal *et al.*, 2024). Unlike traditional automation, which relies on explicit programming, machine learning has the potential to improve autonomously by learning patterns from data, potentially surpassing older methods (Brynjolfsson and Mitchell, 2017). AI systems utilizing machine vision, for instance, can often outperform humans in accuracy and efficiency for specific tasks (Brynjolfsson *et al.*, 2018).

AI's impact on the labor market is multifaceted and differs in various respects from that of earlier waves of automation. Similar to previous automation technologies, AI has the potential to replace workers performing manual jobs that involve routine tasks by expanding the use of industrial robots for these tasks. However, a distinctive feature of AI is its ability to enable machines to perform cognitive tasks, which can lead to the replacement of humans in decision-making roles (Brynjolfsson and McAfee, 2015). Therefore, the labor market effects of AI—specifically regarding wages, employment conditions, and income distribution—are likely to change with the skill levels of workers, but in a manner distinct from that of industrial robots. Earlier evidence indicates that robots reduce the share of low-skill jobs, increase overall employment by creating new types of work, and lead to widespread increases in productivity and wage levels (Graetz and Michaels, 2018). However, whether and how AI influences wages, employment, and, no less importantly, income distribution remains largely unknown. Indeed, AI technologies are likely to reshape wage structures, favoring more educated individuals, particularly those with high educational achievements in STEM fields and technical proficiency (Prettner and Strulik, 2020; Acemoglu *et al.*, 2022; Babina *et al.*, 2023). Despite these advancements, the literature remains inconclusive regarding the distributional impacts of AI technologies, especially concerning different skill levels. While some argue that AI predominantly displaces high-skill workers (Webb, 2020; Bloom *et al.*, 2024b), others predict more severe short-term effects on low-skill workers in various countries (Grant and Üngör, forthcoming). In this context, our contribution to the literature is to provide new evidence on the distributional consequences of AI development.

We also contribute to the broader literature exploring the relationship between innovation and income inequality, an area that has produced mixed results thus far (Akcigit *et al.*, 2017). Several studies have shown that patenting and other intellectual property rights, by enabling the appropriation of innovation rents, can increase income inequality and the capital share of national income (Lee and Rodríguez-Pose, 2013; Koh *et al.*, 2020; Guellec, 2020). While some research suggests that innovation exacerbates inequality at the top but promotes social mobility by introducing new inventors (Aghion *et al.*, 2019a), others argue that innovation, particularly by new market entrants, can reduce inequality among the highest earners by fostering entrepreneurial turnover (Jones and Kim, 2018). Recent studies have also examined how innovation rents are partly appropriated by workers, with wage and occupational benefits unevenly distributed according to employees' skills and job positions (see Blundell *et al.*, 2022 for a survey). Further research has explored how innovation and inequality evolve during the transition from pre-industrial stagnation to modern economic growth (Chu and Peretto, 2023), or how these dynamics are shaped by innovation and monetary policies (Chu and Cozzi, 2018; Chu *et al.*, 2019; Chu *et al.*, 2021). Peretto and Seater (2013) propose a theory where R&D-driven growth increases the capital share of national income through factor-eliminating technical change. Madsen *et al.* (2024b) analyze the decline in the labor share across advanced countries since 1980, attributing it to shifts in the composition of capital. They find that rising building prices decrease the labor share due to the complementary relationship between buildings and labor, while falling machinery prices increase the capital-labor ratio, further reducing the labor share as machinery substitutes for labor. Our study extends these findings by examining the impact of AI patent production on the labor share across European regions. By focusing on emerging technologies, we show that AI advancements exacerbate the decline in the labor share, particularly by compressing the relative wage of high-and medium-skill labor, thereby reinforcing the broader trend of technological progress favoring capital over labor.

As far as spatial effects are concerned, technological progress, as a crucial driver of economic development, shapes opportunities and prosperity across regions. Access to technology is a key factor in this context (Iammarino *et al.*, 2018): disparities in high-speed internet, digital infrastructure, and technological education significantly widen the gap between regions. Areas with inadequate access to these resources struggle to participate in the digital economy, which exacerbates economic disparities. Regions lacking proper internet infrastructure face barriers in accessing online markets and digital resources, limiting their growth potential (de Clercq *et al.*, 2023). Without this infrastructure, regions struggle to attract investment and compete in technology-dependent industries, often leading to economic activity centralizing in core regions, even though higher wages in these areas represent a significant cost for firms (Krenz *et al.*, 2021). Access to quality technological education and training is equally vital for building a skilled workforce capable of driving innovation and adapting to technological advancements (Cruz-Jesus *et al.*, 2012). Disparities in digital literacy and skills further deepen regional inequality. Regions with more educated populations are better positioned to capitalize on technology, while others fall behind, reinforcing these gaps. The concentration of innovation hubs in certain areas amplifies these disparities (Diemer *et al.*, 2022), as regions with a strong tech presence experience rapid economic growth, attracting both investment and talent. This technological edge provides distinct advantages in innovation, productivity, and competitiveness, but the benefits are not evenly shared. As a result, the gap between prosperous tech hubs and less-developed regions continues to widen, perpetuating regional inequality.

Given this context, it is crucial to explore how technological drivers of regional inequality, as identified in the literature, interact with the development and adoption of AI. Building on these insights, we first propose a theoretical framework for analyzing the impact of AI on wages, the labor share, and regional inequality. We then empirically test the model's predictions and assess the effects of AI on regional disparities.

3 AI and the labor share: theoretical considerations

To analyze the effect of AI on the labor share, we build on Bloom *et al.* (2024b) who investigate the effects of AI on the skill premium and extend their framework i) to cover regional disparities and ii) to incorporate technological progress in AI. Suppose time t evolves in discrete steps $t = 0, 1, 2, \ldots \infty$ and that the representative firm in region i has access to the following production function:

$$Y_{i,t} = K_{i,t}^{\alpha} \left\{ \beta_3 \left[\beta_1 L_{u,i,t}^{\theta} + (1-\beta_1) \left(A_{P,i,t} P_{i,t} \right)^{\theta} \right]^{\frac{\gamma}{\theta}} + (1-\beta_3) \left[\beta_2 L_{s,i,t}^{\phi} + (1-\beta_2) \left(A_{G,i,t} G_{i,t} \right)^{\phi} \right]^{\frac{\gamma}{\phi}} \right\}^{\frac{1-\alpha}{\gamma}}, \tag{1}$$

where $Y_{i,t}$ denotes output, $K_{i,t}$ refers to the stock of traditional physical capital (machines, assembly lines, production facilities), $L_{u,i,t}$ denotes employment of low-skill workers, $L_{s,i,t}$ denotes employment of high-skill workers, $P_{i,t}$ is the stock of automation capital in terms of industrial robots, which is a close substitute for low-skill workers, $A_{P,i,t}$ is the productivity of robots as determined by technological progress in automation, $G_{i,t}$ is the stock of AI capital, which is a close substitute for high-skill workers, $A_{G,i,t}$ is the productivity of AI as determined by technological progress in AI (which we measure by patenting in the empirical part). α denotes the elasticity of output with respect to the use of traditional physical capital, θ determines the elasticity of substitution between low-skill workers and robots, ϕ determines the elasticity of substitution between high-skill workers and AI, and γ determines the elasticity of substitution between high-skill intensive work and low-skill intensive work. Realistically, the following parameter restrictions apply: $\theta, \phi, \gamma \in (0, 1)$. This indicates that low-skill workers and robots, high-skill workers and AI, and low-skill intensive work and high-skill intensive work are gross substitutes but not perfect substitutes (Bloom *et al.*, 2024b). In addition, $\phi < \theta$ such that industrial robots are better able to substitute for low-skill workers than AI for high-skill workers. The main question we aim to address is how the labor share in region j reacts to technological progress in AI, that is, an increase in $A_{G,i,t}$.

In a perfectly competitive economy, wages of low-skill workers will be equal to the marginal product of $L_{u,i,t}$, whereas wages of high-skill workers will be equal to the marginal product of $L_{s,i,t}$. We therefore have:

$$w_{u,i,t} = \frac{\partial Y_{i,t}}{\partial L_{u,i,t}} = (1-\alpha)\beta_1\beta_3 K_{i,t}^{\alpha} L_{u,i,t}^{\theta-1}\left[\beta_1 L_{u,i,t}^{\theta} + (1-\beta_1)\left(P_{i,t}A_{P,i,t}\right)^{\theta}\right]^{\frac{\gamma}{\theta}-1}$$
$$\times\left\{\beta_3\left[\beta_1 L_{u,i,t}^{\theta} + (1-\beta_1)\left(P_{i,t}A_{P,i,t}\right)^{\theta}\right]^{\frac{\gamma}{\theta}} + (1-\beta_3)\left[\beta_2 L_{s,i,t}^{\phi} + (1-\beta_2)\left(G_{i,t}A_{G,i,t}\right)^{\phi}\right]^{\frac{\gamma}{\phi}}\right\}^{\frac{1-\alpha-\gamma}{\gamma}}, \tag{2}$$

$$w_{s,i,t} = \frac{\partial Y_{i,t}}{\partial L_{s,i,t}} = (1-\alpha)\beta_2(1-\beta_3) K_{i,t}^{\alpha} L_{s,i,t}^{\phi-1}\left[\beta_2 L_{s,i,t}^{\phi} + (1-\beta_2)\left(G_{i,t}A_{G,i,t}\right)^{\phi}\right]^{\frac{\gamma}{\phi}-1}$$
$$\times\left\{\beta_3\left[\beta_1 L_{u,i,t}^{\theta} + (1-\beta_1)\left(P_{i,t}A_{P,i,t}\right)^{\theta}\right]^{\frac{\gamma}{\theta}} + (1-\beta_3)\left[\beta_2 L_{s,i,t}^{\phi} + (1-\beta_2)\left(G_{i,t}A_{G,i,t}\right)^{\phi}\right]^{\frac{\gamma}{\phi}}\right\}^{\frac{1-\alpha-\gamma}{\gamma}}. \tag{3}$$

