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AI innovation and labor market polarization: Evidence from European regions

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ABSTRACT

We study whether AI innovation changes labor-market polarization by weakening the relative position of high-skilled workers. We develop a CES production framework showing how AI affects the wage-cost ratio between high- and low-skilled workers through wage and employment margins. We test the model's predictions using European regional labor-market data and find that AI reduces the relative wage-cost ratio by nearly 7 percent on average, with effects broadly split between wage and employment adjustments. These results are primarily driven by regions in countries highly specialized in AI technologies. Overall, our evidence suggests that AI may counteract the polarization effects associated with over two centuries of technological change.

1. Introduction

Technological change has driven successive waves of industrialization through technologies that were largely tangible, developed within manufacturing, and typically favored high-skilled workers by expanding their wages and employment opportunities (Prettner and Strulik, 2020; Acemoglu and Restrepo, 2020a,b). Artificial Intelligence (AI), however, may constitute a departure from this historical pattern. In particular, AI increasingly performs cognitive and decision-making tasks traditionally undertaken by high-skilled workers (Felten et al., 2021; Acemoglu et al., 2022; Babina et al., 2023). As a result, AI may challenge or even reverse some of the skill-biased effects of technological progress to date.

This paper develops a framework to analyze how AI affects the labor-market position of high-skilled workers relative to low-skilled workers, as measured by the wage-cost ratio, through adjustments in relative wages, relative employment, or both. We empirically assess these effects using data for 273 European NUTS2 regions over the period 2000–2017. The regional dimension provides a particularly suitable perspective for studying AI, given that the development of this technology remains highly concentrated in a limited number of locations, making AI a potentially important force of spatially uneven labor-market change. We treat the emergence of AI innovation, measured through patent data, as a technological shock that alters regional labor-market conditions. We estimate its impact on the wage-cost ratio between high- and low-skilled workers using a Difference-in-Differences approach that is robust to heterogeneous and dynamic treatment effects. Our results indicate that AI reduces the relative wage-cost ratio by nearly 7 percent on average. This decline occurs through both wage and employment adjustments and is primarily driven by regions located in countries with a strong specialization in AI technologies.

The paper contributes to the literature on automation, AI exposure, and labor-market polarization by showing that AI can weaken the position of workers historically favored by technological change. It also relates to economic geography work on spatial inequality, regional development paths, and income growth traps (Lee and Rodríguez-Pose, 2013; Iammarino et al., 2019; Balland et al., 2019; Diemer et al., 2022), since AI reshapes tasks embedded in local production systems and may therefore contribute to spatially uneven labor-market adjustment.

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2. Modeling AI and labor-market polarization

To guide the empirical analysis, we adapt the framework in Bloom et al. (2025) to a regional economy with two production blocks: a low-tech block, intensive in low-skilled labor and automation capital, and a high-tech block, intensive in high-skilled labor and AI capital. This distinction captures the idea that automation mainly affects manual and routine tasks, while AI increasingly affects cognitive tasks performed by high-skilled workers. Regions differ in the relative importance of these blocks, reflecting differences in productive specialization and in their ability to deploy AI-related knowledge.

Aggregate output in region i at time t is

$$Y_{it} = K_{it}^{\alpha}\left[(1-s_i)\left(Y_{it}^{L}\right)^{\gamma} + s_i\left(Y_{it}^{H}\right)^{\gamma}\right]^{\frac{1-\alpha}{\gamma}},$$

where K_{it} is traditional physical capital, γ governs substitution between the two production blocks, and $s_i \in (0,1)$ captures the region-specific weight of high-tech production. Regions with a higher s_i are more specialized in high-tech, high-skill-intensive activities, while regions with a lower s_i are more specialized in low-tech, low-skill-intensive activities.

Intermediate outputs are

$$Y_{it}^{L} = \left[\beta_1\left(L_{it}^{L}\right)^{\theta} + (1-\beta_1)(A_{P,it}P_{it})^{\theta}\right]^{1/\theta},$$
$$Y_{it}^{H} = \left[\beta_2\left(L_{it}^{H}\right)^{\phi} + (1-\beta_2)(\chi_c A_{G,it}G_{it})^{\phi}\right]^{1/\phi}.$$

Here L_{it}^{L} and L_{it}^{H} denote low- and high-skilled labor, P_{it} automation capital, and G_{it} AI capital. The variables $A_{P,it}$ and $A_{G,it}$ denote the productivity of automation and AI, respectively. The parameter $\chi_c > 0$ captures country-level AI capabilities and governs the extent to which AI-related knowledge is transformed into productive AI input within the region. The parameters θ and ϕ govern labor-technology substitutability within the low- and high-tech blocks, respectively, with higher values implying stronger substitutability.

