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Automation and Jobs:

Skill Requirements and Employment in EU

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Abstract

This study examines how automation, measured by industrial robot adoption and artificial intelligence (AI) exposure, is associated with labor market and production outcomes across Europe. Using a panel dataset covering 32 European countries and 18 industries from 1994 to 2019, we analyze the relationships between automation technologies and employment, wages, output and gross value added. Robot density is consistently associated with employment reductions in routine-intensive activities. In contrast, AI exposure is associated with a moderation of the negative employment effects of robot adoption, consistent with task reallocation and augmentation mechanisms in knowledge-intensive environments. These associations vary across sectors and institutional contexts in Western European and Central and Eastern European economies, highlighting the context-dependent nature of automation's labor market effects and the importance of tailored policy responses.

Keywords: AI, Automation, industrial robots, employment, jobs, labor, wages.
JEL: E24, J24, J31, O33.

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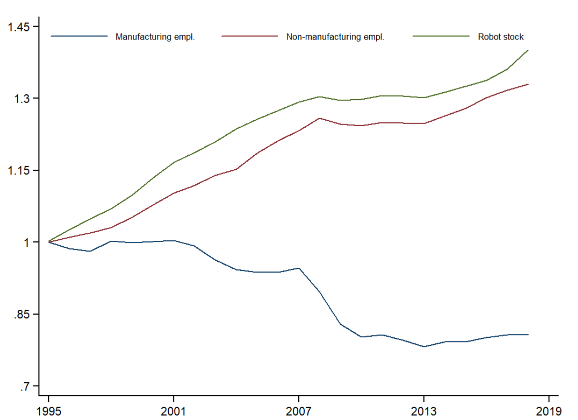
1. Introduction

There is growing evidence that automation, particularly in low- and medium-skill occupations, has contributed to rising wage inequality and labor market polarization (Autor et al., 2003; Goos and Manning, 2007; Michaels et al., 2014; Acemoglu and Restrepo, 2020; Anton et al., 2022). However, despite these concerns, systematic empirical insights into the broader equilibrium effects of automation, especially industrial robotics, on employment and wages remain limited. Importantly, the impact of automation is associated with different patterns across regions and industries, depending on each region's employment distribution across sectors. For instance, countries or regions with higher employment shares in automation-sensitive industries, such as manufacturing, may experience stronger associations with labor displacement or reallocation, whereas regions dominated by service or knowledge-based sectors may exhibit different adjustment patterns. Understanding these intersecting dynamics is crucial to forming effective, context-sensitive policy responses.

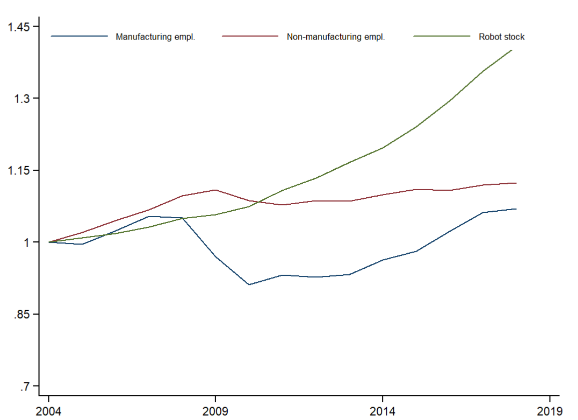
As shown in Figure 1, the relationship between robot adoption and employment diverges markedly across European regions and sectors. In Western EU (WEU) manufacturing, robot stock increases steadily while employment declines, consistent with capital–labor substitution in routine-intensive production. By contrast, in non-manufacturing sectors, rising robot adoption coincides with employment growth, suggesting that automation may be associated with complementary or indirect demand dynamics. In Central and Eastern EU (CEE) countries, robot stock also increases, albeit from a lower initial level, while employment dynamics are more volatile. Manufacturing employment exhibits pronounced cyclical fluctuations with limited long-term expansion, whereas non-manufacturing sectors experience gradual employment gains. Overall, these patterns highlight the importance of sectoral composition and regional adjustment capacity in shaping automation outcomes.

Figure 1: Indexed Robot Stock and Sectoral Employment Trends by Region

(a) WEU — Manufacturing vs. Non-Manufacturing



(b) CEE — Manufacturing vs. Non-Manufacturing



Notes: All series are indexed to the first available year in each region (1995 for WEU and 2004 for CEE), with the base year normalized to 1. Employment is aggregated at the industry level into manufacturing and non-manufacturing sectors. Robot stock refers to the total installed industrial robot stock. Trends are shown for selected WEU countries (Finland, France, Germany, Italy, Spain, Sweden, UK) and CEE countries (Czechia, Estonia, Hungary, Poland, Romania, Slovakia, Slovenia).
Source: Author's illustration based on IFR and Eurostat.