The regional labor income share is then given by:

$$LS_{i,t} = \frac{w_{u,i,t}L_{u,i,t} + w_{s,i,t}L_{s,i,t}}{Y_{i,t}} =$$
$$= \frac{(1-\alpha)\left\{\beta_1\beta_3 L_{u,i,t}^{\theta}\left[\beta_1 L_{u,i,t}^{\theta}+(1-\beta_1)\left(P_{i,t}A_{P,i,t}\right)^{\theta}\right]^{\frac{\gamma}{\theta}-1}+\beta_2(1-\beta_3)L_{s,i,t}^{\phi}\left[\beta_2 L_{s,i,t}^{\phi}+(1-\beta_2)\left(G_{i,t}A_{G,i,t}\right)^{\phi}\right]^{\frac{\gamma}{\phi}-1}\right\}}{\beta_3\left[\beta_1 L_{u,i,t}^{\theta}+(1-\beta_1)\left(P_{i,t}A_{P,i,t}\right)^{\theta}\right]^{\frac{\gamma}{\theta}}+(1-\beta_3)\left[\beta_2 L_{s,i,t}^{\phi}+(1-\beta_2)\left(G_{i,t}A_{G,i,t}\right)^{\phi}\right]^{\frac{\gamma}{\phi}}}. \tag{4}$$

We can directly infer from Eq. (4) that $\gamma \leq \phi$ is a sufficient condition for the labor share to decrease with progress in AI as represented by rising $A_{G,i,t}$. The condition $\gamma \leq \phi$ states that AI is a better substitute for high-skill workers than low-skill workers are for high-skill workers and seems likely to be fulfilled. We summarize this finding in the following proposition.

Proposition 1. *The labor income share always decreases with technological progress in AI if $\gamma \leq \phi$.*

In addition, for a range of realistic parameter values, we can show numerically that the labor income share tends to decrease with progress in AI, that is, we typically have:

$$\frac{\partial LS_{i,t}}{\partial A_{G,i,t}} < 0. \tag{5}$$

Furthermore, the ratio of the high-skill labor share to the low-skill labor share can be computed as

$$\frac{LS_{s,i,t}}{LS_{u,i,t}} = \frac{w_{s,i,t}L_{s,i,t}/Y_{i,t}}{w_{u,i,t}L_{u,i,t}/Y_{i,t}} = \frac{\beta_2(1-\beta_3)L_{s,j,t}^{\phi}\left[\beta_2 L_{s,j,t}^{\phi}+(1-\beta_2)\left(G_{j,t}A_{G,j,t}\right)^{\phi}\right]^{\frac{\gamma}{\phi}-1}}{\beta_1\beta_3 L_{u,j,t}^{\theta}\left[\beta_1 L_{u,j,t}^{\theta}+(1-\beta_1)\left(P_{j,t}A_{P,j,t}\right)^{\theta}\right]^{\frac{\gamma}{\theta}-1}}. \tag{6}$$

From this expression, the following proposition follows immediately:

Proposition 2. *As long as $\gamma \leq \phi$, technological progress in AI leads to a relative decrease of the high-skill labor share to the low-skill labor share.*

For the empirical analysis of the two theoretical predictions, we can generalize the formulation above and write the labor income share as a function of productivity, different types of labor, and physical capital use (Karabarbounis and Neiman, 2014; O'Mahony *et al.*, 2021) such that

$$LS_{i,t} = f(A_{i,t}, k_{i,t}, L_{j,i,t}), \tag{7}$$

where $A_{i,t}$ denotes general productivity, $k_{i,t} = K_{i,t}/Y_{i,t}$ refers to the capital-output ratio, and $L_{j,i,t}$ are different types of labor with skills j. The extent to which changes in productivity as driven by patenting activity impact upon the regional labor income share is an empirical question that depends on the substitutability between different types of labor with different types of capital, innovative activity, and certain region-specific effects. Below, we derive our empirical specifications by adapting Eq. (7) to account for the nature of the variables (see Sub-section 4.1) or the treatment effect that the launch of AI may have had on the regional labor share (see Sub-section 4.2).

4 Empirical model

To explore the relationship between AI innovation and the regional labor share empirically, we use two panel regression approaches. First, we estimate a long-run reduced-form equation where the regional labor share is regressed against a proxy for the degree of regional specialization in AI, reflected by the cumulative number of patent counts developed in this technology domain.Our dynamic regression procedure is asymptotically robust to reverse causality issues, specifically the risk that regions with a higher share of income accruing to workers have greater or smaller incentives to develop AI. Nonetheless, in our second approach, we address this issue more specifically by performing an event analysis that compares the change in the regional labor share after the introduction of AI with the labor share of regions that are not active in this domain. To quantify the differential performance, we apply the local projections procedure to a difference-in-differences (LP-DiD) regression framework, in which the year of AI innovation introduction is considered as the treatment (event).

4.1 Long-run regression

Our first specification corresponds to the stochastic, log-linear version of Eq. (7):

$$\ln LS_{i,t} = \alpha_{i,0} + \alpha_1 \ln k_{i,t} + \alpha_2 \ln A_{i,t} + \alpha_3 \ln X_{i,t} + CSD + \epsilon_{i,t}, \tag{8}$$

where we have data on 273 regions ($i = 1, \ldots, 273$) and 17 years ($t = 2000, \ldots, 2017$). The term $\alpha_{i,0}$ represents region-specific fixed effects, which account for unchanging regional characteristics, like the political setting, that may influence even indirectly the labor share, while $\epsilon_{i,t}$ denotes spherical errors.

The variable k denotes the capital intensity of production, which, as described above, is typically expressed in terms of the value of capital relative to output (both in real terms). In line with the latest developments in national accounting principles, the capital endowment of each region (k) includes various asset types: tangible (physical) assets (pk), intangible (R&D) capital (ik), and realized knowledge capital (ak). The latter primarily consists of AI patents but also includes patents related to Fourth Industrial Revolution (4IR) technologies, ICT, and general patents. Since our key explanatory variable is defined as the stock of knowledge achieved in the new technology field, k is expressed per unit of labor in this analysis. A denotes the level of regional productivity, alternatively defined in terms of Total Factor Productivity (TFP) or Average Labor Productivity (ALP). The latter is expressed as output per worker or output per hour worked. A reveals whether technical change is input-specific, namely if it promotes the displacement of labor in favor of greater usage of new capital inputs. Gross substitutability between factor inputs emerges when a negative parameter is estimated for k. By contrast, a positive parameter for this explanatory variable would indicate that capital and labor are gross complements.

Given the potential endogeneity resulting from omitted variables, we account for various confounding factors. In this regard, X is a vector of control variables reflecting the structure of the technology market, the size of the industrial base, and the process of structural change that may be affecting the economy of a region. These characteristics are approximated by the degree of technological concentration, the share of the manufacturing sector in total employment, and the rate of employment change, respectively.

The effect of unobservable factors that generate cross-sectional dependence (CSD) across regions is modeled in different ways. CSD may be caused by co-movements induced by technological shocks, globalization, and changes in institutional settings. The effect of CSD is primarily captured by common time dummies, which control for temporary variations in patenting incentives that might arise from fluctuations in product demand, advancements in technology, or short-term research incentives (such as tax breaks). By using time fixed effects, we assume that common exogenous shocks have weak effects on the dynamics of the labor share and that these effects are similar across regions (weak CSD). However, unobservable factors can produce effects on the labor share that are heterogeneous across space; we model these through a set of latent factors that can be approximated by Common Correlated Effects (CCE), constructed as the unweighted mean value of the dependent variable and regressors (strong CSD). Finally, as an alternative to the previous procedure, we model the transmission of shocks across space as inversely related to the distance between regions (distance-shaped strong CSD). In this case, we use a spatial lag model with inverse-distance weighting to account for spatial dependence, ensuring that the influence of shocks diminishes with increasing distance between regions.

We exploit the dynamic properties of regional data and employ an Auto-Regressive Distributed Lag (ARDL(1,1)) model to estimate Eq. (8). This regression method is known to produce consistent estimates that are robust to issues such as simultaneity bias and the integration order of variables, provided that the lag structure of the variables is sufficiently rich (Chudik *et al.*, 2016). In Subsections 6.1-6.2, we present the long-run coefficients derived from these regressions.

