



AI innovation and the labor share in European regions

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ABSTRACT

This paper examines how the development of Artificial Intelligence (AI) affects the distribution of income between capital and labor, and how these shifts contribute to regional income inequality. To investigate this issue, we analyze data from European regions dating back to 2000. We find that for every doubling of regional AI innovation, the labor share declines by 0.5% to 1.6%, potentially reducing it by 0.09 to 0.31 percentage points from an average of 52%, solely due to AI. This new technology has a particularly negative impact on high- and medium-skill workers, primarily through wage compression, while for low-skill workers, employment expansion induced by AI mildly offsets the associated wage decline. The effect of AI is not driven by other factors influencing regional development in Europe or by the concentration of the AI market.

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 increasing inequality is driven by various factors, including productive specialization, the shift towards service-based economies (tertiarisation), 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. As a result, 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; Mallick and Sousa, 2017, 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

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and Restrepo, 2018; Cords and Prettnner, 2022).¹ Finally, the global decline in labor income shares has mechanically contributed to rising income inequality, given that labor income tends to be more evenly distributed than capital income. For the decline in the labor income share, various reasons have been suggested in the literature, such as globalization, the declining bargaining power of labor unions, technological change that increases the productivity of capital that substitutes for labor by more than the productivity of other types of capital, and demographic changes, which affect the relative returns to capital and labor (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, delivers productivity benefits (Drydak, 2024), though these are typically delayed (Brynjolfsson et al., 2021; Venturini, 2022). 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). However, 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. While some argue that AI could reduce inequality (Agrawal et al., 2023, 2024a; Bloom et al., 2025), others are more pessimistic (Acemoglu, 2023; Grant and Üngör, 2024), particularly due to AI's potential to reduce labor demand through automation, leading to a decoupling of productivity gains from employment and wages (Lane and Saint-Martin, 2021).² In this context, Korinek and Stiglitz (2019) argue that the increasing use of AI may lead to greater inequality, but that sound policies can strongly mitigate its inequality-enhancing effects.

On top of country-wide aggregate effects, 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 impacted substantially, with AI hubs advancing and other regions being 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 affects different types of labor in distinct ways. For some workers, AI-driven technological change reduces demand, leading to a decline in the labor income share, particularly if efficiency gains primarily benefit capital owners. In contrast, other workers may experience less disruption or even benefit from new opportunities. Additionally, rapid economic growth in regions with high patent activity could exacerbate regional disparities if AI's benefits are unevenly distributed. To explore these dynamics, we begin by discussing the likely effects of AI innovation on various types of workers and on the labor income share. We then empirically test these implications using regional data on AI patenting and labor income.

Empirical trends suggest a potential link between AI-driven innovation and labor market shifts. From 2000 to 2017, the number of AI patents per million workers steadily increased across European regions.³ Over the same period, the labor income share exhibited a general decline, with a temporary peak during the global economic and financial crisis of 2007–2009. This divergence raises important questions about the distributional consequences of AI.

Building on these observations, we analyze the relationship between technological innovation and labor market outcomes to better understand AI's influence on income distribution. Using post-2000 data from European regions, we investigate whether AI-specialized regions experience greater inequality and identify the worker skill groups most affected by this technological shift. To this end, we implement a dynamic regression that accounts for various economic factors that may drive the dynamics of the regional labor share, including alternative sources of technological development, accumulation of fixed investment and R&D assets, productivity improvements, structural change, demographic shifts, and market concentration. We also address several econometric issues that may affect estimation results, such as spatial dependence, the count nature of patent data, and dynamic adjustment, among others.

Our analysis reveals a significant pattern of effects: with each doubling of regional AI innovation, the labor share decreases between 0.5% and 1.6%. The impact is even larger – around 2.1% – when considering the years following the Great Recession (see also Eden and Gaggl, 2018; Guimarães and Mazedo Gil, 2022). Overall, our estimates suggest that the labor share may have decreased by between 0.09 and 0.31 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 impacts the income share of all worker categories negatively, this effect is more pronounced for high- and medium-skill workers compared to low-skill workers.

¹ When focusing on wealth inequality, lower capital taxation over time, increasing inheritances since the 1970s, and demographic factors such as declining fertility, which has led to a concentration of inherited wealth, have all been suggested as drivers (Piketty and Zucman, 2014; Alvaredo et al., 2017).

² 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. Additionally, Bonfiglioli et al. (2023) examine 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. Finally, Drydak (2024) shows that knowledge, skills, and the capabilities to work with AI boost job interview invitations and salary prospects for university graduates, which suggests an inequality-enhancing effect of AI through this channel.

³ Please refer to the working paper version of the manuscript for further insights into trends in AI patenting within Europe: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4971431.

Regarding the mechanisms, our estimates suggest that AI innovations are unrelated to the employment share of high- and medium-skill workers but are (mildly) positively associated with the employment share of low-skill workers. This suggests that the reduction in the labor share for high- and medium-skill workers is primarily driven by wage compression, while for low-skill workers, employment expansion facilitated by AI partially offsets the corresponding wage decline. For high- and medium-skill workers, the impact of AI appears to arise mainly from its substitutability/complementarity with other production inputs, rather than from changes in labor demand induced by the concentration of new technology production in a limited number of firms and regions. However, for low-skill workers, the effect of AI on the labor share – and its underlying drivers – remains uncertain.

The rest of the paper is structured as follows: Section 2 provides an overview of the relevant literature, highlighting how our study contributes to and extends existing research. Section 3 outlines the predictions tested empirically. Section 4 details the econometric model, while Section 5 describes the dataset used in the analysis. Section 6 presents the results of the baseline specification, performs several robustness checks, and examines the impact of AI innovation across different skill levels. Finally, Section 7 concludes the paper.

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; 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.⁴

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. While some argue that AI predominantly displaces high-skill workers (Webb, 2020; Bloom et al., 2025), others predict more severe short-term effects on low-skill workers in various countries (Grant and Üngör, 2024). 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 on the relationship between innovation and income inequality—an area that has yielded mixed results so far (Akcigit et al., 2017). Several studies have shown that patenting and other intellectual property rights, by enabling the appropriation of innovation rents, may contribute to income inequality and to the rising capital share of national income (Lee and Rodríguez-Pose, 2013; Koh et al., 2020; Guelllec, 2020). While some research suggests that innovation exacerbates inequality at the top of the income distribution 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) and 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 in which 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.

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

⁴ 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., 2024b). 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).

proper internet infrastructure face barriers to accessing online markets and digital resources, limiting their growth potential (de Clercq et al., 2023). 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 the technological drivers of regional inequality, as identified in the literature, interact with the development of AI.