Under perfect competition, wages equal marginal products. Letting

$$\Omega_{it} \equiv (1-s_i)\left(Y_{it}^{L}\right)^{\gamma} + s_i\left(Y_{it}^{H}\right)^{\gamma},$$

and differentiating with respect to labor inputs yields

$$w_{it}^{L} = (1-\alpha)\beta_1(1-s_i)K_{it}^{\alpha}\left(L_{it}^{L}\right)^{\theta-1}\left(Y_{it}^{L}\right)^{\gamma-\theta}\Omega_{it}^{(1-\alpha-\gamma)/\gamma},$$
$$w_{it}^{H} = (1-\alpha)\beta_2 s_i K_{it}^{\alpha}\left(L_{it}^{H}\right)^{\phi-1}\left(Y_{it}^{H}\right)^{\gamma-\phi}\Omega_{it}^{(1-\alpha-\gamma)/\gamma}.$$

These expressions show that an increase in effective AI input, $\chi_c A_{G,it}G_{it}$, affects high-skilled labor through the high-tech block Y_{it}^{H}. The effect combines a scale channel, operating through the expansion of the high-tech block, and a substitution channel, operating through the replacement of high-skilled tasks by AI. When $\gamma < \phi$, the substitution channel is sufficiently strong relative to the scale channel, putting downward pressure on the relative wage cost of high-skilled labor. This pressure is expected to be stronger in regions located in countries with deeper AI capabilities, as captured by χ_c, and in regions where high-tech activities account for a larger share of production, as captured by s_i.

Let total labor costs be defined as $y_{it}^{L} \equiv w_{it}^{L}L_{it}^{L}$ and $y_{it}^{H} \equiv w_{it}^{H}L_{it}^{H}$. Combining wages and labor inputs gives

$$\ln\frac{y_{it}^{H}}{y_{it}^{L}} = \ln\frac{\beta_2 s_i}{\beta_1(1-s_i)} + \phi\ln L_{it}^{H} - \theta\ln L_{it}^{L} + (\gamma-\phi)\ln Y_{it}^{H} - (\gamma-\theta)\ln Y_{it}^{L}.$$

The term $(\gamma-\phi)\ln Y_{it}^{H}$ makes the main mechanism explicit. If $\gamma < \phi$, an AI-driven expansion of the high-tech block lowers the relative wage cost of high-skilled labor. Conversely, when the scale channel dominates, the response may be positive. We interpret this case as consistent with economies where AI capabilities are still being built and firms require high-skilled workers to implement, adapt, and complement the new technology. The terms s_i and χ_c capture the two sources of exposure emphasized in the empirical analysis: regional specialization in high-tech production and country-level AI capabilities. The model therefore predicts stronger negative AI effects where high-tech production is more important and AI capabilities are more developed.

This mechanism motivates the empirical outcomes. Letting Δ_G denote a change in effective AI input $\chi_c A_{G,it}G_{it}$, the effect on relative labor costs can be decomposed as

$$\Delta_G \ln\frac{y_{it}^{H}}{y_{it}^{L}} = \underbrace{\Delta_G \ln\frac{w_{it}^{H}}{w_{it}^{L}}}_{\text{wage margin}} + \underbrace{\Delta_G \ln\frac{L_{it}^{H}}{L_{it}^{L}}}_{\text{employment margin}}.$$

Thus, AI can affect labor-market polarization through both relative wages and relative employment. The empirical analysis estimates these margins separately and examines whether the response is stronger in regions located in countries with deeper AI capabilities. Empirically, we interpret the first observed AI innovation in a region as marking the local onset of AI-related knowledge and the beginning of subsequent increases in effective AI input.

3. Empirical specification, data and results

Empirical model

We estimate whether AI reshapes income and employment opportunities across workers at opposite ends of the skill distribution. The empirical design treats the first regional AI patent as an event that anticipates subsequent flows of related technologies and triggers product- and factor-market adjustment (see Gazzani and Natoli, 2024; Miranda-Agrippino et al., 2025). The identifying variation therefore comes from the timing with which regions enter AI innovation, rather than from cross-sectional differences in their average level of development. We also test whether effects are stronger in countries more specialized in AI, as predicted by the model.