In this paper, we examine whether displacement or productivity effects are likely to dominate in the AI era across European regions, industries and skill levels. While a substantial body of research has investigated these dynamics in the United States, the Europe labor market remains comparatively underexplored, despite its significant structural diversity and varying rates of technological adoption. Internal disparities within the Europe further complicate the picture. WEU countries, characterized by more advanced technological infrastructure and workforce adaptation frameworks, may be better positioned to accommodate automation-related adjustment processes. In contrast, CEE countries, characterized by lower robot penetration, slower integration of new technologies and a higher concentration of routine-intensive industries, are more frequently associated with labor displacement pressures and skill mismatches (Klenert et al., 2022).

The heterogeneously distributed impact of automation on labor markets across regions and sectors presents intricate challenges for labor markets. On the one hand, automation is often linked to productivity-enhancing processes and innovation, though their aggregate employment and wage effects remain uneven (Autor and Salomons, 2018). Conversely, it reduces demand for middle-wage positions, particularly in routine-intensive industries, intensifying wage polarization and economic vulnerability for lower-skilled workers (Autor and Dorn, 2013; Bessen, 2019). The resulting employment pressures in routine-intensive occupations, coupled with heightened demand for highly skilled positions, could further deepen inequality and restrict social mobility (Arntz et al., 2017). Economic literature reflects divided opinions regarding automation's net effects on employment and wage dynamics. While productivity-enhancing technologies can boost labor demand, task-specific displacement risks remain substantial, creating potential mismatches between production growth and employment opportunities (Acemoglu and Restrepo, 2017). Regions equipped with advanced workforce transition programs and robust policy frameworks exhibit greater resilience, underscoring the crucial role institutional readiness plays in managing automation-induced transitions (Acemoglu and Restrepo, 2020).

Our paper makes two important contributions to the existing literature. The first contribution of this paper is to document how automation is associated with worker displacement in robot-intensive manufacturing while generating labor demand through positive spillovers in non-manufacturing sectors. This dual effect does not manifest uniformly across Europe. In WEU, higher robot adoption in manufacturing is strongly associated with lower routine labor demand, yet it also coincides with employment expansion in some non-manufacturing activities and other non-manufacturing fields. Meanwhile, CEE countries differ substantially in terms of production patterns, policy capacities and adoption timelines, thereby experiencing distinct adjustment pathways. By emphasizing these contrasting regional effects, our analysis moves beyond previous researches that extrapolated automation impacts primarily from larger WEU economies.

Second, we discuss the debate by investigating the extensive role of AI in the labor market, an area not yet thoroughly examined in empirical work. Unlike industrial robots, which mainly affect routine tasks in manufacturing and require considerable workforce retraining, AI has the potential to be applied across a wide range of sectors. It not only influences low-skill tasks but increasingly targets higher-skilled, cognitive roles as well. This AI-centred perspective is consistent with a creative-destruction view in which AI both displaces and reassigns tasks while enabling new activities and firms (Aghion et al., 2021). Examining AI at the industry level using EU-based exposure measures thus highlights a distinct dimension of automation relative to robotics, offering valuable insights into skill requirements, sectoral shifts and broader adaptive challenges faced by the European workforce.

The remainder of this paper is structured as follows: Section 2 examines the role of automation across different structural labor markets. Section 3 outlines the conceptual framework. Section 4 introduces the dataset and empirical strategy. Section 5 presents the main results. Section 6 concludes with a discussion of the key findings and their policy implications.

2. Literature Review

Technological change is transforming labor markets across Europe, primarily through two key mechanisms: skill-biased technological change (SBTC) and routine-biased technological change (RBTC). SBTC posits that advanced technologies complement skilled labor, increasing demand and wages for highly educated workers while displacing lower-skilled ones (Acemoglu and Autor, 2011). RBTC, by contrast, highlights how automation replaces routine tasks across the skill spectrum, disproportionately affecting mid-wage occupations reliant on repetitive work (Autor and Dorn, 2013; Goos and Manning, 2007; Goos et al., 2014).

Early task-based assessments of susceptibility to computerisation also predicted uneven occupational risks across Europe, especially in routine-intensive roles (Frey and Osborne, 2017), while subsequent evidence documents a reversal in the demand for cognitive tasks that helps explain recent polarization dynamics (Beaudry et al., 2016). Empirical evidence from European labor markets provides substantial support for the RBTC framework. Digital technologies and industrial robots have had a particularly pronounced impact on routine-intensive sectors such as automotive and metalworking industries, long central to Europe's industrial base (Klenert et al., 2022; Anton et al., 2022). Complementary evidence from developing economies shows that rising robot adoption can also pressure manufacturing employment under limited absorptive capacity and weaker adjustment institutions (Plumwongrot and Pholphirul, 2023). Studies suggest that automation in these sectors has led to measurable job displacement (Dauth et al., 2017; Chiacchio et al., 2018). While SBTC remains influential, RBTC offers a compelling explanation for recent trends in job polarization and the decline of middle-income employment.