3. AI and the labor share: theoretical considerations

To investigate the impact of AI development on the labor share, we build upon several key contributions. Karabarbounis and Neiman (2014) show that, globally, the labor income share has declined across most countries and industries due to capital deepening and associated technological changes. In particular, the emergence of computers and advancements in information technology, which have significantly reduced the price of investment goods, account for approximately half of the reduction in the labor share since the 1980s. O'Mahony et al. (2021) emphasize, however, that R&D and other knowledge investments – intensive in high-skilled (highly educated) labor – help counteract this declining trend. At the same time, Aghion et al. (2019a) show that as innovation increases, particularly through patenting, the income share accounted for by non-entrepreneurial wage income tends to decline, thereby highlighting the unequal distribution of innovation rents. More recently, studies such as Drozd et al. (2022) and Trammell and Korinek (2023) have focused specifically on the effects of ICT-powered automation and AI on the labor share. Their findings suggest that innovation, especially in labor-replacing technologies, plays a major role in driving the decline in the labor income share.

Since different parts of the labor force may be affected by AI innovation in distinct ways, we build on Krusell et al. (2000)'s concept of capital-skill complementarity. They show how capital that disproportionately complements skilled labor can increase inequality between low-skill and high-skill workers. Extensions of this framework, such as those in Cords and Prettnner (2022) and Bloom et al. (2025), apply the idea of capital-skill complementarity specifically to automation technologies like industrial robots and AI. These models explore how automation influences labor demand and the distribution of income, particularly when differentiated by skill level. Industrial robots exert downward pressure on the wages of low-skill workers and, depending on the elasticities of substitution, they can lead to upward pressure on the wages of high-skill workers. In contrast, AI has the opposite effect: it tends to push wages down for high-skill workers and, depending on the elasticities of substitution involved, can push wages up for low-skill workers. This suggests that, overall, industrial robots may increase inequality, while AI could have an inequality-reducing effect.⁵

These contributions collectively highlight the complex and multifaceted impact of these recent cutting-edge technologies on the labor share, emphasizing the role of skill-level differences and the various types of technological advancements shaping labor dynamics. Based on these insights, we can now formulate two hypotheses to be tested empirically.

Hypothesis 1. The labor income share decreases with AI innovation.

Hypothesis 2. AI innovation reduces the high-skill labor share more than the low-skill labor share.

The impact of AI innovation on the regional labor income share is an empirical question that depends on several factors, including the substitutability between different types of labor and capital, the nature of innovative activity, and certain region-specific characteristics. To analyze our hypotheses empirically, we express the labor income share as a general function of productivity, various types of labor, and physical capital usage (Karabarbounis and Neiman, 2014; O'Mahony et al., 2021). Specifically, we model the labor income share as

$$S_{i,t}^j = f(A_{i,t}, k_{i,t}), \quad (1)$$

where $A_{i,t}$ represents general productivity in region i at time t , and $k_{i,t}$ denotes the capital intensity of production. Additionally, L_j represents different types of labor categorized by skill level, with $j = l, m, h$, where l corresponds to low-skill labor, m to medium-skill labor, and h to high-skill labor. It is worth noting that our model includes medium-skill workers, whereas much of the theoretical literature focuses exclusively on low-skill and high-skill workers. Below, we derive our empirical specifications by adapting Eq. (1) to account for the specific characteristics of the variables in our sample (see Section 4).

⁵ Other – for various reasons less related – contributions on the economic effects of AI include Agrawal et al. (2019), who discuss the differences in the labor market effects of automating prediction versus enhancing human decision-making; Acemoglu (2024) and Filippucci et al. (2024), who quantify the impact of AI use on economic growth; Felten et al. (2021), who construct a measure for AI use at the occupational level; Prytkova et al. (2024), who analyze the effects of exposure to digital technologies on employment; Brynjolfsson et al. (2019), who discuss explanations for the modern productivity paradox, noting that despite the astonishing progress of AI, productivity growth is not yet accelerating significantly; Eloundou et al. (2024), who analyze how large language models such as ChatGPT impact the tasks that workers perform in their jobs, finding that for a large share of jobs, more than half of the tasks they perform are strongly affected; and Korinek (2023), who describes various use cases of large language models such as ChatGPT for enhancing the productivity of economic researchers.

4. Empirical model

Our first specification corresponds to the stochastic, log-linear version of Eq. (1):

$$\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^{AI} + \alpha_2 \ln A_{i,t} + \alpha_3 \ln X_{i,t} + CSD + \varepsilon_{i,t}, \quad (2)$$

based on data from 273 regions ($i = 1, \dots, 273$) collected over 17 years ($t = 2000, \dots, 2017$). 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 $\varepsilon_{i,t}$ denotes spherical errors.

The variable k^{AI} represents the knowledge capital intensity of production, which, in this context, is defined as the stock of technological knowledge developed in the field of AI, expressed per unit of labor. In line with the latest developments in national accounting principles, the overall capital endowment of each region includes various asset types: fixed investment, R&D, and realized knowledge capital. The last is measured by the number of patents applied for in various technology domains, such as AI, Fourth Industrial Revolution (4IR) technologies, Information and Communication Technologies (ICT), and, residually, other technological categories. Gross substitutability between AI knowledge capital and labor emerges when a negative parameter is estimated for k^{AI} . In contrast, a positive parameter for this explanatory variable would indicate that capital and labor are gross complements. A similar rationale applies to other measures of knowledge and physical assets. A denotes the level of regional productivity, which is alternatively defined in terms of either 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, meaning that it promotes production towards a more intensive use of some factor inputs.

Our specification operationalizes the idea that AI-driven innovation creates new technological capabilities, which can be leveraged to introduce more efficient production methods or better products. This results in an increase in worker productivity, which in turn expands output. Some of the productivity gains are passed on to employees through higher wages. However, if wages do not increase proportionally to productivity, profits rise faster than worker income, leading to a decline in the labor share. This mechanism is further complicated by employment changes induced by AI innovation. To identify the underlying channels at work, we complement our labor share regressions with the estimation of an employment equation. In this analysis, we ensure that changes in the labor share are not driven by advancements in other technology domains. This is achieved by controlling for patents in other fields, such as those related to ICT, 4IR, or general innovations. Since not all innovation output is patented, and because research productivity varies with regional innovativeness, we also control for the level of research effort, measured as R&D stock per worker. Finally, by including the fixed capital stock per worker, we account for the adoption of capital assets, including traditional machinery, industrial robots, and AI-driven equipment, thus capturing the effect of AI usage.

Given the potential endogeneity resulting from omitted variables, we account for a range of potential 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. We also account for a set of regional characteristics that reflect the effectiveness of regional institutions in shaping market functioning, namely the quality of government, the degree of regional market business dynamism, and the endowment of physical and digital infrastructures. See below for more data details.