Our empirical strategy relies on a Difference-in-Differences (DiD) design. Conditional on technological capabilities and initial labor-market conditions, treated and never-treated regions are assumed to have followed parallel trends absent AI innovation. The treatment group includes regions observed before and after their first AI patent, while the control group consists of regions that never record AI innovation during the sample period. We estimate

$$\ln\frac{y_{it}^{H}}{y_{it}^{L}} = \alpha_i + \beta\cdot AI_{it} + \gamma\cdot X_{it} + \mu_t + e_{it}, \tag{1}$$

where i denotes regions and t time. The dependent variable is either the log wage-cost ratio or the log employment ratio between high- and low-skilled workers, α_i and μ_t are region and year fixed effects, and AI_{it} equals one from the first regional AI patent onward. The vector X_{it} includes the stock of non-AI patents per worker, which controls for broader regional innovativeness, the lagged dependent variable, which reduces selection concerns related to pre-existing labor-market conditions, and one-year lead and lag terms, which capture anticipation and delayed adjustment. We estimate the staggered design using de Chaisemartin and D'Haultfœuille, which is robust to heterogeneous and dynamic treatment effects. This is important because regions become treated in different years and the effect of AI need not be constant over time. In the figures, we report the dynamic response of treated regions relative to never-treated regions and use the pre-treatment coefficients to assess the plausibility of the identifying assumption.

Data

Our analysis complements (Minniti et al., 2025) and uses panel data for 273 European NUTS2 regions, including the UK, over 2000–2017. Employment by skill group is from Eurostat; average wages by skill group are from EU KLEMS (Bontadini et al., 2023). Regional wage

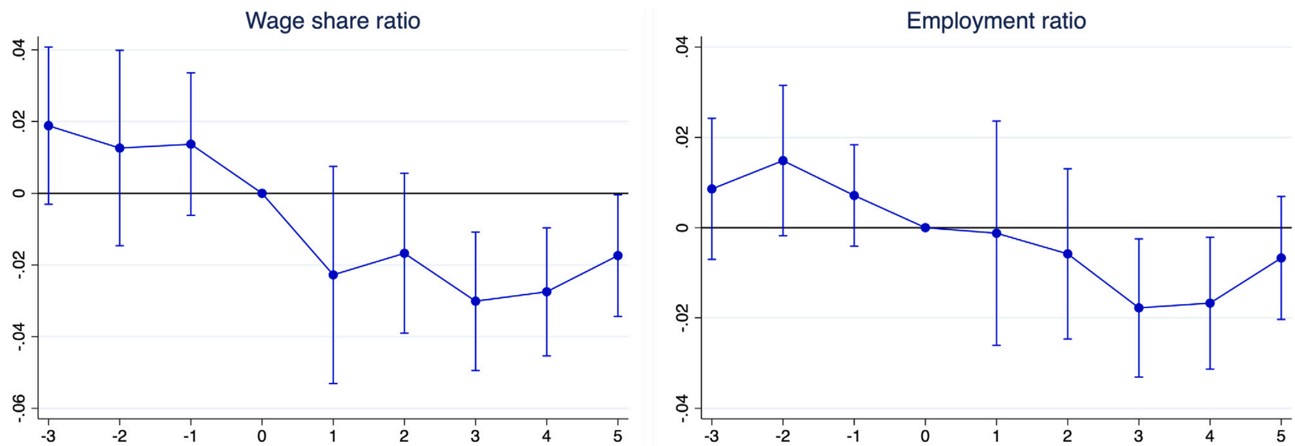

Fig. 1. Wage-cost and employment responses, full sample (2000–2017).

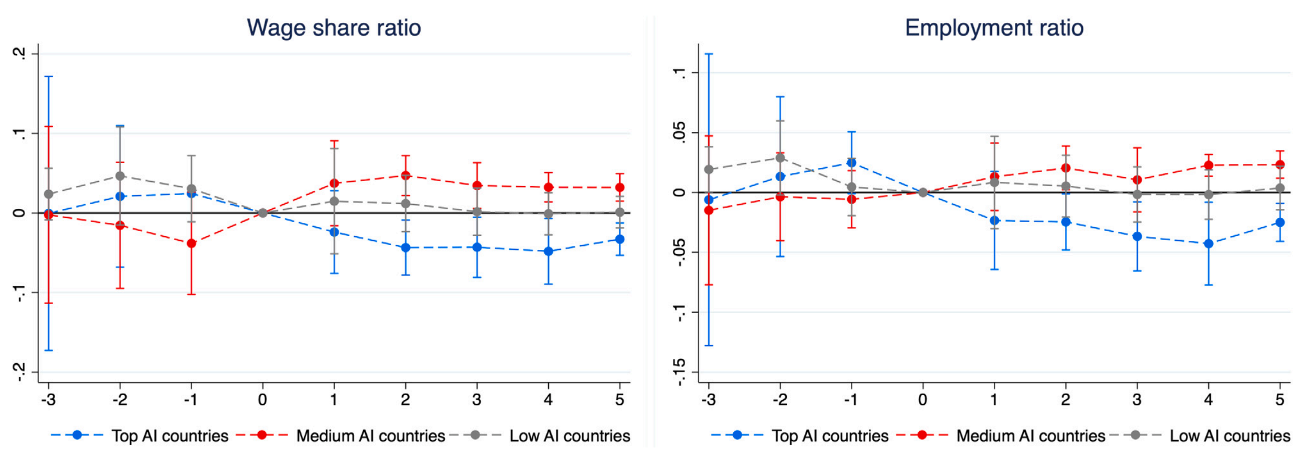

Fig. 2. Wage-cost and employment responses by AI specialization (2000–2017).