A central issue in the automation debate is whether displacement or productivity effects prevail. Displacement arises when automation substitutes labor, reducing employment (Acemoglu and Restrepo, 2020), whereas productivity effects may emerge when automation boosts efficiency and lowers costs, potentially stimulating output and employment in complementary sectors (Dauth et al., 2021). Evidence is mixed: some studies report localized job losses tied to increased robot adoption (Chiacchio et al., 2018), while others find employment gains in service-oriented sectors that help offset losses in manufacturing (Dauth et al., 2017, 2021). Similarly, AI exposure may displace routine jobs while being associated with task reallocation toward higher-skilled occupations (Domini et al., 2021).

Europe's regional economic diversity further shapes automation's impact. WEU countries, with their advanced infrastructure and higher R&D investments, are generally better positioned to accommodate automation-related adjustment processes (Anton et al., 2022). In contrast, CEE economies, while growing rapidly since the 1990s, face challenges due to lower rates of automation and a greater reliance on routine labor (Krenz et al., 2021). Although advanced robotics may contribute to narrowing the regional divide, robot adoption in CEE still trails behind that of Western Europe (International Federation of Robotics, 2021).

While automation has traditionally been concentrated in manufacturing, its use is expanding into services such as logistics, warehousing and retail (Klenert et al., 2022; International Federation of Robotics, 2021). In these sectors, automation tends to complement rather than replace labor, with more muted employment effects than in manufacturing (Anton et al., 2022). This variation highlights the need for sector-specific analyses when assessing automation's labor market effects.

At the macroeconomic level, several studies document positive associations between robot adoption and productivity across European economies (Graetz and Michaels, 2018). These associations appear stronger when combined with AI, especially in economies with strong digital infrastructure and skilled labor (Acemoglu and Restrepo, 2019). However, benefits remain uneven, CEE countries capture smaller gains unless supported by targeted investments in education, skills and technology diffusion.

Sectoral wage effects are heterogeneous. In routine-intensive manufacturing, displacement pressure tends to depress wages, whereas productivity-driven complementarities raise wages in knowledge-intensive, high-skill occupations (Dauth et al., 2017; Anton et al., 2022). In the United Kingdom, wage polarization accompanies the expansion of high-skill jobs and the contraction of routine employment (Goos and Manning, 2007). Wage-setting institutions mediate these adjustments: changes in the German wage structure show how collective bargaining and decentralization shape the distributional impact of technological shocks (Dustmann et al., 2009). Taken together, these patterns underscore the importance of workforce adaptability and targeted upskilling to mitigate inequality (Bessen, 2019).

Research on AI's labor market effects is still emerging. Current studies, mostly U.S.-based, find limited evidence of large-scale job losses and mixed wage effects, particularly in occupations requiring software and analytical skills (Felten et al., 2019; Lane and Saint-Martin, 2021). While the productivity benefits of AI appear promising, more empirical work is needed to assess its long-term implications in the European context, particularly as AI begins to affect cognitive and service-sector tasks.

In summary, robotics and AI are reshaping labor markets in complex and uneven ways. While they are often associated with productivity-enhancing processes, they also bring challenges in terms of job displacement, wage inequality and regional disparities, especially in CEE and routine-intensive sectors. This paper contributes to the literature by offering a detailed analysis of regional and sectoral dynamics across Europe, incorporating both industrial robotics and sector-level AI exposure. By highlighting employment, production and gender-specific outcomes, it offers policy-relevant insights for fostering inclusive and adaptive economic growth.

3. Conceptual Framework

This paper builds on the task-based local labour market equilibrium framework developed by Acemoglu and Restrepo (2020), extending it to explicitly incorporate artificial intelligence (AI) exposure alongside industrial robots. While the original framework models automation exclusively through physical capital embodied in robots, recent technological change increasingly operates through AI systems that augment, rather than fully replace, human labour in cognitive and non-routine tasks. Accounting for this distinction is essential for understanding heterogeneous employment responses to automation across regions and industries.

Consider an economy with country indexed by c and industries indexed by i. Each industry produces output by combining a continuum of tasks indexed by $s \in [0, 1]$. Tasks differ in their susceptibility to automation and are partitioned into three segments. First, tasks $s \in [0, M_i]$ can be fully automated using industrial robots. Second, tasks $s \in (M_i, N_i]$

are affected by AI systems that augment labour productivity without fully substituting for workers. Third, tasks $s \in (N_i, 1]$ must be performed exclusively by labour. We assume $0 \leq M_i \leq N_i \leq 1$.

Following the task-based literature, industry output can be expressed as a constant elasticity of substitution (CES) aggregate over tasks:

$$Y_{ic} = \left(\int_0^1 y_{ic}(s)^{\frac{\sigma-1}{\sigma}} ds \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $\sigma > 1$ denotes the elasticity of substitution across tasks. This formulation captures the idea that automation reallocates tasks within industries rather than replacing entire jobs, allowing employment effects to arise gradually through changes in task composition.