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 the institutional setting. The effect of CSD is primarily captured by common time dummies; these control for the effect of changes 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 exogenous shocks have effects on the dynamics of the labor share that are similar across regions (weak CSD). However, unobservable factors can produce effects 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 geographical proximity weights 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. (2). This regression method is known to produce consistent estimates that are relatively 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 Sections 6.1–6.2, we present the long-run coefficients derived from the following dynamic reformulation of Eq. (2):

$$\ln S_{i,t}^L = \beta_{i,0} + \beta_1^{LS} \ln LS_{i,t} + \beta_0^k \ln k_{i,t}^{AI} + \beta_1^k \ln k_{i,t-1}^{AI} + \dots + CSD + \varepsilon_{i,t}, \quad (3)$$

where the coefficient α_1 in Eq. (2) is obtained as $\alpha_1 = (\beta_0^k + \beta_1^k)/(1 - \beta_1^{LS})$ and $-\beta_1^{LS}$ is the rate at which variables return to their equilibrium relationship following an exogenous shock. A negative and significant adjustment speed coefficient would confirm that our specification effectively captures the dynamics of the variables and their relationship. Dynamic estimates use Newey–West standard errors, which are robust to heteroskedasticity and auto-correlation. The lag order of auto-correlation is determined using the conventional rule $p = 4(T/100)^{2/9}$, where T represents the number of time observations in the sample.⁶

⁶ Long-run estimates are obtained using the Stata command `xtddcce2`, developed by Jan Ditzen (release: June 6th, 2024).

5. Data and summary statistics

Our analysis is developed using annual data for a panel of 273 European regions at the NUTS2 level, including the UK, between 2000 and 2017. We rely on a diverse array of data sources. Our main data are sourced from Eurostat regional accounts, which provide information on employee compensation, total employment, and gross value added. The labor share of income is calculated as the ratio of employee compensation to regional gross value added, expressed at current prices. Additionally, we use data on gross fixed capital formation and R&D expenditures.⁷ The value of the corresponding stocks is derived using the perpetual inventory method from the real value of these investments. The constant price value of both series is obtained by deflating nominal investment with the implicit deflator for regional value added. For the investment stock, we adopt an annual depreciation rate of 10%, and a rate of 15% for the stock of R&D assets. The formula used to compute the annual stock of fixed assets is $K_{it} = I_{it} + K_{it-1} \cdot (1 - \delta)$, and the initial stock is derived as $K_{i1} = I_{i1}/(\delta + g)$, where I is the real investment flow, δ is the annual rate of capital depreciation, and g is the average annual rate of investment growth in the time interval of the analysis (Hall and Mairesse, 1995). A similar procedure is used for constructing both the stocks of R&D capital and patented innovations. In robustness checks, we assess the sensitivity of our estimates to the assumption made on the depreciation rate for capital stocks, providing estimates using variables in which δ ranges from 5% to 15% for fixed investment assets and from 15% to 45% for the cumulative value of either R&D expenses or patented innovations.

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).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.

To quantify realized innovation across various technological domains, including AI, we use data on patent applications sourced from the OECD EPO Regpat database. This database assigns patent applications filed at the European Patent Office to regional levels based on applicant information, using an automated name disambiguation procedure. 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, Appendix Table 2) to identify AI patents,⁹ which was previously used by Buarque et al. (2020) to map AI innovations in European regions. However, unlike that study, we do not integrate AI categorization with keyword searches in patent abstracts. This implies that our count of AI patent applications is more conservative. For 4IR patents, we use the classification from EPO (2017), while for ICT patents, we rely on the J-tag classification system developed by Inaba and Squicciarini (2017).

AI patents typically relate to advanced technologies such as machine learning, artificial neural networks, and natural language processing. For example, they may involve AI-based recommendation algorithms used by e-commerce platforms, deep learning-based image recognition systems for autonomous vehicles, or speech recognition technologies in virtual assistants like Siri or Alexa. 4IR patents, on the other hand, encompass technologies such as the Internet of Things (IoT), blockchain, advanced manufacturing, and smart technologies, which are aimed at real-time monitoring, supply chain management, and 3D printing. ICT patents focus on traditional information and communication technologies, such as telecommunications, networking, and software innovations. AI-related patent codes are excluded from the 4IR and ICT classifications, and any overlapping 4IR codes covered by the J-tag classification are similarly excluded from the ICT list. See the Online Appendix for the full list of CPC/IPC codes used.

To address the issue of missing values for patents and other investment series in some regions, all stock variables Z are augmented by one unit and divided by employment L . We then take the logarithm of this transformed variable, resulting in the following transformation: $\ln\left(\frac{1+Z}{L}\right)$. In the regression analysis, we carefully address potential biases in our estimates arising from this transformation. Finally, in robustness checks, we include a large set of control variables to account for potential confounding factors. For brevity, these variables will be introduced later, alongside the presentation of sensitivity estimates.

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 million 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 million workers,

⁷ Based on the European System of Accounts (ESA 2010), regional gross fixed capital includes expenditures on produced tangible and intangible assets that are used in the production process for more than one year. These can be both tangible (dwellings and non-residential buildings; civil engineering works; transport equipment; machinery, equipment, and computers; cultivated assets such as trees and livestock) and intangible assets (mineral exploration; computer software; entertainment, literary, or artistic originals). Statistics on regional R&D expenditure are provided separately.

⁸ ISCED Classification. Level 0: Early childhood education. Level 1: Primary Education. Level 2: Lower Secondary Education. Level 3: Upper Secondary Education. Level 4: Post-secondary non-Tertiary Education. Level 5: Short-cycle tertiary education. Level 6: Bachelors degree or equivalent tertiary education level.

⁹ Our dataset does not specifically cover innovations related to Generative AI, particularly those associated with Large Language Models. Patenting activity in this area began in 2017, with the launch of ChatGPT – the most prominent Generative AI platform developed by OpenAI – occurring in November 2022. For a more detailed discussion, see Venturini (2024).

Table 1
Summary statistics (unweighted values).

	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 Labor share	12.2	7.0	7.1	10.0	16.9	31.2
Medium-skilled Labor share	23.6	7.6	19.4	23.6	29.7	37.5
Low-skilled Labor share	16.3	8.3	10.6	15.5	21.5	41.7
AI patent stock p.w. (counts per million)	7.4	21.4	0.0	0.7	5.3	120.0
4IR patent stock p.w. (counts per million)	112.0	320.3	1.1	26.1	99.8	1,862.7
ICT patent stock p.w. (counts per million)	145.2	526.3	1.7	25.5	92.5	2,745.0
All patent stock p.w. (excl. AI, 4IR, ICT; counts per million)	628.6	939.9	38.3	272.0	840.6	5,073.8
All patent stock p.w. (excl. AI; counts per million)	884.5	1439.5	48.4	363.0	1,124.0	8,054.6
Fixed capital stock p.w. (constant euros, thousands)	79.4	53.7	40.3	78.2	113.0	194.5
R&D capital stock p.w. (constant euros, thousands)	2.9	3.8	0.1	1.7	4.0	16.5