4.2 Event analysis

To unveil the causal nature of the linkage between AI and the regional labor share, we also implement an event analysis by reformulating Eq. (8) as a DiD regression. In this specification, the labor share of regional income (in logs) is regressed against a treatment variable, namely a dummy variable that is equal to one from the year of AI introduction and zero otherwise. Essentially, we assume that once a region receives the treatment, it remains treated for the entire observation period. This corresponds to a fully absorbing-type treatment, also known as a post-treatment effect (Athey and Imbens, 2022). Note that in our setup, the timing of treatment varies across regions, implying that the model is staggered.

The coefficient associated with the post-treatment variable can be interpreted as causal, specifically as the Average Treatment on the Treated (ATT) effect, under the following conditions: (i) in the absence of the treatment, the labor share of AI and non-AI innovating regions would have followed parallel trends; and (ii) the introduction of AI innovation (treatment) does not affect the labor share before its actual implementation. To meet these conditions, we enrich our DiD specification with regional fixed effects, common time dummies, and the stock of general patents per worker (in logs) as control. Moreover, we use a one-year lag of the treatment variable to account for the delayed response of the labor share to the treatment, and a one-year lead of the treatment variable to exclude the possibility that the labor share changes in anticipation of the arrival of the new technology. Finally, to rule out the possibility that regions with a higher (or lower) labor share select into the treatment group—potentially another important source of endogeneity—we include the lagged value of the dependent variable among the controls.

We estimate the impact of AI innovation on the labor share by applying the Local Projections procedure to our DiD framework (see Dube *et al.*, 2023). This involves estimating a set of forward-effect regressions in which our DiD regression is expressed in first differences, as follows:

$$\ln LS_{i,t+h} - \ln LS_{i,t-1} = \delta_h^{LP} \Delta D_{i,t}^{AI} + \sum_{j=-1}^{1} \theta_j D_{i,t+j}^{AI} + \varphi \ln ak_{i,t-1} + TD + e_{i,t}, \tag{9}$$

where δ_h^{LP} denotes the ATT effect at horizon h after the event, $e_{i,t} = \epsilon_{i,t} - \epsilon_{i,t-1}$ is the error term, while $D_{i,t}^{AI}$ is our post-treatment dummy and TD denotes common time dummies. We will present the results as event analysis, plotting the response of the outcome variable h years following the treatment (δ_h^{LP}) and comparing it to its pre-event trend over h periods, in relation to the change in the labor share observed for the control group. The latter consists of regions that have never introduced AI innovation. Hence, the LP-DiD regression is also useful for addressing the issue of regions without AI, which may be problematic in estimations of a log-log specification as in Eq. (8). We discuss this issue in more depth later.

In order to obtain consistent estimates for the ATT, we address two other important issues that could potentially influence our DiD regression. First, we seek to avoid the risk that the changing composition of the control group over time may bias the estimates; therefore, we adopt the same (minimum) set of control regions in all forward-effect regressions. We also account for the fact that regions may have post-treatment periods of different lengths. In this case, the concern is that the precision of estimates may be affected by regions treated near the end of the sample interval, where the post-treatment period available to evaluate the effect of AI is relatively short. To mitigate this, we rescale the ATT proportionally to the length of the post-treatment period (equally-weighted treatment). In Sub-section 6.3, we present and discuss the results from the LP-DiD regression.

5 Data and summary statistics

Our analysis is developed using panel data for 273 European regions at NUTS2 level, including the UK, between 2000 and 2017. We rely on a diverse array of data sources. Our primary economic data are sourced from Eurostat regional accounts, which provide essential information on employee compensation, total employment, and gross value added. The labor share of income is expressed as the ratio of the compensation of employees with respect to regional gross value added, expressed at current prices. Additionally, we use data on gross fixed capital formation and R&D expenditures to develop proxies for tangible and intangible capital stocks. The value of these stocks is derived using the perpetual inventory method from the real value of these fixed investments. The constant price value of both of these series is obtained by deflating nominal investment with the implicit deflator for regional value added. For the tangible capital stock we adopt an annual depreciation rate of 5%, and 15% for the stock of intangible (R&D) assets.

To gain insights into the heterogeneous impact of AI across different groups of workers, we gather detailed information on the distribution of employment and wages by skill type. The skill types are defined using the ISCED classification system, which segments educational attainment into three categories: Low (covering educational levels 0-2), Medium (covering levels 3-4), and High (covering levels 5-8). Employment by skill type is sourced from Eurostat. Data on the average wage per worker, categorized by skill type, are derived from EU KLEMS. This dataset provides information on wage compensation by skill, by industry, and by country, collected from various European Labor Force Surveys (see Bontadini *et al.*, 2023). We regionalize the average compensation per employee by exploiting information on the industry share of regional employment and the distribution of the skill composition of regional employment.

For quantifying realized innovation across various technological domains, including AI, we utilize patent data sourced from the OECD EPO Regpat database. This database assigns patent applications at the European Patent Office to NUTS3 level regions using information about the applicant, through an automatic procedure of name disambiguation. We classify patents by technology fields using the International Patent Classes (IPC) or Cooperative Patent Classes (CPC) reported in the patent documents. Specifically, we employ the patent classification provided by WIPO (2019) to identify AI patents, the classification sourced from EPO (2017) for 4IR patents, and the Inaba and Squicciarini (2017) J-tag classification system to single out ICT patents. Note that, to circumvent the problem of including regions with missing values for patents and other investment series, all stock variables Z are augmented by one unit and divided by employment L. Afterwards, we take the logarithm of the transformed variable, which results in the following transformation $\ln\left(\frac{1+Z}{L}\right)$.

Table 1 presents summary statistics for labor share, innovation, and capital measures across European regions during the study period. The average total labor share is 51.8, with high-skill, medium-skill, and low-skill labor shares averaging 12.2, 23.6, and 16.3, respectively. For innovation, the average AI patent stock is 7.4 per 1,000 workers, with a high standard deviation (SD) of 21.4, indicating significant regional variation. The average 4IR and ICT patent stocks are 112.0 and 145.2 per 1,000 workers, respectively, with SDs of 320.3 and 526.3, highlighting considerable disparities in the development of these technologies. The total patent stock, excluding AI, 4IR, and ICT patents, averages 624.4 per 1,000 workers, and 884.5 when excluding only AI patents. Regarding capital investments, the tangible capital stock averages 58.3 thousand euros per worker, while the R&D capital stock averages 2.9 thousand euros per worker (both at constant 2010 prices). These statistics suggest substantial regional disparities in labor shares, innovation, and capital investments.

Table 1: Summary statistics

	Mean	SD	25th pct.	50th pct	75th pct.	99th pct.
Labor share (total; %)	51.8	7.2	46.4	53.7	57.3	63.7
High-skilled LS	12.2	7.0	7.1	10.0	16.9	31.2
Medium-skilled LS	23.6	7.6	19.4	23.6	29.7	37.5
Low-skilled LS	16.3	8.3	10.6	15.5	21.5	41.7
AI patent stock p.w. (# per 1,000)	7.4	21.4	0.0	0.7	5.3	120.0
4IR patent stock p.w. (# per 1,000)	112.0	320.3	1.1	26.1	99.8	1862.7
ICT patent stock p.w. (# per 1,000)	145.2	526.3	1.7	25.5	92.5	2745.0
All patent stock p.w. (excl. AI, 4IR, ICT; # per 1,000)	624.4	1439.5	48.4	363.0	1124.0	8054.6
All patent stock p.w. (excl. AI; # per 1,000)	884.5	34.4	33.5	60.7	82.1	130.1
Tangible capital stock p.w. (thousands of constant euros)	58.3	34.4	33.5	60.7	82.1	130.1
R&D capital stock p.w. (thousands of constant euros)	2.9	3.8	0.1	1.7	4.0	16.5

Figure 2: Labor share and cumulative change (2000-2017)