The task-level production function for industry i in country c is given by

$$y_{ic}(s) = \begin{cases} n_{ic}(s) + \gamma l_{ic}(s), & s \leq M_i, \\ \phi(N_i)\gamma l_{ic}(s), & M_i < s \leq N_i, \\ \gamma l_{ic}(s), & s > N_i, \end{cases} \tag{2}$$

where $n_{ic}(s)$ denotes robot input, $l_{ic}(s)$ denotes labour input, $\gamma > 0$ is baseline labour productivity, and $\phi(N_i) > 1$ captures AI-induced labour augmentation in cognitively intensive tasks.

Industry output is produced by combining tasks in fixed proportions,

$$Y_{ic} = A_{ic} \min_{s \in [0,1]} \{y_{ic}(s)\}, \tag{3}$$

where A_{ic} denotes industry-country productivity. As in Chiacchio et al. (2018), labour and robots compete as inputs at the task level, while equilibrium wages and employment are determined by regional labour supply and product demand conditions.

Aggregating across tasks and industries, regional labour demand can be expressed as

$$d \ln L_c = -\sum_i s_{ic} \frac{dM_i}{1 - M_i} + \sum_i s_{ic} \psi(N_i) + \underbrace{\left(d \ln Y_c - \sigma \sum_i s_{ic} \, d \ln P_{ir} \right)}_{\text{general equilibrium spillovers}} \tag{4}$$

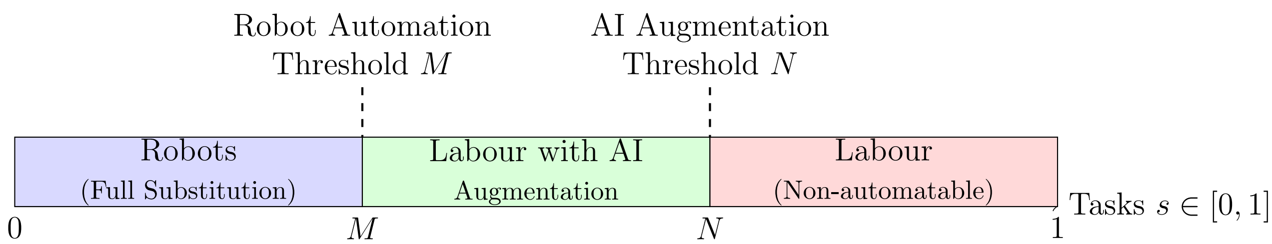
where s_{ic} denotes the pre-period employment share of industry i in country c. The first term captures the displacement effect of robots, as an expansion in M_i reduces the mass of tasks performed by labour. The second term reflects the AI augmentation effect, whereby higher AI exposure raises labour productivity in non-routine tasks and increases labour demand. General equilibrium spillovers arise through price reductions, output expansion, and cross-industry labour reallocation.

A key implication of this framework is that robot adoption and AI exposure interact in shaping employment outcomes. AI reduces the effective substitutability between robots and labour by reallocating workers toward complementary tasks and increasing the elasticity of labour demand. Formally, the model predicts

$$\frac{\partial^2 L_c}{\partial M_i \partial N_i} > 0, \tag{5}$$

implying that the negative employment effects of robot adoption are attenuated in industries and countries with higher AI exposure.

Figure 2: Task Allocation under Dual Automation: Robots and AI



Note: Robots fully substitute for labour in routine tasks up to threshold M, while AI augments labour productivity in cognitive and non-routine tasks between M and N. Tasks beyond N remain non-automatable.

Figure 2 illustrates task allocation under dual automation. Robot adoption expands the set of fully automated routine tasks up to threshold M, while AI technologies augment labour productivity in cognitive and non-routine tasks between M and N. As automation technologies improve and their relative costs decline, both thresholds shift, reallocating tasks across robots and labour and altering employment outcomes across industries and regions.

Consistent with the local labour market approach, regional exposure measures are constructed as employment-share-weighted industry shocks. Let ΔM_i denote the change in robot adoption at the industry level. For AI, we treat the augmentation threshold N_i as a time-invariant industry characteristic capturing the structural extent of AI-relevant tasks. Regional robot and AI exposure are then defined as

$$\Delta RobotExposure_r = \sum_i s_{ir,0}\, \Delta M_i, \qquad AIExposure_r = \sum_i s_{ir,0}\, N_i, \tag{6}$$

where $s_{ir,0}$ denotes baseline employment shares in region r, used to construct exposure measures and avoid mechanical feedback from contemporaneous employment adjustments. The empirical employment equation implied by the framework is

$$\begin{aligned} \Delta Employment_r \ &= \beta_1\, \Delta RobotExposure_r + \beta_2\, AIExposure_r \\ &\quad + \beta_3\big(\Delta RobotExposure_r \times AIExposure_r\big) + X_r'\gamma + \varepsilon_r, \end{aligned} \tag{7}$$

with theoretical predictions $\beta_1 < 0$, $\beta_2 \geq 0$, and $\beta_3 > 0$.