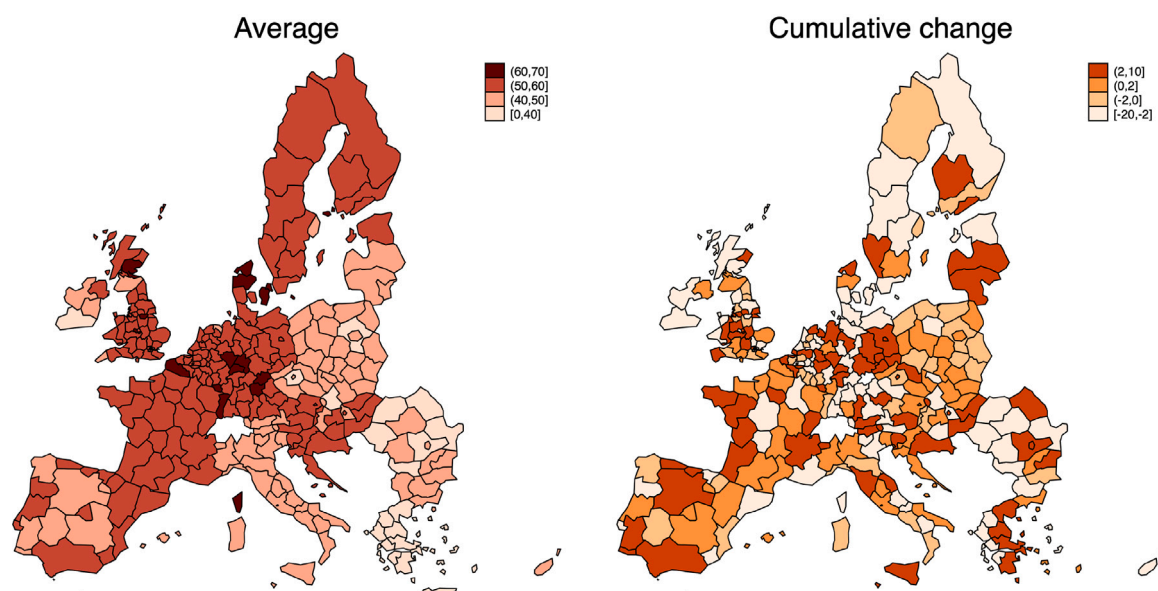


Fig. 1. Labor share and cumulative change (2000–2017).

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 627.3 per million workers, and 884.5 when excluding only AI patents. Regarding capital investments, the fixed capital stock averages 79.4 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.

To complete the description of the available data, Figs. 1 and 2 offer further insights into the trends and variability in labor shares and patent activities. Specifically, the left panel of Fig. 1 displays the average labor share across European regions, representing the mean value of the labor share over the study period for each region. The right panel of Fig. 1 shows the cumulative change in the labor share over time, tracking the total change from the beginning to the end of the period for each region. Fig. 2, 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. Fig. 1 indicates 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. Fig. 2 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

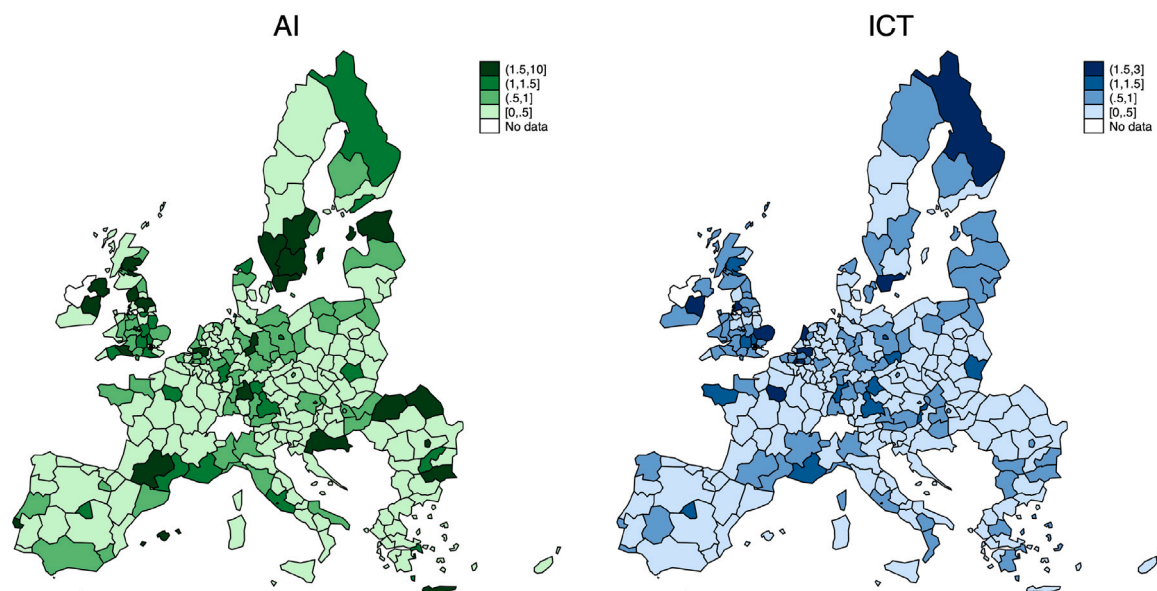


Fig. 2. AI and ICT technology specialization, RCA (avg.2000–2017).
Notes: RCA: Revealed Comparative Advantage.

−0.014. According to this baseline estimation, a one-standard-deviation increase in the AI patent stock per worker would result in a 4.1% decrease in the labor share. Several possible explanations could account for this result. First, this finding may be driven by the technological characteristics of production, suggesting a substitution effect: 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 their reliance on human labor. Admittedly, our proxy for AI innovation may indirectly capture the increasing effect of AI adoption on the labor share, driven by the enhanced competencies developed in emerging digital fields through innovation. The negative association between AI innovation and the labor share 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, our evidence conflicts with the positive effect on the labor share found for R&D capital, used as a proxy for knowledge generation effort, by [O'Mahony et al. \(2021\)](#) for industrial economies.

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 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 other resources within the firm, allowing it 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 productivity and total factor productivity 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 relatively less specialized roles declines, which still account for the largest proportion of the labor share overall. Furthermore, 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 the development of 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. Similarly, the decline in the regional labor share may result from the rise of big-tech 'superstar' firms operating in digital and service markets, which are less labor-intensive than manufacturing companies ([Autor et al., 2020](#)). Overall, these factors may have reduced the ability of workers, or at least a subset of them, to benefit from the returns of innovations in emerging digital fields, such as AI, resulting in a smaller share of regional income.

The negative association between the labor share and AI innovation remains robust even after controlling for numerous economic factors that have been found to influence the factor income distribution in earlier literature ([Table 2](#)). Next, we expand the