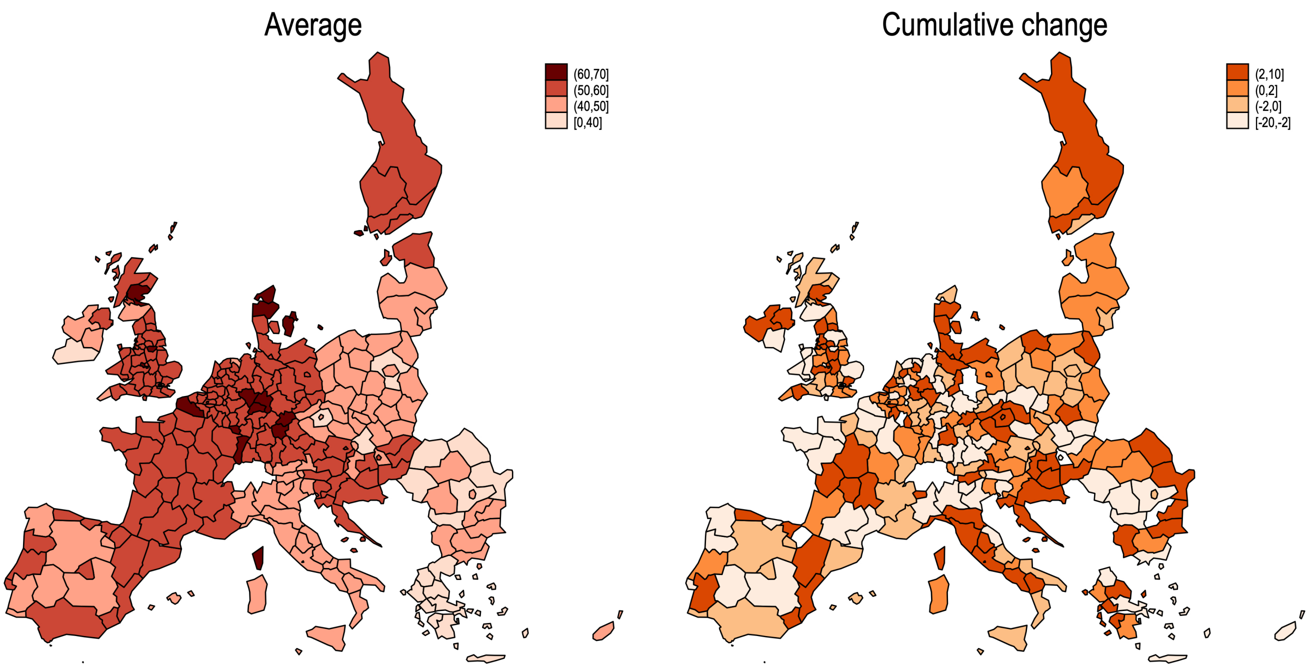
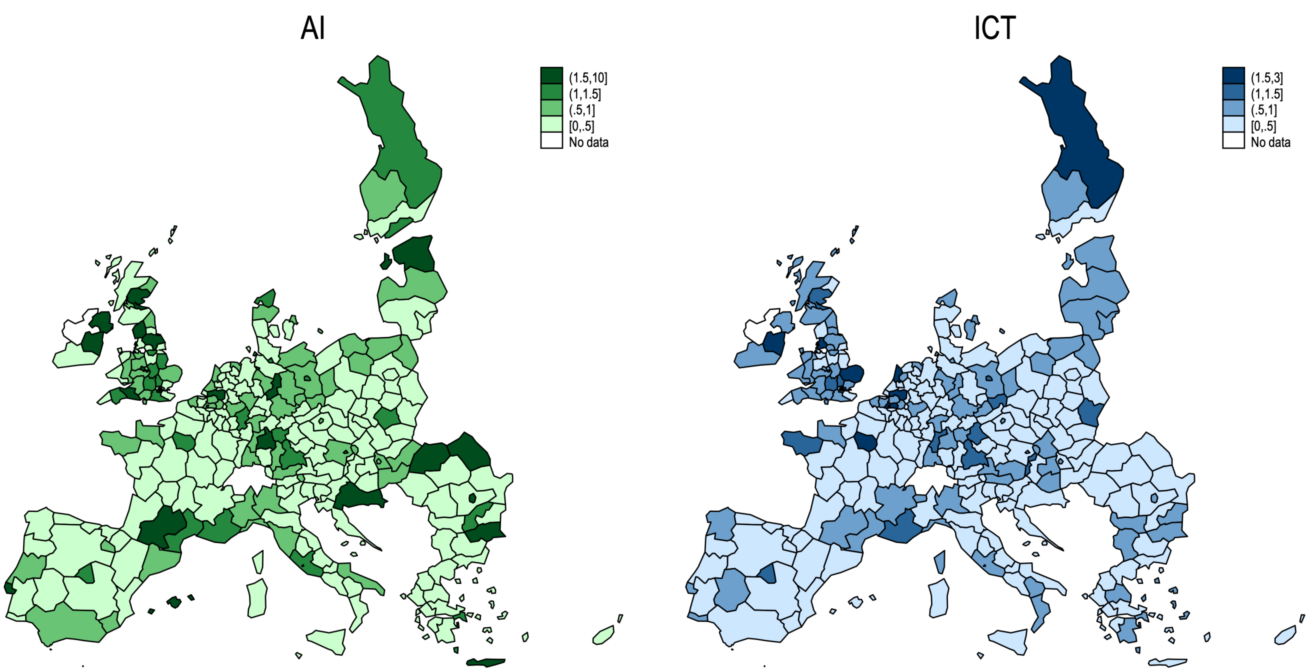


Figure 3: AI and ICT technology specialization, RCA (avg. 2000-2017)



Notes: RCA: Revealed Comparative Advantage

To complete the description of the available data, Figures 2 and 3 offer further insights into the trends and variability in labor shares and patent activities. Specifically, the left panel of Figure 2 displays the average labor share across European regions, representing the mean value of labor share over the study period for each region. The right panel of Figure 2 shows the cumulative change in labor share over time, tracking the total change from the beginning to the end of the period for each region. Figure 3, on the other hand, depicts the variation in AI patents (left panel) and the variability in ICT patents (right panel), both defined by the technological Revealed Comparative Advantage (RCA) index. Figure 2 shows that the average labor share follows well-defined country-specific patterns, but the variation over time is substantial, with some regions experiencing an increase in the share of regional income accruing to workers, while others observe a decline, even within the same nations. Figure 3 also highlights the significant overlap between AI and ICT specialization in Europe, though the production of AI technologies remains concentrated in a few areas.

6 Results

6.1 Baseline estimates

Table 2 presents the results for our baseline specification, reporting the long-run coefficients associated with the auto-regressive distributed lag model. In column (1), we regress the labor share on the stock of AI patents per worker, finding an elasticity of -0.014. This result is consistent with evidence from U.S. states provided by Aghion *et al.* (2019a), where patenting is found to be positively correlated with various income inequality indicators. Conversely, it conflicts with the positive effect found for R&D capital, used as a proxy for knowledge generation effort, by O'Mahony *et al.* (2021) for industrial economies.

Several possible explanations could account for this result. First, based on the premises of our theoretical background, this finding may be driven by the technological characteristics of production, suggesting that a substitution effect might be at play: as AI technologies advance, new technological capabilities are created and made available to firms. These capabilities could be used to automate cognitive tasks, as well as a range of routine manual tasks previously performed by humans. In this respect, our proxy for AI innovation captures the tendency of firms to produce an increasingly larger share of output using machines, thereby decreasing reliance on human labor.

Second, productivity gains induced by AI innovation might be a factor driving the dynamics of the labor share. Earlier firm-level evidence illustrates that AI development can deliver significant

Table 2: Baseline estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI patent stock per worker	-0.014***	-0.011***	-0.013***	-0.010***	-0.012***	-0.011***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ALP - Output per worker		0.016*			0.012	0.008	0.018*
		(0.009)			(0.009)	(0.009)	(0.009)
ALP - Output per hour			0.004				
			(0.009)				
TFP				-0.289***			
				(0.005)			
Tangible capital stock p.w.					0.002***	0.002***	0.003***
					(0.000)	(0.000)	(0.000)
R&D capital stock p.w.						-0.001***	0.001***
						(0.000)	(0.000)
Adjustment term	-0.220***	-0.213***	-0.218***	-0.291***	-0.212***	-0.212***	-0.212***
	(0.014)	(0.013)	(0.014)	(0.012)	(0.014)	(0.014)	(0.014)
Scaling factor	Employment	Employment	Employment	Employment	Employment	Employment	Value added
Obs.	4,576	4,557	3,989	3,913	4,452	4,452	4,452
R-squared	0.384	0.349	0.363	0.197	0.348	0.348	0.348
Regions	278	277	236	236	262	262	262

Notes: The dependent variable is the labor share, defined as the ratio of employees' compensation to regional gross value added (at current prices). All variables are measured in logs. Long-run estimates are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey-West standard errors are in parentheses. ***, ** and * significant at 1, 5 and 10%, respectively.

productivity gains ranging between 10% and 20% (Calvino and Fontanelli, 2023b, Marioni *et al.*, 2024). When companies introduce AI innovations, they typically enhance their production processes by streamlining tasks, optimizing resource use, and achieving greater operational efficiency. These improvements often result in a more efficient allocation of labor and resources within the firm, allowing them to produce more output with the same or fewer inputs, including labor. Consequently, the proportion of labor's contribution to total output could decrease, leading to a lower regional labor share. Since other productivity-enhancing factors may contribute to the impact attributed to AI, we explicitly include labor and total factor productivity levels among the regressors below.

A third explanation involves skill complementarity. While AI technologies may displace some types of labor, they can also enhance the skills of workers in other areas. AI innovation results from extensive research and the efforts of skilled professionals who identify, develop, and apply new technologies within their organizations. In regions with a high stock of AI patents, labor demand may shift towards more specialized or higher-skilled roles, reducing the overall labor share in the regional economy as demand for less specialized roles declines. Finally, the observed inverse relationship between AI and the labor share might reflect the broader effects of structural change and the tertiarisation of the economy. Regions specializing in developing AI technologies could be undergoing transformations in their industrial composition or economic structure, potentially leading to a reduction in the prominence of labor-intensive sectors or a shift in production towards regions with more intensive capital inputs.

The negative association between the labor share and AI innovation remains robust even after controlling for various factors. In columns (2) through (4), we account for measures of regional productivity. The analysis reveals that the labor share is only marginally positively related to output per worker, has an insignificant relationship with output per hour, and is negatively related to TFP with an elasticity of -0.289.[2] These productivity measures appear to mitigate the negative impact of AI innovation on the labor share.