This extended framework preserves the core structure of the Chiacchio et al. (2018) approach while allowing automation to operate through both displacement and augmentation channels. It provides a unified theoretical foundation for analysing why robot adoption may have strongly negative employment effects in some countries, yet weaker or offsetting effects in AI-intensive, knowledge-based environments.

Overall, this framework provides a coherent bridge between task-based theory and industry-and region-level empirical analysis. It motivates the use of interaction terms between robot density and AI exposure by highlighting how physical automation and cognitive augmentation jointly shape task reallocation and labour demand. Automation effects are therefore allowed to vary systematically with industry task composition and regional adjustment capacity. While the framework is presented in levels for expositional clarity, the empirical analysis estimates reduced-form relationships in first differences, consistent with the identification strategy and the available variation in automation exposure.

4. Data and Methodology

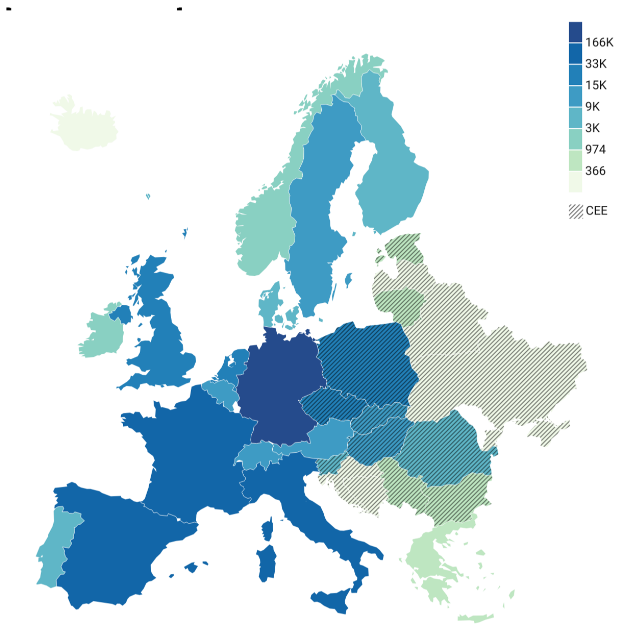
To empirically assess the effects of automation on labor market and production outcomes, we compile a panel dataset covering 32 European countries and 18 industries over the period 1994–2019. Industrial robot adoption is measured using data from the International Federation of Robotics (IFR), while sectoral employment and production variables are obtained from Eurostat. The analysis additionally controls for macroeconomic conditions, including human capital, persons engaged and trade-related indicators, using data from the PWT (10.01). This data construction follows the standard approach in empirical studies of automation and labor markets in Europe (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018).

Industrial robots are defined according to the IFR as automatically controlled, reprogrammable machines capable of performing a variety of tasks in manufacturing environments. They represent physical automation in capital-intensive sectors, particularly affecting tasks that are routine, codifiable and repetitive, as emphasized in task-based models of automation (Autor and Dorn, 2013; Goos et al., 2009; Acemoglu and Restrepo, 2020). Robot adoption is measured via robot density, defined as the number of robots per 1,000 workers in each country-sector-year cell:

$$\mathrm{RD}_{ict} = \left(\frac{\mathrm{RobotStock}_{ict}}{\mathrm{Employment}_{ict}}\right) \times 1000 \tag{8}$$

Robot density is incorporated into the regression analysis in logarithmic form to facilitate proportional interpretation and to mitigate the influence of extreme values. In some specifications, changes in robot adoption over time are examined to capture shifts in automation intensity. This measure reflects the intensity of robot use relative to employment and follows established practice in the automation literature (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2017).

Figure 3: Robot Stock Change Across European Countries, 1994–2019



Note: The map shows the cumulative increase in robot stock across Europe countries from 1994 to 2019. Darker shades represent higher growth, lighter shades slower adoption. Cross-hatched areas denote CEE countries.

Source: Author's calculation based on IFR and Eurostat data.

Figure 3 illustrates the cumulative increase in robot stock across European countries between 1994 and 2019, revealing clear regional disparities. WEU economies such as Germany and Italy experienced the largest absolute increases, consistent with their capital-intensive manufacturing bases and early adoption of automation technologies. In contrast, most CEE economies lagged behind, reflecting their later integration into global value chains and more routine-intensive production structures. For many CEE countries, robot stock data start only in 2004, mechanically limiting their cumulative growth relative to WEU. Nevertheless, Czechia and Hungary exhibit comparatively stronger increases within the CEE group. This divergence suggests that automation may reinforce existing productivity gaps in the absence of complementary institutional and policy adjustments (De Backer et al., 2016; Antràs, 2020; Timmer et al., 2014).