Table 2
Baseline estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI patent stock per worker (p.w.)	-0.014*** (0.001)	-0.011*** (0.001)	-0.013*** (0.001)	-0.011*** (0.001)	-0.012*** (0.001)	-0.011*** (0.001)	-0.005*** (0.001)
ALP - Output per worker (p.w.)		0.016* (0.009)			0.013 (0.009)	0.008 (0.009)	0.017* (0.009)
ALP - Output per hour			0.004 (0.009)				
TFP - Total Factor Productivity				-0.276*** (0.005)			
Fixed capital stock p.w.					0.002*** (0.000)	0.002*** (0.000)	0.003*** (0.000)
R&D capital stock p.w.						-0.001*** (0.000)	0.001*** (0.000)
Adjustment term	-0.220*** (0.014)	-0.213*** (0.013)	-0.218*** (0.014)	-0.276*** (0.012)	-0.212*** (0.014)	-0.212*** (0.014)	-0.212*** (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	0.208	0.348	0.348	0.348
No. of 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 expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^{A'} + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

set of control variables. In columns (2) through (4) of Table 2, we account for various 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 worked, and is negatively related to TFP with an elasticity of -0.289 . One issue with using the TFP index (in logs) as an empirical proxy for productivity is that it is derived under the assumption of constant returns to scale and perfectly competitive markets, as a Solow residual or, as in our case, from a Cobb–Douglas production function, namely as $\ln A_{i,t} = \ln Y_{i,t} - S_{i,t}^L \ln L_{i,t} - (1 - S_{i,t}^L) \ln K_{i,t}$ with $S_{i,t}^L = w L_{i,t} / (p_{i,t} Y_{i,t})$, where w denotes the nominal wage rate and $p_{i,t}$ represents the price level (or deflator) for region i at time t . One concern with these methods is that they assume constant input substitutability, whereas our conceptualization is based on flexible substitution or complementarity between production factors, typically described by the CES production technology. Equally important, TFP is itself computed using the labor share of income. Accordingly, although one may use lagged values of the productivity indicator in Eq. (1), reverse causality could seriously bias the effect estimated for TFP on the labor share. On this basis, output per worker remains our preferred measure of productivity in the following part of the analysis. Note that, despite the use of all productivity measures in Table 2, which mitigate the negative impact of AI innovation on the labor share, our key explanatory variable remains significant at the maximum level.

In columns (5) and (6), we introduce controls for fixed capital and R&D capital, both measured on a per-worker basis. The coefficient for fixed capital is positive (0.002), indicating that investments in fixed capital, such as machinery and equipment, complement labor. This may be happening in regions with a specialization in manufacturing. Conversely, the coefficient for R&D capital is negative (-0.001). R&D spending may foster technological advancements that lead to either replacing workers engaged in routinized manual jobs or cognitive tasks with machines, or generating 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 stem from the fact that R&D workers command relatively high wages. Their income grows 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).¹⁰ 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.

In Table A.1 of the Appendix, we assess the sensitivity of our estimates to the depreciation rate used to compute the stock of fixed capital, R&D assets, and realized knowledge. In our baseline regression, we use a benchmark depreciation rate of 10% for fixed capital, which is in the middle range of the rates used in national accounts for residential buildings (1.1%) and other constructions (3.2%) on one side, and for computers, communication equipment, and software (31.5%) on the other side (Bontadini

¹⁰ Using historical data for OECD countries, Madsen et al. (2024a) document that the declining productivity (or, equivalently, the increasing cost-effectiveness) of R&D accounts for approximately 30% of the reduction in income inequality (including the capital-to-labor income ratio) since 1920.

et al., 2023). Among intangibles, R&D capital and the cumulative value of patents are usually depreciated between 15% and 22% annually. However, recent evidence suggests that technological knowledge developed in certain sectors of the economy, such as the software or computer system design industries, may depreciate much faster, even between 40% and 70% per year, depending on the assumptions and methods used to estimate R&D capital depreciation (Li and Hall, 2020; Ma, 2021). For these reasons, in Table A.1 we provide estimates obtained using an annual depreciation rate for fixed capital ranging between 5% and 15%, and between 15% and 45% for R&D and realized knowledge stocks. These robustness regressions illustrate that our dynamic estimates for the impact of AI innovation on the labor share are insensitive to the assumed rate of depreciation.

6.2. Role of confounders

In Table 3, we expand the analysis by accounting for a broader set of factors that may influence income distribution across inputs at the regional level. We consider two main groups of confounders: 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 still 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), but exclude AI. This broader category of emerging digital technologies is rapidly expanding and increasingly finds wider applications, partly due to the integration of AI within these systems. Overall, 4IR technologies are found to have a modest economic impact on aggregate productivity, although 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 IoT, can have a quantitatively substantial impact on productivity (Edquist et al., 2021). Although 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 underestimated, given that it is the enabler of the full cluster of 4IR technologies. 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, reflecting thus its technological capabilities and the capacity to generate innovation-led rents.

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 at the aggregate level (Aghion et al., 2019b). This effect goes beyond the impact on researchers' wages, as their compensation is already accounted for in R&D expenditures, which are included among the control variables (not shown in the table for the sake of brevity). 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 income share (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.

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. First, we include a proxy for the concentration of the regional technology market, measured using the Hirsch-Herfindahl Index (HHI), calculated for patent classes based on the 4-digit International Patent Classification (IPC). The employment share in manufacturing serves as a proxy for industrial specialization, while the annual change in employment is intended to capture the pace of structural change.

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 income (including gross operating surplus or profits) than into labor income, likely appropriating a larger portion of rents from innovations protected by patents (see Aghion et al., 2019a). Another possibility is that in regions where the technology market is concentrated, the entry rate of high-tech start-ups 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). The positive coefficient for the change in employment levels suggests that regions with a higher prevalence of

Table 3
Alternative sources of realized knowledge and structural characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI patent stock p.w.	-0.011*** (0.001)	-0.012*** (0.001)	-0.015*** (0.001)	-0.016*** (0.001)	-0.016*** (0.001)	-0.011*** (0.001)	-0.017*** (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.				0.047*** (0.004)	0.047*** (0.004)	-0.029*** (0.004)	0.049*** (0.004)
Tech concentration					-0.011*** (0.001)		
Manuf. employment share						0.155*** (0.006)	
Employment change							0.118*** (0.032)
Adjustment term	-0.212*** (0.014)	-0.212*** (0.014)	-0.214*** (0.014)	-0.214*** (0.014)	-0.211*** (0.017)	-0.216*** (0.013)	-0.232*** (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	0.373
No. of 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 expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^{AJ} + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. Controls: Fixed capital stock per worker; R&D capital stock per worker; Output per worker. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

expanding sectors experience an increase in the labor share of the economy (column (7)). This indicates heightened labor demand and potentially rising wages driven by a shortage of available workers.

We also account for life expectancy and fertility in our analysis (results not reported but available upon request). 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., 2024). In this context, workers in regions with longer-living populations are able to appropriate a relatively larger portion of income. Similarly, the positive coefficient for fertility may reflect the impact of a larger proportion of younger individuals entering the workforce. If wages are downwardly 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 A.2 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.¹¹ 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 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 the total number of active companies in each region. In the Schumpeterian tradition, new entrants drive competition and the process of creative destruction, which can erode the rents of incumbents (i.e., their profits and capital ownership). Accordingly, if increased competition reduces incentives to innovate by making rents short-lived or compressing markups and profits, a higher entry rate may be associated with lower income inequality, as 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 between the short run and the 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 (see Hounghonon and Liang, 2021 for a study on France).

¹¹ Using data from 2010 onward helps neutralize the potential bias caused by the financial crisis. However, a drawback is that these data are available only for a subset of regions, making the results in Table A.2 not fully comparable with those presented earlier in this section.