In columns (5) and (6), we introduce controls for tangible capital and R&D capital, both mea-

[2] One issue with using the TFP index as an empirical proxy for productivity is that it is typically derived as a Solow residual or from a Cobb-Douglas production function. These methods assume constant input substitutability, whereas our conceptualization is based on flexible substitution or complementarity between production factors, as described by the CES production technology. On this basis, output per worker remains our preferred measure of productivity in the following part of the analysis.

sured on a per-worker basis. The coefficient for tangible capital is positive (0.002), indicating a small but favorable effect on the labor share. This suggests that investments in tangible capital, such as machinery and equipment, complement labor. Conversely, the coefficient for R&D capital is negative (-0.001), reflecting a decrease in the labor share. R&D spending may foster technological advancements that either replace workers engaged in routinized manual jobs or cognitive tasks with machines, or lead to productivity gains that may not be fully captured by our controls. Additionally, R&D may generate rents that do not proportionally benefit labor. Consequently, while R&D capital fosters innovation and efficiency, these advancements may reduce the relative importance of labor in both the production process and the distribution of income. However, these results change in column (7), where we replicate the regression analysis from column (6), but scale all variables by value added rather than by employment. The finding that the labor share is negatively related to the cumulative value of R&D per worker, but positively related to research expenses expressed as a ratio to value added, may be due to the fact that R&D workers command relatively high wages. Their income grows proportionally faster than that of other factors, including capital inputs (Igna and Venturini, 2019). This is consistent with the trend of increasing cost-effectiveness and declining productivity in R&D (Bloom *et al.*, 2020; Mason *et al.*, 2020).[3] Note that while the main results in column (6) remain consistent with our earlier estimates, we observe that the effect of AI innovation on the labor share diminishes.

6.2 Role of confounders

In Table 3, we expand the analysis by accounting for a larger set of factors that may influence income distribution across inputs at the regional level. We consider two main groups of counfounders: the first group includes proxies for alternative sources of technological (realized) knowledge (columns (2)-(4)), while the second group captures broader (structural) characteristics of the regions that could nonetheless affect the dynamics of the labor share (columns (5)-(7)).

In column (1), we report the results of our benchmark regression, as illustrated earlier (i.e., column (6) in Table 2). In column (2), we focus on 4IR patents, which encompass technologies such as flexible automation, additive manufacturing, big data, and the Internet of Things (IoT),

[3]Using historical data for OECD countries, Madsen *et al.* (2024a) document that the declining productivity (or, equivalently, the increasing cost-effectiveness) of R&D may account for approximately 30% of the reduction in income inequality (including the capital-to-labor income ratio) since 1920.

but exclude AI. This broader category of emerging digital technologies is rapidly expanding and has increasingly wider applications, thanks to the integration of AI within these systems. Overall, 4IR technologies are found to have a modest economic impact on aggregate productivity, though these effects are statistically significant (Venturini, 2022) and observable even at the regional level (Capello and Lenzi, 2024). However, certain technologies within this group, such as the IoT, can have a quantitatively substantial impact on productivity (Edquist *et al.*, 2021). While the integration of next-generation digital technologies poses challenges in identifying the impact of individual innovations, there is also the risk that the effect of AI on the labor share could be understated. The results in column (2) suggest that the effect estimated for AI does not capture the influence of a broader set of technologies. In fact, 4IR technologies are found to have a positive and significant effect on the labor share, in contrast to the effect observed for AI.

Column (3) focuses on ICT patents, which include innovations in computing, telecommunications, and related fields. These are considered antecedent technologies of AI, paving the way for the development of the new generation of digital technologies (Igna and Venturini, 2023). Earlier evidence highlights that the most prolific firms previously innovating in ICT, as well as those employing a higher share of ICT specialists, tend to move earlier into new technology domains (Calvino and Fontanelli, 2023a, 2023b). In column (4), we consider the aggregate of patents developed outside the technology field of AI. This variable should therefore capture the effect of general knowledge created in the region.

Regressions using this first group of controls in columns (2)–(4) notably illustrate that all forms of realized knowledge, except AI, are positively associated with the labor share. This finding suggests that innovation processes that successfully lead to the development of new knowledge are likely to create rents that are (partly) appropriated by workers, as technological knowledge complements labor on aggregate (Aghion *et al.*, 2019b). This effect goes beyond the impact on researchers' wages, as their compensation is already accounted for in the R&D expenditures, which are included among the control variables (not shown in the table). Two additional points are worth noting. First, the positive effect found for both old and new generations of digital technologies (namely, ICT and 4IR) differs from the standard mechanism of capital deepening, which, according to prior studies, tends to be detrimental to the dynamics of the labor share of income (Karabarbounis and Neiman, 2014; O'Mahony *et al.*, 2021). Second, there is a scale effect associated with realized knowledge, as the coefficient for this control variable increases in magnitude with the broader base of patents considered (from 0.002 for 4IR to 0.047 for total patents). Overall, these findings support the view that realized innovation increases the labor income share and reduces factor income inequality, although the development of AI may have its own unique impact.

Table 3: Alternative sources of realized knowledge and structural characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI patent stock p.w.	-0.011***	-0.012***	-0.015***	-0.016***	-0.016***	-0.011***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
4IR patent stock p.w.		0.002**					
		(0.001)					
ICT patent stock p.w.			0.009***				
			(0.001)				
All patent stock p.w. (excl. AI)				0.047***	0.047***	-0.029***	0.049***
				(0.004)	(0.004)	(0.004)	(0.004)
Tech concentration					-0.011***		
					(0.001)		
Manuf. employment share						0.154***	
						(0.006)	
Employment change							0.114***
							(0.032)
Adjustment term	-0.212***	-0.213***	-0.214***	-0.214***	-0.211***	-0.216***	-0.233***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)	(0.013)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,452	4,452	4,452	4,452	3,445	4,452	4,190
R-squared	0.348	0.348	0.347	0.347	0.346	0.344	0.372
Regions	262	262	262	262	204	262	262

Notes: The dependent variable is the labor share, defined as the ratio of employees' compensation to regional gross value added (at current prices). All variables are measured in logs. Long-run estimates are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey-West standard errors are in parentheses. ***, ** and * significant at 1, 5 and 10%, respectively.
Controls: Tangible capital stock per worker; R&D capital stock per worker; Output per worker.

In columns (5) to (7), we account for the second group of control variables that reflect the structural characteristics of economies and may impact the labor share. The negative coefficient for technological concentration (column (5)) suggests that as the overall technology market becomes more concentrated, the proportion of economic output allocated to labor decreases. This occurs because firms can translate their market power more into capital than labor income, likely appropriating a larger portion of rents from innovations protected by patents.Another possibility is that in regions where the technology market is concentrated, the entry rate of new companies is lower, leading to higher profits for incumbents and an increasing relative portion of income accruing to entrepreneurs and capital owners. This reflects a weakening of the typical Schumpeterian mechanism of creative destruction. These effects may be even more pronounced when the technology market is dominated by capital-intensive firms, which is a common scenario in digital markets and those controlled by big tech companies (Autor *et al.*, 2020). We will further investigate this issue later. Conversely, the positive coefficient for the manufacturing employment share (column (6)) may reflect the relatively strong bargaining power of labor unions. In this sector, workers usually secure better wage and employment conditions, thereby appropriating a larger proportion of income (Askenazy *et al.*, 2018; Cordoba *et al.*, 2024). Finally, in column (7), we account for the effect of structural change by considering changes in employment levels. The positive coefficient for this explanatory variable suggests that in regions with a greater incidence of expanding sectors, the labor share in the economy increases. This reflects higher labor demand and potentially greater wages due to the shortage of available labor.

We also account for life expectancy and fertility in our analysis (results not reported). Our findings show positive coefficients for both variables. Specifically, the positive coefficient for life expectancy suggests that healthier individuals may invest more in education, be more productive in the workplace, and, given their longer lifespan, contribute more to the economy (Bloom *et al.*, 2024a). Similarly, the positive coefficient for fertility may reflect the impact of a larger proportion of younger individuals entering the workforce. If wages are downward rigid, an increase in the number of young workers can expand the labor share. Both positive coefficients for life expectancy and fertility align with previous findings on the demographic determinants of the labor income share (Schmidt and Vosen, 2013).