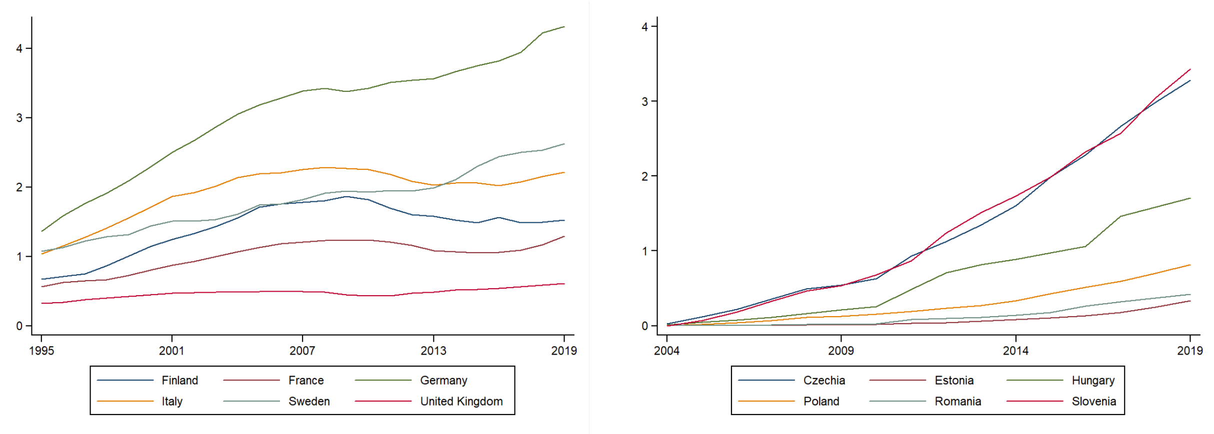
Figure 4 compares the evolution of robot density across WEU and CEE countries. In WEU, robot density rose steadily from the mid-1990s, led by capital-intensive sectors such as automotive and machinery. By contrast, CEE countries show a discernible uptick only after the early 2000s, coinciding with WEU accession and deeper integration into supply chains. The delayed yet rapid catch-up in several CEE economies suggests scope for convergence but also uneven adjustment: routine-intensive industries may struggle to translate robotisation into stable employment without complementary skill upgrading and organisational change. Differences in absorptive capacity, industrial specialisation and institutional readiness likely underpin these paths, consistent with evidence that automation interacts with reshoring incentives and supply-chain reconfiguration, with heterogeneous consequences for mid-skill employment (De Backer et al., 2016; Antràs, 2020).

To complement the analysis of robot adoption, we also incorporate an industry-level measure of exposure to AI. AI technologies are understood as systems capable of performing tasks that typically require human intelligence, including prediction, information processing and pattern recognition.

Our starting point is the occupation-level AI Occupational Exposure Index (AIOE) developed by Felten et al. (2021). The AIOE quantifies the extent to which the task content

Figure 4: Robot Density Trends for Selected European Countries

(a) WEU (b) CEE



Note: Robot density is measured as the number of industrial robots per 1,000 workers, calculated using total robot stock and total employment at the country-year level. The WEU panel covers the period 1995-2019, while the CEE panel starts in 2004 due to data availability.
Source: Author's illustration based on data from IFR and Eurostat.

of occupations overlaps with technological domains where recent advances in artificial intelligence have been most pronounced (Felten et al., 2021; Brynjolfsson et al., 2017). These exposure scores are constructed by linking detailed O*NET task descriptors to benchmarks of AI progress and are defined at the U.S. Standard Occupational Classification (SOC) level. In this study, we translate this framework to the European context by constructing AI exposure measures using European employment data, rather than applying U.S.-based employment structures directly.

Although the AIOE is originally constructed using U.S. occupational data, its application in a European context does not imply that labor market institutions, skill endowments or employment structures are identical across countries. In this study, the index is recalculated using European employment data to reflect the occupational and sectoral composition of European labor markets. Rather, the index captures the *functional task content* of occupations, which task-based models identify as the primary channel through which automation and AI affect labor demand (Autor and Dorn, 2013; Acemoglu and Restrepo, 2020). A growing literature shows that the core tasks performed within narrowly defined occupations exhibit substantial similarity across advanced economies, even when wages, institutions and employment shares differ (Goos et al., 2014; Arntz et al., 2017). This interpretation is consistent with evidence that AI systems diffuse through globally standardized software platforms and operate on comparable task inputs across countries, allowing occupation-based exposure measures to be used as relative indicators of technological exposure in European labor markets (Brynjolfsson et al., 2017; Lane and Saint-Martin, 2021; Felten et al., 2019; Webb, 2019).

Accordingly, we retain the original AIOE scores without rescaling, preserving their relative interpretation at the occupational level and adapt them to the European context through employment-weighted aggregation. Occupational exposure scores are mapped from U.S. SOC to ISCO classifications using established crosswalks (Hardy et al., 2016; Arntz et al., 2016) and subsequently aggregated to the NACE Rev.2 industry level based on Eurostat employment shares, thereby reflecting the occupational structure of European industries. Formally, the resulting AI Industry Exposure Index (AIIE) is defined as:

$$\mathrm{AIIE}_i = \sum_{o \in i} \omega_{o,i}^{EU} \cdot \mathrm{AIOE}_o \tag{9}$$

where o indexes occupations, i denotes industries, $\omega_{o,i}^{EU}$ represents the Europe employment share of occupation o within industry i and AIOE_o corresponds to the occupation-level AI exposure score reported by Felten et al. (2021). The resulting index is standardized to have a mean of zero across industries, such that positive (negative) values indicate above- (below-) average AI exposure relative to the European industry mean. By construction, it captures cross-industry heterogeneity in AI-relevant task content specific to European employment structures, rather than differences in occupational distributions across countries.