In summary, the results in [Table A.2](#) illustrate that the adverse effects of AI on the labor share do not overshadow the impact of other drivers of factor income distribution, such as business dynamism and physical infrastructure, which are identified in this paper as further key factors influencing the dynamics of the labor share across European regions.

6.3. Some econometric issues, and quantification of the effects

In this section, we discuss key econometric aspects that may affect our dynamic estimates and quantify the extent to which the results explain variations in regional labor shares.

In [Table A.3](#) of the [Appendix](#), we examine whether the impact of AI depends on threshold effects, particularly its variation with the degree of AI specialization or the size of the regional knowledge stock. First, we compare AI's effect between regions specialized and de-specialized in this domain. Specialization is identified using a technological Revealed Comparative Advantage (RCA) index in AI above unity, while de-specialized regions have an RCA below unity. The results do not indicate substantial differences between the two groups. Second, to assess whether the effect of AI depends on the scale of developed innovations, we estimate separate regressions focusing on regions above the 25th, 50th, and 75th percentiles of the AI distribution. These thresholds correspond to regions with 1, 5.8, and 19 patent counts, respectively. The analysis is performed over the entire sample period and separately for the post-Great Recession years. The findings suggest that AI's impact is only slightly stronger in regions with higher patenting activity.

[Table A.4](#) presents additional econometric checks. 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 three 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 the dynamic model restricting the sample to regions with at least one patent over the full sample period, applying the inverse hyperbolic sine transformation for the patent variables (instead of logarithms). Again, we obtain findings that are consistent with those presented above.

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 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 A.5](#), we examine the role of spatial dependence in our setting using the spatial lags of the dependent variable and our key regressor, namely the labor share and the AI patent stock per worker. We find 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 favorable employment conditions can attract workers from adjacent areas, with this effect typically being stronger for more educated workers, who earn more, are more mobile, and therefore more responsive to better job opportunities ([Langella and Manning, 2022](#)). We validate the effectiveness of our approach to handling spatial dependence by applying the test proposed by [Pesaran and Xie \(2021\)](#) to each specification in [Table A.5](#). This test assesses whether residuals exhibit weak cross-sectional dependence, with rejection of the null hypothesis indicating potential biases.¹² The results confirm that only regressions incorporating CCE terms are free from cross-sectional dependence. Importantly, AI's estimated impact on the labor share in these regressions remains consistent with results obtained using fixed-effects regressions with time dummies and spatially lagged regressors, reinforcing the robustness of our findings.

Estimates from this first part of the analysis reveal a notable sensitivity of the labor share to AI innovation. We identify a range of effects, from a lower-bound response of -0.005 (column (7), [Table 2](#)), to an upper-bound response of -0.016 (column (4), [Table 3](#)). These findings imply that, in percentage terms, doubling AI would reduce the proportion of regional income accruing to workers by 0.5% to 1.6%. Using these parameter estimates as lower and upper bounds, we can quantify the variation in the labor share

¹² This test builds on the Cross-Sectional CD test developed by [Pesaran \(2015\)](#), incorporating a correction for biases that arise when applied to the residuals of panel fixed-effects regressions with time dummies or common correlated effects. [Pesaran and Xie \(2021\)](#) adjust the CD test using a correction function based on factor loadings estimated via principal component analysis ($p=3$ in our case).

Table 4
Quantification of effects.

	Mean	25pct	50pct	75pct	99pct
Lower bound	-0.09%	-0.10%	-0.09%	-0.08%	-0.07%
Upper bound	-0.31%	-0.35%	-0.30%	-0.28%	-0.26%

Notes: Estimates are based on parameter values from the ARDL regression in Column (7), Table 2 for the lower bound, and Column (4), Table 3 for the upper bound.

Table 5
Quantification of effects: country-specific scenario.

#	Country	Lower bound	Upper bound	#	Country	Lower bound	Upper bound
1	AT	-0.12%	-0.44%	11	HR	-0.09%	-0.33%
2	BE	-0.10%	-0.36%	12	HU	-0.03%	-0.10%
3	BG	0.18%	0.63%	13	IE	-0.17%	-0.60%
4	CZ	0.01%	0.04%	14	IT	-0.09%	-0.30%
5	DE	-0.10%	-0.36%	15	NL	-0.08%	-0.27%
6	DK	-0.08%	-0.30%	16	PT	-0.16%	-0.58%
7	EL	-0.07%	-0.24%	17	RO	0.04%	0.13%
8	ES	-0.06%	-0.23%	18	SE	-0.11%	-0.40%
9	FI	-0.09%	-0.32%	19	SK	0.19%	0.67%
10	FR	-0.11%	-0.39%	20	UK	-0.07%	-0.24%

Notes: Estimates are based on parameter values from the ARDL regression in Column (7), Table 2 for the lower bound, and Column (4), Table 3 for the upper bound. The quantification relies on within-country variation in the AI patent stock per worker and the labor income share.

explained by our regression model. Table 4 presents the explained change in the labor share, expressed in percentage (absolute) points. This can be derived by multiplying the estimated elasticities by the absolute change in the stock of AI per worker between 2000 and 2017 (0.1%) and expressing the resulting figure in relation to the mean labor share over the sample period (51.8%). Using our lower bound estimates (-0.005), the effect of AI innovation would have led to a decrease in the labor share of 0.09% (from its mean of 51.8%), and by 0.31% using our upper bound estimates (-0.016). Put differently, our results suggest that, in the least conservative case, AI innovation may account for up to one third of a percentage point of the labor share decline observed since the early 2000s. These figures are not excessively high and therefore 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 25th percentile) or labor-intensive regions (above the 75th percentile).

Table 5 provides a country-level quantification of the labor share reduction attributable to AI. These figures are derived by replicating the computation described earlier, using the average values for regions within each national economy with AI innovations. The most substantial reductions in the labor share are predicted for countries where the development of new digital innovations has been most rapid. In Ireland, for example, the labor share is expected to decline by 0.17% to 0.60%. For Germany, one of the countries with the highest technological specialization in AI, the predicted reduction in the labor share is a somewhat larger than the average for the entire sample of European regions, ranging from 0.10% to 0.36%.

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

We now investigate the effect of AI in 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. This set of regressions is limited to a consistent set of regions to eliminate potential compositional effects of the sample on the estimates.

We present the results of our main specification by skill level on the left-hand side of Table 6. On the right-hand side, we report the findings of a similar specification using the employment share as the dependent variable, with 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 type of innovation 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 on the employment share would indicate that one mechanism through which AI operates is by altering relative factor compensation. Relative factor compensation is found to drive variation in the 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 impacts both the employment and wage shares negatively. 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. 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.