measures combine industry-level wage information with the sectoral and skill composition of regional employment. We compare low-skilled workers, defined by ISCED levels 0–2, with high-skilled workers, defined by ISCED levels 5–8, excluding medium-skilled workers to match the theoretical comparison between routine/low-tech and cognitive/high-tech tasks.

Results

Fig. 1 reports the full-sample event study. The wage-cost ratio falls after AI introduction, with a peak effect of about −3%, while relative employment falls by about −2%. The pre-treatment coefficients are small, supporting the view that treated and never-treated regions were not already diverging before the first AI patent. After treatment, the two outcomes move in the same direction, but the wage-cost response is larger. Table 1 shows that the cumulative wage-cost effect is −6.6%, compared with −3.2% for employment. AI therefore affects both margins: the employment margin explains an important part of the decline, while the difference between the two estimates indicates that relative wages also adjust. This is precisely the pattern implied by the decomposition, in which AI can compress the relative position of high-skilled workers through both prices and quantities.

Fig. 2 shows that this average masks strong heterogeneity. In AI-intensive countries, the wage-cost ratio decreases by 12% and relative employment by 9.4%. These estimates are larger than in the full sample and indicate that the compression of high-skilled labor costs is concentrated where AI capabilities are already more developed. Lagging countries show no significant response, suggesting that isolated AI patents are not sufficient to reshape relative labor-market outcomes when the surrounding technological base is weak. Medium-intensity AI countries exhibit the opposite pattern: the wage-cost ratio increases by 10.5% and relative employment by 5.2%. This is consistent with a transitional phase in which firms still expand high-skilled tasks needed to implement, adapt, and reorganize production around AI before stronger substitution effects emerge in AI-intensive economies.

ICT placebo tests, reported in the Online Appendix, show a different pattern. This comparison is useful because ICT is a technological antecedent of AI and may capture longer-run digitalization trends (Igna and Venturini, 2023). ICT is positively associated with high-skilled employment, consistent with skill-biased technological change, but the full-sample ICT response fails the parallel-trends test. Once countries are separated by AI specialization, the positive ICT effect is concentrated in medium-intensity economies, where pre-treatment trends are more comparable. The placebo evidence therefore supports the interpretation that the negative effects in AI-intensive countries are specific to AI rather than to broader digitalization.

4. Conclusions

This paper provides evidence that AI weakens the relative labor-market position of high-skilled workers. Using European regional data

Table 1
Event-study parameter estimates.

	Estimates	Standard errors	N	Switch × Periods	Average periods after treatment	Joint nullity of period effects (p-value)	Equality of of period effects (p-value)	Joint nullity of placebos (p-value)
	Wage-cost ratio							
All countries	−0.066	0.025	1238	407	2.857	0.005	0.029	0.333
Top AI countries	−0.120	0.045	175	115	3.000	0.000	0.000	0.374
Medium AI countries	0.105	0.026	265	100	3.000	0.000	0.015	0.226
Low AI countries	0.009	0.040	737	140	3.000	0.414	0.305	0.380
	Employment ratio							
All countries	−0.032	0.021	1376	441	2.864	0.009	0.010	0.359
Top AI countries	−0.094	0.033	188	126	2.929	0.000	0.363	0.184
Medium AI countries	0.052	0.014	295	128	2.727	0.000	0.000	0.776
Low AI countries	0.005	0.030	755	153	2.908	0.768	0.305	0.083

Notes: Estimates obtained with the Difference-in-Differences estimator robust to intertemporal treatment effects (de Chaisemartin and D'Haultfœuille). The table reports aggregate ATT estimates; the figures plot the corresponding dynamic event-study coefficients. Standard errors are reported in the second column.

since 2000, we show that the emergence of AI innovation reduces the relative wage-cost ratio of high-skilled workers through both wage and employment margins. The effect is concentrated where AI capabilities are more developed, suggesting that cognitive-task substitution becomes economically relevant only once AI technologies are sufficiently mature.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used ChatGPT and Claude in order to improve the fluency and readability of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2026.113180.

Data availability

Data will be made available on request.

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