Since the index reflects structural task exposure rather than realized AI adoption, it is treated as a time-invariant industry characteristic and merged with country–industry–year

Table 1: AIIE by NACE Rev.2 Industry

NACE_R2 classification	Exposure	NACE_R2 classification	Exposure
Manufacturing	-0.312	Communication	0.645
Agriculture	-0.869	Education	0.607
Transportation	-0.302	Health & social	0.240
Mining	-0.413	Finance	0.583
Utility	-0.096	Arts & recreation	0.345
Accommodation	-0.239	Real estate	0.220
Construction	-0.496	Professional and technical	0.634
Wholesale trade	-0.120	Other services	-0.056
Support service	-0.321	Public administration	0.260

Note: AI Exposure is time-invariant at the industry level.
Source: Author's calculations based on Felten et al. (2021) and Eurostat.

observations. Occupational employment weights are fixed using EU-wide shares from a common reference year (2019), ensuring that variation in AI exposure reflects persistent differences in task composition rather than short-run labor market fluctuations. This approach isolates systematic cross-industry differences in AI-related task exposure and avoids conflating technological exposure with contemporaneous adjustment processes. Results are robust to alternative weighting schemes based on adjacent reference years, consistent with the treatment of task-based exposure measures as slow-moving technological characteristics in the literature (Felten et al., 2021; Acemoglu and Restrepo, 2020).

The baseline regression model is estimated at the industry-country-year level and is specified as follows:

$$\Delta \ln Y_{ict}^{dep} = \beta_1 \Delta \ln RD_{ict} + \beta_2 AI_i^E + \beta_3 \Delta(lnRD \times AI^E)_{ict} + \mathbf{X}'_{ct}\Delta\gamma + \mu_i + \lambda_c + \tau_t + \varepsilon_{ict} \quad (10)$$

where Y_{ict}^{dep} denotes the dependent variable for industry i, country c and year t; RD_{ict} is robot density; AI_i^E is sectoral AI exposure; $\mathbf{X}'_{ct}$ is a vector of control variables including persons engaged, human capital index and trade values; μ_i, λ_c and τ_t represent industry, country and year fixed effects, respectively; and ε_{ict} is the error term. Country–industry–year cells with missing or inconsistent data in variables entering the regression are excluded from the estimation sample.

A central objective of the analysis is to assess whether the employment effects of robot adoption depend on industries' exposure to AI-related tasks, as captured by the AIIE. To this end, we include an interaction term between robot density and AIIE. This specification reflects the idea that physical automation and AI-based cognitive automation operate through distinct yet interrelated task channels. While robots primarily substitute for routine and manual tasks, AI technologies tend to affect cognitive, analytical and non-routine activities. In industries with higher AIIE, robot adoption may therefore be accompanied by task reallocation and complementarities that mitigate pure displacement effects, consistent with task expansion mechanisms emphasized in the task-based literature (Bresnahan et al., 2002; Acemoglu and Restrepo, 2020).

This interaction allows the marginal effect of robot adoption on employment to vary systematically across industries with different levels of AI-related task exposure (Felten et al., 2021). A positive interaction coefficient indicates that higher AIIE attenuates the negative employment effects of robot adoption, whereas a negative coefficient would imply an amplification of displacement effects.

Table 2 reveals substantial cross-industry heterogeneity in automation exposure. Robot density ranges from zero to nearly 30 robots per 1,000 workers, indicating that while some industry–country cells remain virtually unautomated, others operate at very high levels of physical automation. AI exposure likewise exhibits wide dispersion, spanning strongly negative to high positive values, suggesting pronounced differences in the cognitive task content of industries and, consequently, in their potential susceptibility to AI-driven task reallocation.

The empirical models include a set of control variables to account for confounding factors affecting employment dynamics. Human capital is included to account for cross-country differences in skill endowments, which condition the ability of workers and firms to adapt to

Table 2: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Robot Density	15,584	0.264	1.655	0	29.228
AI Exposure	20,387	-0.030	0.467	-0.887	0.645
RD_AI interaction	15,584	-0.021	0.125	-1.222	0.596
Employment	15,584	373,109	757,269	400	8,879,800
Employment (male)	14,919	215,112	469,502	400	6,353,600
Employment (female)	14,569	177,317	374,166	400	4,220,000
Output (mln EUR)	17,560	36,861	99,760	0.100	2,076,587
Value Added (mln EUR)	17,564	17,939	42,211	0.100	687,379
Wages (mln EUR)	16,763	7,706	20,110	0.600	378,310
Persons Engaged (thsnd)	18,981	6,839	9,488	136	44,795
Human Capital Index	17,442	3.129	0.328	2.019	3.849
Export (mln EUR)	20,387	128,364	217,486	0	1,568,289
Import (mln EUR)	20,387	121,315	199,788	0	1,378,637

automation technologies (Acemoglu, 2002). The logarithm of the number of persons engaged is included as a proxy for labor supply conditions and aggregate labor market size.