Table 6
The impact of AI innovation on 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*** (0.001)	−0.026*** (0.002)	−0.031*** (0.008)	−0.033*** (0.003)	−0.021*** (0.007)	−0.002 (0.005)	0.001 (0.003)	0.011* (0.006)
All patent stock p.w.	0.047*** (0.004)	0.016 (0.019)	1.657*** (0.091)	−0.031 (0.026)	−1.146*** (0.085)	1.368*** (0.057)	−0.214*** (0.028)	−0.843*** (0.059)
ALP - Output p.w.	0.000 (0.009)	−0.431*** (0.058)	0.018 (0.074)	0.018 (0.031)	−0.335*** (0.071)	0.034 (0.032)	−0.042** (0.020)	−0.237*** (0.051)
Fixed capital stock p.w.	−0.001* (0.000)	0.111*** (0.014)	−0.324*** (0.034)	−0.126*** (0.014)	0.248*** (0.014)	−0.333*** (0.032)	−0.137*** (0.018)	0.309*** (0.023)
R&D capital stock p.w.	−0.002*** (0.000)	0.003*** (0.001)	0.038*** (0.004)	0.006*** (0.001)	0.011*** (0.003)	0.022*** (0.003)	0.006*** (0.001)	−0.007*** (0.002)
Adjustment term	−0.214*** (0.014)	−0.388*** (0.049)	−0.279*** (0.022)	−0.268*** (0.021)	−0.374*** (0.025)	−0.225*** (0.020)	−0.403*** (0.037)	−0.357*** (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	0.522	0.447	0.401	0.528	0.303	0.555	0.475
No. of Regions	262	260	243	243	243	243	243	243

Notes: The dependent variable is the labor share, defined 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 of total employment in columns (6)–(8). All variables are expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^H + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,0) regression, which includes region and year fixed effects. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

The results in Table 6 suggest that AI is detrimental to the income share of each worker category, but this effect is slightly larger for medium- and high-skill workers. This finding lends support to the view that AI shifts the income distribution from workers at the top end of the skill distribution towards those at the bottom (Bloom et al., 2025). 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 medium- and high-skill workers but are positively associated with the employment share of low-skill workers (albeit at a 10% significance level only). 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.

Among the control variables, labor productivity is found to be negatively associated with the shares of labor income and employment for workers on the bottom end of the skill distribution (the low-skilled). Fixed assets 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, realized knowledge capital acts as a complementary input for high-skill workers and a substitute input for low-skill workers. Finally, in the post-Great Recession period, R&D has a positive effect on the labor share for all worker categories, while in occupational terms, it is detrimental for low-skill workers. 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 the regional labor share is due to technological substitutability across factor inputs 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 Fig. 2). 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, 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 helps determine 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 the mismatch between the skills of the regional workforce and the new labor demand (Bonfiglioli et al., 2023). This represents the *between-region effect* of AI concentration.

Table 7 unambiguously indicates that, for medium- and high-skill workers, the effect of AI is mainly driven by substitutability (or 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 the labor share – whether through the channel of factor substitutability or market concentration – remains

Table 7
The impact of AI concentration on the labor share by skill (2010–2017).

	(1) High skill	(2)	(3) Medium skill	(4)	(5) Low skill	(6)
AI patent stock p.w.	−0.031*** (0.008)	−0.044*** (0.008)	−0.033*** (0.003)	−0.037*** (0.003)	−0.021*** (0.007)	−0.011 (0.007)
AI concentration (within-region)		−0.004 (0.009)		−0.006** (0.003)		−0.009 (0.009)
AI concentration (between-region)		−0.694 (0.434)		−0.699*** (0.199)		0.097 (0.365)
Adjustment term	−0.279*** (0.022)	−0.272*** (0.021)	−0.268*** (0.021)	−0.264*** (0.022)	−0.374*** (0.025)	−0.369*** (0.025)
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
No. of Regions	243	243	243	243	243	243

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 expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{it}^L = \alpha_{i0} + \alpha_1 \ln k_{it}^{AJ} + \alpha_2 \ln A_{it} + \dots + \epsilon_{it}$. Long-run elasticities are derived from an ARDL(1,0) regression, which includes region and year fixed effects. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. Controls: R&D capital stock per worker; Non-AI patent stock per worker. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

ambiguous, as both the key explanatory variable and the controls 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-skill workers, primarily through the *between-region* channel, thus emerging as a force that strongly polarizes factor income distribution (Michaels et al., 2014).¹³

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, and, based on the effects derived from previous theoretical literature, analyzed empirically how AI innovation has influenced regional disparities in labor shares.

Our findings indicate that AI innovation is associated with a significant decline in the labor share, potentially accounting for up to one third of a percentage point of the overall decrease observed since the early 2000s. This highlights the notable impact of AI in exacerbating income inequality in terms of functional income distribution, particularly in regions more engaged in developing AI-related technologies, underscoring AI's role in driving regional disparities in labor income distribution. The empirical finding of an overall decrease in the labor income share in response to AI innovation is consistent with [Hypothesis 1](#).

We also document that the effects of AI innovation vary across different skill levels. This new technology has a particularly adverse impact on high- and medium-skill labor, primarily through wage compression. In contrast, for low-skill workers, the expansion of employment opportunities somewhat mitigates the wage decline associated with AI advancements. Our analysis suggests that these differential impacts stem from the varying degrees to which AI technologies substitute for or complement the tasks performed by workers of different skill levels. Medium- and high-skill workers, who engage in cognitive and repetitive decision-making tasks, experience greater negative effects, while low-skill workers may benefit from shifts in labor demand towards roles that are less automatable or that complement AI technologies. The empirical findings related to the differential effects of AI innovation on workers of different skill levels align with [Hypothesis 2](#).

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 protection 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. Finally, it would be interesting to see whether AI has different effects on wage inequality among service sector and public sector workers than among manufacturing workers (Rattsø and Stokke, 2023).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

¹³ 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).

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Appendix A

In this Appendix, we include additional tables referenced in the paper but not shown in the main text.

Table A.1

Sensitivity to the depreciation rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI patent stock per worker (p.w.)	-0.016*** (0.001)	-0.016*** (0.001)	-0.016*** (0.001)	-0.016*** (0.001)	-0.016*** (0.001)	-0.016*** (0.001)	-0.015*** (0.001)
All patent stock p.w. (excl. AI)	0.047*** (0.004)	0.047*** (0.004)	0.047*** (0.004)	0.047*** (0.004)	0.047*** (0.004)	0.039*** (0.005)	0.036*** (0.006)
Fixed capital stock p.w.	0.001* (0.000)	0.000 (0.000)	0.000 (0.000)	0.001* (0.000)	0.001* (0.000)	0.001*** (0.000)	0.001*** (0.000)
R&D capital stock p.w.	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
ALP - Output p.w.	0.000 (0.009)	0.001 (0.009)	0.000 (0.009)	0.000 (0.009)	0.000 (0.009)	0.004 (0.009)	0.006 (0.009)
Adjustment term	-0.214*** (0.014)	-0.214*** (0.014)	-0.214*** (0.014)	-0.214*** (0.014)	-0.214*** (0.014)	-0.213*** (0.014)	-0.212*** (0.014)
Annual depreciation rates							
Fixed assets	10%	5%	15%	10%	10%	10%	10%
R&D assets	15%	15%	15%	30%	45%	15%	15%
Realized (patented) knowledge	15%	15%	15%	15%	15%	30%	45%
Obs.	4,452	4,452	4,452	4,452	4,452	4,452	4,452
R-squared	0.347	0.347	0.347	0.347	0.347	0.347	0.347
No. of Regions	262	262	262	262	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 expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^{AI} + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table A.2

Role of the institutional setting (2010–17).