In Table A1 of the Appendix, we control for characteristics related to the institutional setting of the region, with data available only for the second decade of the sample interval.[4] Specifically, we control for the quality of government services, the degree of business dynamism, and the endowment of both physical and digital infrastructure. These dimensions reflect the ability and

[4]Using data from 2010 onward helps neutralize the potential bias caused by the financial crisis, as illustrated in Figure 1. However, a drawback is that this data is available only for a subset of regions, making the results in Table A1 not fully comparable with those presented earlier in this section.

willingness of regional governments to create conditions conducive to the social and economic well-being of residents and businesses. The quality of government is assessed based on regional public services, which recent studies have found to be positively associated with regional development (Rodríguez-Pose, 2020). Business dynamism is measured by the proportion of new firms relative to total active companies. In the Schumpeterian tradition, new entrants drive competition and the process of creative destruction, which can erode incumbents' rents (i.e., profits and capital ownership). However, if increased competition reduces incentives to innovate by making rents short-lived or compressing mark-ups and profits, a higher entry rate may be associated with lower income inequality, reflected in a higher labor share in our analysis (Aghion *et al.*, 2005; Blundell *et al.*, 2022). The endowment of physical infrastructure is measured by the number of kilometers of motorways per square kilometer, while digital infrastructure is assessed based on the broadband coverage of the population (i.e., the percentage of households with fast internet access). Generally, public infrastructure facilitates access to productive opportunities, increasing the relative returns to assets and education (Calderon and Serven, 2014). However, the impact may differ in the short and long run depending on how these policies are financed (Chatterjee and Turnovsky, 2012). Digital infrastructure is generally less costly to fund than physical infrastructure, but its effect on the labor share may depend on its influence on regional specialization, potentially widening the digital divide across areas and affecting the demand for skilled labor and returns to education (Houngbonon and Liang, 2021 for a study on France).

In summary, the results in Table A1 illustrate that the adverse effects of AI on the labor share are stronger in the most recent years. These effects do not overshadow the impact of other drivers of factor income distribution, such as business dynamism and physical infrastructure, which are found in this paper to drive the dynamics of the labor share across European regions.

6.3 Causality, other econometric issues, and quantification of the effects

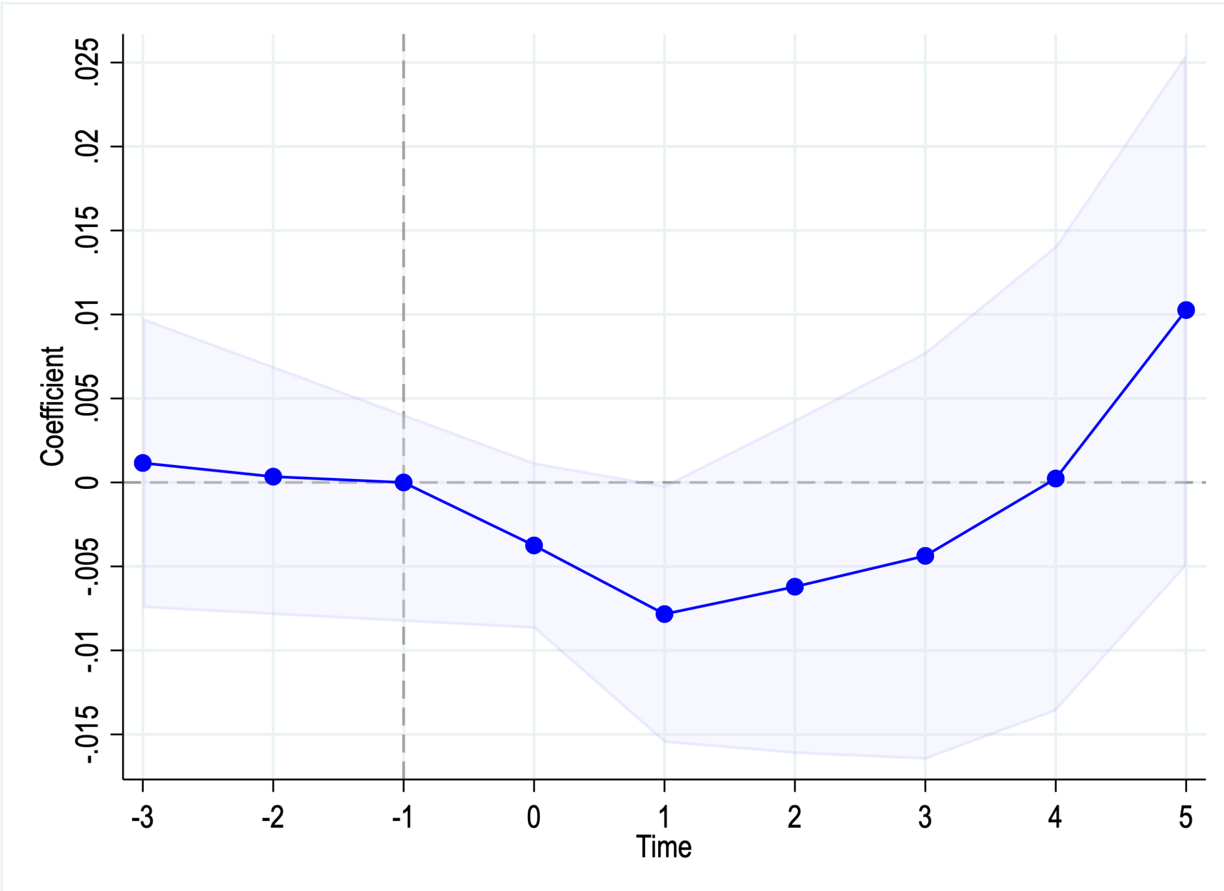
In this section, we first investigate in depth whether the nexus between AI and the labor share is causal through an event analysis. Then, we discuss various other econometric issues that may affect our estimates. Finally, we quantify the variation in regional labor shares explained by the results obtained in the first part of the analysis.

Our main dynamic regression procedure yields consistent estimates when the lag structure of the variables is optimally chosen. In this section, we use an alternative identification procedure and examine the response of the labor share to the launch of AI innovation using the LP-DiD regression. Figure 4 presents the outcomes of this event analysis procedure, specifically reporting the change in the log-value of the labor share within a horizon of six years after the introduction of AI, which we consider the event. The estimated parameter corresponds to an elasticity and is fully comparable with the coefficients of the dynamic regression shown in Table 2. The figure shows a reduction in the labor share two years after the event. The decrease amounts to 0.7% in response to a unit increase in the explanatory variable and is significant at the 5% level. The magnitude of this impact remains stable for half a decade, but, as is standard with these procedures, the precision of estimates diminishes over time (Jordà and Taylor, forthcoming). By the end of the period, the effect of AI falls outside the 95% significance region. The effect estimated for AI using the LP-DiD regression is at the lower bound of the range of elasticities found with the dynamic (ARDL) regression.

In Table A2 of the Appendix, we assess the robustness of our main estimates to various econometric issues. First, we run the dynamic regression using a richer lag structure for the model variables to ensure the consistency of estimates. Specifically, we estimate the baseline specification with more than one lag (ranging from two to five) for both the dependent variable and the regressors, obtaining similar results. Second, we evaluate how our estimates are affected by the log-transformation of patent stocks, $\ln(1 + Z)$, which we use to include all European regions in the regression sample. To address this, we run our log-log model restricting the sample to regions with at least one patent over the full sample period. Moreover, to investigate whether the effect of AI varies with the technological capability of the region, we run separate regressions considering regions that, in order, lie at the 25th, 50th, and 75th percentiles of the distribution of AI innovation. This involves including regions with 1, 5.8, and 19 patent counts, respectively. In all cases, the results of our baseline regression are broadly confirmed. In the last robustness check for sample composition issues, we run the baseline specification using the inverse hyperbolic sine transformation for the variables (instead of logarithms). Again, we obtain findings that are consistent with the baseline regression.

One key feature of economic processes that spread through space is the dependence they create among geographically contiguous units. These factors may not be fully observable and, therefore, may not be entirely accounted for, generating co-movements across regions that can be misinterpreted as the effect of specific characteristics of the area. In other cases, cross-sectional dependence

Figure 4: Effect of the introduction of AI: Event analysis (LP-DiD regression)



Notes: Event-analysis estimates for the effect of AI innovation on the log level of the labor share are obtained using the LP-DiD regression method. This method employs one-year leads and lags of the treatment variable, as well as the one-year lag of the total stock of patents (excluding AI) per worker and the labor share (in logs). The control group consists of 'never treated' regions. Standard errors are clustered at the regional level, and bandwidths are set to achieve 95% confidence.

is driven by purely idiosyncratic shocks, whose geographical propagation undermines estimation efficiency. In our analysis, we primarily assume that contemporaneous co-movements across regions are driven by unobservable factors that generate weak levels of cross-sectional dependence, with effects that are homogeneous across space and can be accounted for using time dummies. However, if the impact of such common shocks is strong and affects regional performance asymmetrically, it is preferable to use common correlated effects (CCE). These can be computed as simple averages of the variables used in the empirical model or, more structurally, as the mean of these variables weighted inversely by the distance between pairs of regions. As Pesaran (2006) points out, one advantage of the former method is that it does not require assumptions or tests regarding the channel of shock propagation (e.g., geographical or technological distance, bilateral trade, worker mobility, etc.). However, measures of spatial dependence based on proximity metrics remain highly informative about which mechanisms may be at play (see Coe and Helpman, 1995, Bottazzi and Peri, 2003, and related works in this journal). In Table A3 of the Appendix, we examine the role of spatial dependence in our setting, finding evidence that neighboring regions influence each other's economic outcomes. Specifically, there is a negative association between factor income distribution among adjacent areas, with the labor share in one region being higher when that of neighboring regions is lower, while innovations in nearby regions are positively associated with the local labor share. However, the spatial lag effect of AI patents becomes insignificant when CCE terms are included in the analysis. This suggests that the impact of neighboring regions' patenting activities may be an artifact of the weighting scheme used and, in practice, that these types of spillovers are very difficult to identify (Eberhardt *et al.*, 2013). The negative association of labor shares between contiguous areas may reflect labor mobility: regions with relatively higher wages or more job opportunities can attract workers from adjacent areas, with this effect typically being stronger for more educated workers who earn more (Langella and Manning, 2022).

Table 4: Quantification of effects

		Mean	25 pct.	50 pct	75 pct	99 pct
Lower bound	LP-DiD	-0.20%	-0.17%	-0.20%	-0.22%	-0.25%
Upper bound	ARDL	-0.46%	-0.41%	-0.48%	-0.51%	-0.58%

Notes: Lower bound values use parameter estimates from the LP-DiD regression (-0.007). Upper bound values use parameter estimates from the ARDL regression in column 4, Table 3 (-0.016).

Estimates from this part of the analysis reveal a noticeable sensitivity of the labor share to AI innovation. In percentage terms, doubling AI would decrease the proportion of regional income accruing to workers by 0.7% using the event-analysis estimates as a lower bound (-0.007; Figure 4), and by 1.6% using the dynamic estimates as an upper bound (-0.016; Table 3). We can also quantify variation in the labor share explained by our estimates in percentage (absolute) points. This can be derived by multiplying the estimated elasticities with the absolute change in the stock of AI per worker between 2000 and 2017 (0.3%), and expressing the resulting figure as ratio to the mean of the labor share over the sample period (51.8%). Using our lower bound estimates (-0.007), due to the effect of AI innovation the labor share would have fallen by 0.20% (from its mean of 51.8%), and by 0.46% using our upper bound estimates (-0.016). Put differently, our results suggest that

AI innovation may account for up to one-half percentage point of the labor share decline observed since the early 2000s. These figures are not overly high and, thus, appear plausible. Table 4 also illustrates that the percentage reduction in the labor share is fairly uniform across the distribution of the variable, whether for capital-intensive regions (above the 25^{th} percentile) or labor-intensive regions (above the 75^{th} percentile).

6.4 Impact of AI innovation by skill type and underlying mechanisms (2010-2017)

We now investigate the effect of AI during the period following the Great Recession of 2008-09, where we can disentangle the labor share by skill type (educational level). We then explore the mechanisms that may be driving the overall effect of AI.

We present the results of our main specification by skill level on the left-hand side of Table 5. On the right-hand side, we report the findings of a similar specification using the employment share as the dependent variable, and the same set of covariates as explanatory variables. The goal is to examine whether the effect of AI on the labor income share can be explained by the heterogeneous impact of this innovation type on job opportunities for different categories of workers, as proxied by their share in total regional employment. A substantial difference between the effect of AI on the labor income share and the employment share would indicate that one mechanism through which AI operates is by altering relative factor compensation. From an accounting perspective, relative factor compensation drives variation in labor income share, alongside changes in relative employment (Azmat *et al.*, 2012). A full displacement effect on the labor share emerges when the new technology negatively impacts both the employment and wage shares. A full productivity effect emerges when AI is positively related to both employment and wage shares. In the former case, the elasticity of AI in the labor share specification would be negatively signed, and in the latter case, it would be positively signed. Whenever AI has opposing effects on wage and employment shares, the net effect on the labor share depends on which of these two forces prevails. This phenomenon is known as the reinstatement effect of the new technology (Albanesi *et al.*, 2023). Note that, for this group of regressions, the table also presents the coefficients of all control variables to illustrate the differences in their effects and, overall, to corroborate the robustness of these estimates.

The results in Table 6 suggest that AI is detrimental to the income share of each worker category, but this effect is larger for high-skill workers and smaller for low-skill workers. This finding supports the prediction of our theoretical framework that AI shifts income distribution away from workers at the top end of the skill distribution toward those at the bottom. Interestingly, estimates on employment shares point to large heterogeneity in the transmission mechanism of AI's effects. These innovations are unrelated to the employment shares of high- and medium-skill workers but are positively associated with the employment share of low-skill workers. These two sets of estimates suggest that the decline in the labor share of medium- and high-skill workers is mainly driven by wage compression, potentially due to a reduced ability to capture the benefits of innovation rents, as their job opportunities remain unaffected by AI. Conversely, relative to other worker groups, employment opportunities for low-skill workers increase as a result of AI, which mitigates the gross negative effect of wage compression. For low-skill workers, however, the reinstatement effect of new digital technology remains negative.

Among the control variables, labor productivity is found to be negatively associated with the shares of labor income and employment for workers on the right-hand side of the skill distribution (the low-skilled). Tangible assets, such as machinery, equipment, and structures, complement low-skill labor—a finding observed in both relative measures of income and employment—while the reverse holds for the other two groups of employees. In contrast, knowledge capital acts as a complementary input for high-skill workers and a substitute input for low-skill workers, regardless of whether it is measured in terms of innovation output (total patents) or innovation input (R&D). The heterogeneity in the effects of the control variables aligns with the main findings of earlier literature, lending strong support to the robustness of our regressions by skill group (vom Lehn, 2018; O'Mahony *et al.*, 2021).

One may question whether the statistical association between AI innovation and regional labor share is due to technological substitutability across factor inputs, as outlined by our theoretical framework, or if it is instead the outcome of some other unaccounted mechanism. An alternative force that could be at play is the increasing concentration of AI. These new technologies are produced by a few large firms, which were previously successful in the ICT field, and drive the technological specialization of the regions where they are located (see Figure 1). This trend is common to both the manufacturing and service sectors, where a larger market share is held by a few big tech companies (WIPO, 2019; Baruffaldi *et al.*, 2020).

In the final part of the work, we investigate this issue by replicating the regressions by skill,

Table 5: The impact of AI innovation the shares of labor and employment by skill (2010-2017)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Labor share					Employment share		
	Total		High skill	Medium skill	Low skill	High skill	Medium skill	Low skill
AI patent stock p.w.	-0.016***	-0.025***	-0.033***	-0.034***	-0.020***	-0.005	0.002	0.012**
	(0.001)	(0.002)	(0.008)	(0.003)	(0.007)	(0.005)	(0.003)	(0.006)
ALP - Output per worker	0.000	-0.440***	0.031	0.024	-0.347***	0.037	-0.023	-0.260***
	(0.009)	(0.059)	(0.075)	(0.032)	(0.071)	(0.033)	(0.019)	(0.051)
Tangible capital stock p.w.	0.000	0.128***	-0.316***	-0.125***	0.244***	-0.297***	-0.168***	0.325***
	(0.000)	(0.015)	(0.036)	(0.015)	(0.033)	(0.018)	(0.012)	(0.025)
R&D capital stock p.w.	-0.002***	-0.003***	0.038***	0.006***	0.011***	0.022***	0.007***	-0.008***
	(0.000)	(0.001)	(0.004)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
All patent stock p.w. (excl. AI)	0.047***	0.011	1.652***	-0.033	-1.141***	1.355***	-0.205***	-0.844***
	(0.004)	(0.019)	(0.091)	(0.026)	(0.085)	(0.057)	(0.028)	(0.060)
Adjustment term	0.786***	0.608***	-0.278***	-0.269***	-0.374***	-0.223***	-0.411***	-0.357***
	(0.014)	(0.049)	(0.022)	(0.021)	(0.025)	(0.020)	(0.037)	(0.020)
Period	2000-17	2010-17	2010-17	2010-17	2010-17	2010-17	2010-17	2010-17
Obs	4,452	2,080	1,944	1,944	1,944	1,944	1,944	1,944
R-squared	0.347	0.520	0.447	0.401	0.528	0.303	0.551	0.474
Regions	262	260	243	243	243	243	243	243

Notes: The dependent variable is the labor share, expressed as the ratio of employees' compensation to regional gross value added (at current prices) in columns (1)-(5) and the share of employment by skill type on total employment in columns (6)-(7). All variables are in logs. Long-run estimates are obtained from an ARDL(1,0) regression. Region and year fixed effects are included in the regression. Newey-West standard errors.***, ** and * significant at 1, 5 and 10%, respectively.

including two concentration measures of AI innovation. The first indicator is the four-firm concentration ratio (CR4) of AI patents within each region. This variable is used to understand whether the success and growth of larger (superstar) firms may have an aggregate effect on the labor share of regional income, particularly if these companies are relatively less labor-intensive (Autor *et al.*, 2020). This represents the *within-region effect* of AI concentration. The second indicator corresponds to the share of each region in total AI patents developed in Europe. This variable is used to capture the increasing specialization of certain areas and the fact that these may become more (or less) attractive to workers from adjacent regions, depending on their skills and the new labor demand (Bonfiglioli *et al.*, 2023). This represents the *between-region effect* of AI concentration.