	(1)	(2)	(3)	(4)	(5)	(6)
AI patent stock p.w.	-0.016*** (0.001)	-0.026*** (0.002)	-0.035*** (0.003)	-0.023*** (0.003)	-0.024*** (0.003)	-0.026*** (0.003)
Regional characteristic			0.001 (0.006)	-1.201*** (0.077)	0.042*** (0.007)	0.055 (0.041)
Adjustment term	-0.214*** (0.014)	-0.388*** (0.049)	-0.369*** (0.047)	-0.408*** (0.046)	-0.379*** (0.041)	-0.369*** (0.042)
			Government quality	Business dynamism	Physical infrastructure	Digital infrastructure

(continued on next page)

Table A.2 (continued).

	(1)	(2)	(3)	(4)	(5)	(6)
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	0.522	0.533	0.512	0.572	0.565
No. of Regions	262	260	108	94	136	128

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 expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^{AJ} + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,1) regression for those estimations using data from 2000, while those using data from 2010 are derived from an ARDL(1,0) regression. Region and year fixed effects are included in all regressions. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10%, respectively. Controls: Output per worker; Fixed capital stock per worker (column (1) only); R&D capital stock per worker; Total patent stock (excluding AI) per worker.

Table A.3

Robustness checks: threshold effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
AI patent stock p.w.	-0.016*** (0.001)	-0.015*** (0.001)	-0.011*** (0.002)	-0.013*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	0.004*** (0.001)	-0.019*** (0.002)	-0.028*** (0.002)	-0.024*** (0.002)
Adjustment term	-0.214*** (0.014)	-0.215*** (0.016)	-0.242*** (0.029)	-0.220*** (0.014)	-0.214*** (0.017)	-0.203*** (0.022)	-0.207*** (0.027)	-0.332*** (0.056)	-0.330*** (0.074)	-0.366*** (0.085)
Controls	Yes	No	No	No	No	No	No	No	No	
AI - VCR	-	< 1	> 1	-	-	-	-	-	-	
AI regions (percentiles)	100	100	100	100	25	50	75	25	50	
Time period	2000–17	2000–17	2000–17	2000–17	2000–17	2000–17	2000–17	2010–17	2010–17	
Obs.	4,452	3,566	1,010	4,491	3,456	2,299	1,156	1,661	1,093	
R-squared	0.347	0.377	0.409	0.385	0.389	0.389	0.361	0.572	0.542	
No. of Regions	262	218	60	273	208	137	68	208	137	

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 expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^{AJ} + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table A.4

Robustness checks: econometric issues.

	(1)	(2)	(3)	(4)	(5)	(6)
AI patent stock p.w. (elasticity)	-0.016*** (0.001)	-0.014*** (0.001)	-0.011*** (0.001)	-0.013*** (0.002)	-0.022 (0.025)	-0.004*** (0.001)
AI patent stock p.w. (coefficient)					-0.023*** (0.002)	-0.409*** (0.049)
Adjustment term	-0.214*** (0.014)	-0.220*** (0.014)	-0.249*** (0.016)	-0.322*** (0.020)	-0.236*** (0.040)	-0.333*** (0.040)
Time period	2000–17	2000–17	2000–17	2000–17	2000–17	2010–17
ARDL	1,1	1,1	3,3	5,5	1,1	1,1
Model	Log–log	Log–log	Log–log	Log–log	Log–Arcsinh	Log–Arcsinh
Controls	Yes	No	No	No	No	No
Obs.	4,452	4,576	3,945	3,419	4,298	2,224
R-squared	0.347	0.384	0.422	0.455	0.41	0.201
No. of Regions	262	278	263	263	278	281

Notes: The dependent variable is the labor share, defined as the logarithm of the ratio of employees' compensation to regional gross value added (at current prices). The stock of AI patents per worker is measured as $\log(1+z)/L$ in columns (1)–(4). Columns (5) and (6) report the coefficients estimated with the arcsinh transformation of the explanatory variable ($\hat{\beta}$) and the associated elasticity $\beta = \left(\frac{\hat{\beta}}{\beta} \cdot \frac{\bar{x}}{\sqrt{\hat{\beta}^2 + 1}} \right)$, where the bars denote the mean of the dependent and explanatory variables (in logs and non-transformed, respectively) over the sample period. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t}^{AJ} + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table A.5
Spatial and cross-sectional dependence.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI patent stock p.w.	-0.016*** (0.001)	-0.016*** (0.001)	-0.016*** (0.001)	-0.017*** (0.001)	-0.011*** (0.001)	-0.006*** (0.001)	-0.014*** (0.002)	-0.012*** (0.003)
Labor share (spatial lag)		-0.049*** (0.010)		-0.083*** (0.011)	-0.080*** (0.011)	-0.080*** (0.012)	-0.099*** (0.022)	-0.076*** (0.034)
AI patent stock p.w. (spatial lag)			0.003** (0.001)	0.009*** (0.002)	0.007*** (0.002)	0.008*** (0.002)	0.000 (0.003)	0.001 (0.004)
Adjustment term	-0.214*** (0.014)	-0.214*** (0.014)	-0.214*** (0.014)	-0.213*** (0.014)	-0.216*** (0.014)	-0.230*** (0.014)	-0.711*** (0.042)	-0.761*** (0.043)
Cross-Sectional Dependence	TD	TD	TD	TD	NO	NO	CCE	CCE
CCE lags	-	-	-	-	-	-	0	1
Controls	Yes	Yes	Yes	Yes	Yes	No	No	No
Pesaran and Xie (2021) test	9.24	9.15	9.27	14.28	38.01	24.69	-0.14	1.81
P-value	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.89]	[0.08]
Obs.	4,452	4,452	4,452	4,420	4,420	4,471	4,471	4,208
R-squared	0.347	0.347	0.347	0.347	0.342	0.400	0.904	0.937
No. of Regions	262	262	262	260	260	263	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 expressed in logarithmic form. Long-run estimates as of Eq. (2): $\ln S_{i,t}^L = \alpha_{i,0} + \alpha_1 \ln k_{i,t} + \alpha_2 \ln A_{i,t} + \dots + \epsilon_{i,t}$. Long-run elasticities are derived from an ARDL(1,1) regression, which includes region and year fixed effects. Cross-sectional dependence is addressed by time fixed effects (TD) in columns (1)–(4), and by common correlated effects (CCE) in columns (7)–(8). Newey–West standard errors, robust to heteroskedasticity and auto-correlation, are reported in parentheses. The Pesaran and Xie (2021) test evaluates the null hypothesis of weak cross-sectional dependence in the regression residuals, against the alternative hypothesis of strong cross-sectional dependence. Controls: Output per worker; Fixed capital stock per worker; R&D capital stock per worker; Total patent stock (excluding AI) per worker. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.eurocorev.2025.105043>.

Data availability

The data are included in Appendix B.

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