Table 6 unambiguously indicates that, for high- and medium-skill workers, the effect of AI is mainly driven by substitutability (complementarity) with other production inputs, rather than by changes in labor demand fueled by AI concentration. For low-skill workers, the effect of AI on labor share—whether through the channel of factor substitutability or market concentration—remains ambiguous, as both variables are insignificant in column (6). This finding highlights the weak income effects of AI at the bottom end of the skill distribution. Finally, it should be noted that AI concentration is detrimental only to the labor share of medium-skilled workers, primarily through the *between-region* channel, thus emerging as a force that strongly polarizes factor income distribution (Michaels *et al.*, 2014).[5]

Table 6: The impact of AI concentration on the labor share by skill (2010-2017)

	(1)	(2)	(3)	(4)	(5)	(6)
	High skill		Medium skill		Low skill	
AI patent stock p.w.	-0.033***	-0.044***	-0.034***	-0.037***	-0.020***	-0.011
	(0.008)	(0.008)	(0.003)	(0.003)	(0.007)	(0.007)
AI concentration (within-region)		-0.004		-0.006**		-0.009
		(0.009)		(0.003)		(0.009)
AI concentration (between-region)		-0.694		-0.699***		0.097
		(0.434)		(0.199)		(0.365)
Obs.	1,944	1,944	1,944	1,944	1,944	1,944
R-squared	0.447	0.449	0.401	0.403	0.528	0.531
Regions	243	243	243	243	243	243

Notes: The dependent variable is the labor share, expressed as the ratio of employees' compensation to regional gross value added (at current prices). All variables are in logs. Long-run estimates are obtained from an ARDL(1,0) regression. Region and year fixed effects are included in the regression. Newey-West standard errors.***, ** and * significant at 1, 5 and 10%, respectively. **Controls:** R&D capital stock per worker; Non-AI patent stock per worker.

[5] These findings are confirmed even when we control for the within- and between-effects of ICT innovation concentration (not shown for the sake of brevity).

7 Conclusions

In this paper, we have investigated the complex relationship between technological innovation, regional economic development, and labor market outcomes, specifically examining how advances in AI impact income inequality and factor returns. We have focused on the labor income share across European regions since 2000, using a theoretical framework and empirical analyses to explore how AI innovation has influenced regional disparities in labor shares.

Our findings indicate that AI innovation is linked to a significant decline in the labor share, potentially accounting for between one-fifth and one-half of a percentage point of the overall decrease observed since the early 2000s. This highlights the noticeable impact of AI on exacerbating income inequality, especially in regions that specialize in AI-related technologies, underscoring AI's role in driving regional disparities in labor income distribution.

We also document that the effects of AI innovation are heterogeneous across different skill levels. High- and medium-skill workers face adverse outcomes in both wages and employment, as AI development is negatively correlated with their income and employment shares. For low-skill workers, the adverse impact is more concentrated on income, while employment prospects improve as a result of AI innovation. Our analysis suggests that these differential impacts are driven by the varying degrees to which AI technologies substitute or complement tasks performed by workers of different skill levels. High- and medium-skill workers, who implement cognitive and repetitive decision-making tasks, experience greater negative effects, whereas low-skill workers may benefit from shifts in labor demand towards roles that are less automatable or complementary to AI technologies.

Future research could further investigate how the interaction between technological advancements and contextual factors, such as policy interventions, labor market dynamics, and educational systems, shapes regional income inequality. Assessing the effectiveness of various policy measures, including social protections and labor regulations, in addressing the distributional impacts of AI will be essential for mitigating potential negative outcomes. Moreover, expanding the analysis to include metrics beyond the labor share, such as wage inequality and access to high-skill jobs, would provide a more comprehensive understanding of the multifaceted nature of inequality driven by AI advancements. Incorporating these broader dimensions would enable future studies to better capture the complex ways in which AI influences different segments of the workforce and contributes to regional disparities.

Acknowledgements

We would like to thank participants at the seminars at the University of Bologna, the 5th Assisi Workshop in Economics on *The Future of Education, Skills, and Productivity*, the *Technology, Innovation, and Growth* conference in Gdańsk, the *Labour Market Effects and Social Impact of Technological Transformation, Globalisation, and Demographic Change* conference in Leuven, and the *Capital vs. Labor: Perspectives on Inequality and Taxation in the 21st Century* conference in St. Gallen for their valuable comments and suggestions. Antonio Minniti acknowledges financial support from the Italian Ministry for the University and Scientific Research. Klaus Prettner is grateful for the financial support from grants 09/03-03-V04-00516 funded by the Slovak Research and Development Agency and OPUS 26 No. 2023/51/B/HS4/00096 funded by NCN Poland.

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Appendix A

Table A1: Role of the institutional setting (2010-2017)

	(1)	(2)	(3)	(4)	(5)	(6)
AI patent stock p.w.	-0.016***	-0.025***	-0.035***	-0.023***	-0.024***	-0.026***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Regional characteristic			0.001	-1.201***	0.042***	0.055
			(0.006)	(0.077)	(0.007)	(0.041)
			Government quality	Business dynamism	Physical infrastructure	Digital infrastructure
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Period	2000-17	2010-17	2010-17	2010-17	2010-17	2010-17
Obs	4,452	2,080	864	752	1,088	1,024
R-squared	0.347	0.520	0.533	0.512	0.572	0.565
Regions	262	260	108	94	136	128

Notes: The dependent variable is the labor share, expressed as the ratio of employees' compensation to regional gross value added (at current prices). All variables are in logs. Long-run estimates using data from 2000 are obtained from an ARDL(1,1), those using data from 2010 are obtained from an ARDL(1,0). Region and year fixed effects are included in the regression. Newey-West standard errors.

Controls: Output per worker; Tangible capital stock per worker (column (1) only); R&D capital stock per worker; Total patent stock (excluding AI) per worker.

Table A2: Econometric issues

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
AI patent stock p.w. (elasticity)	-0.016***	-0.014***	-0.011***	-0.016***	-0.007***	-0.007***	0.004***	-0.013***	-0.015***	-0.024***	-0.022	-0.005***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.005)	(0.025)	(0.001)
AI patent stock p.w. (Arcsinh)											-0.024***	-0.401***
											(0.002)	(0.005)
Adjustment term	-0.214***	-0.220***	-0.249***	-0.352***	-0.214***	-0.203***	-0.207***	-0.332***	-0.301***	-0.366***	-0.220***	-0.333***
	(0.014)	(0.014)	(0.016)	(0.014)	(0.017)	(0.022)	(0.027)	(0.056)	(0.075)	(0.084)	(.0138)	(.040)
Model	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic
	ARDL	ARDL	ARDL	ARDL	ARDL	ARDL	ARDL	ARDL	ARDL	ARDL	ARDL	ARDL
Lags	1,1	1,1	3,3	5,5	1,1	1,1	1,1	1,0	1,0	1,0	1,1	1,0
AI sample (percentiles)	100	100	100	100	25	50	75	25	50	75	100	100
Time period	2000-18	2000-18	2000-18	2000-18	2000-18	2000-18	2000-18	2010-18	2010-18	2010-18	2000-18	2010-18
Specification	Log-log	Log-log	Log-log	Log-log	Log-log	Log-log	Log-log	Log-log	Log-log	Log-log	Log-Arcsinh	Log-Arcsinh
Controls	Yes	No	No	No	No	No	No	No	No	No	No	No
Obs	4,452	4,576	3,945	3,419	3,456	2,299	1,156	1,656	1,093	544	4298	2224
R-squared	0.347	0.384	0.422	0.420	0.389	0.389	0.361	0.572	0.541	0.604	0.410	0.572
Regions	262	278	263	263	208	137	68	208	137	68	278	281

Notes: The dependent variable is the labor share, expressed as the log-ratio of employees' compensation to regional gross value added (at current prices). The stock of AI patents per workers is measured as $\log(1+z)/L$ in columns (1)-(10). Columns (11) and (12) report the coefficients estimated with arcsin value of the explanatory variable ($\tilde{\beta}$) and the associated elasticity $\beta = (\tilde{\beta}/\bar{y} \cdot \bar{x}/\sqrt{\bar{x}^2+1})$ where the bars denote the mean of the dependent and the explanatory variable (in logs and not-transformed, respectively) in the sample period. Newey-West standard errors are in parentheses. ***, ** and * significant at 1, 5 and 10%, respectively.

Controls: Output per worker Tangible capital stock per worker; R&D capital stock per worker; All patent stock per worker (excluding AI).

Table A3: Spatial dependence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI patent stock p.w.	-0.016***	-0.016***	-0.016***	-0.017***	-0.011***	-0.006***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Labor share (spatial lag)		-0.049***		-0.083***	-0.080***	-0.080***	-0.076**
		(0.010)		(0.011)	(0.011)	(0.012)	(0.034)
AI patent stock p.w. (spatial lag)			0.003**	0.009***	0.007***	0.008***	0.001
			(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
Adjustment term	-0.214***	-0.214***	-0.214***	-0.213***	-0.216***	-0.230***	-0.761***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.043)
Cross-Sectional Dependence	TD	TD	TD	TD	NO	NO	CCE
Controls	Yes	Yes	Yes	Yes	Yes	No	No
Obs.	4,452	4,452	4,452	4,420	4,420	4,471	4,208
R-squared	0.347	0.347	0.347	0.347	0.342	0.400	0.937
Regions	262	262	262	260	260	263	263

Notes: The dependent variable is the labor share, defined as the ratio of employees' compensation to regional gross value added (at current prices). All variables are measured in logs. Long-run estimates are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey-West standard errors are in parentheses. ***, ** and * significant at 1, 5 and 10%, respectively.

Controls: Output per worker; Tangible capital stock per worker; R&D capital stock per worker; All patent stock per worker (excluding AI).