To control for exposure to international trade, exports and imports of goods and services are included in logarithmic form. Trade openness is a key confounder in studies of automation and employment, as globalization and technological change often evolve jointly and may exert similar pressures on labor markets (Autor and Dorn, 2013; Acemoglu and Restrepo, 2020). All control variables are measured at the country-year level and enter the regression models in first differences where appropriate.

In complementary analyses, the framework is extended to alternative outcome variables, including employment by gender, wages and salaries, gross value added and output. These outcomes allow assessment of whether automation affects not only employment quantities but also income and production margins.

5. Results

This section presents the empirical findings on how automation, measured by robot density and AI exposure, affects labor market and production outcomes across European countries and industries. Using fixed-effects regressions on a panel dataset covering 1994–2019, we assess whether automation is associated with labor displacement and whether productivity gains are observable once sectoral, temporal and country heterogeneity are fully accounted for, as well as how these effects vary across sectors and institutional contexts.

Table 3 reports the results for total employment. Across all specifications, robot density is consistently associated with statistically significant reductions in employment. In the most comprehensive model (Column 8), a 1% increase in robot density corresponds to a 0.208% decline in sectoral employment. This finding is consistent with earlier empirical evidence documenting robot-related employment displacement in routine-intensive industries (Acemoglu and Restrepo, 2020; Chiacchio et al., 2018). The stability of the negative coefficient across alternative specifications suggests that the observed employment effects are closely linked to routine task substitution, rather than to cyclical fluctuations or country-specific shocks.

AI exposure exhibits a more nuanced pattern. Due to the time- and country-invariant nature of the AIIE measure, its coefficient is positive and statistically significant in baseline specifications without fixed effects (Table 3, Columns 1–4). However, once industry, year and country fixed effects are introduced in the preferred specifications (Table 3, Columns 6–8), the direct effect of AI exposure is no longer statistically robust. In contrast, the interaction between robot density and AI exposure remains positive and statistically significant. This pattern suggests that higher AI exposure is associated with a moderation of the negative employment effects of robot adoption, consistent with task reallocation and augmentation mechanisms in knowledge-intensive environments. These results are therefore suggestive of the "augmentation hypothesis" discussed by Brynjolfsson (2022) and Acemoglu and Restrepo (2022), although they should be interpreted as reduced-form associations.

Regional heterogeneity is also pronounced. Conditional on automation intensity and other covariates, employment growth is systematically lower in WEU countries than in CEE, as indicated by the negative and statistically significant WEU region coefficient and

Table 3: Impact of Robot and AI Exposure on Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot Density	-0.353***	-0.327***	-0.292***	-0.258***	-0.223***	-0.210***	-0.208***	-0.208***
	(0.063)	(0.062)	(0.053)	(0.055)	(0.062)	(0.057)	(0.058)	(0.057)
AI Exposure		0.036***	0.035***	0.034***	0.011	0.011	0.009	0.010
		(0.003)	(0.003)	(0.004)	(0.021)	(0.021)	(0.020)	(0.021)
RD_AI interaction			0.125	0.160	0.237*	0.263**	0.265**	0.263**
			(0.116)	(0.101)	(0.100)	(0.099)	(0.102)	(0.100)
Person Engaged				0.926***	0.927***	0.912***	0.958***	0.937***
				(0.077)	(0.076)	(0.088)	(0.102)	(0.091)
Human Capital				-0.007*	-0.008***	-0.007*	0.003	-0.008**
				(0.004)	(0.002)	(0.003)	(0.023)	(0.003)
Export				0.039	0.039	0.044	0.042	0.042
				(0.034)	(0.034)	(0.035)	(0.036)	(0.035)
Import				-0.041	-0.040	-0.054	-0.053	-0.053
				(0.034)	(0.034)	(0.036)	(0.037)	(0.036)
Region (WEU)								-0.005**
								(0.002)
Constant	0.016***	0.017***	0.016***	0.032**	0.033*	0.019	-0.014	0.027
	(0.001)	(0.001)	(0.001)	(0.011)	(0.014)	(0.015)	(0.072)	(0.015)
Observations	14838	14838	14838	13359	13359	13359	13359	13359
R^2	0.034	0.174	0.172	0.205	0.555	0.551	0.584	0.555
Ind. FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	Yes	Yes

Note: All regressions include fixed effects as indicated. Standard errors in parentheses
Source: Author's estimates based on IFR, Eurostat and PWT data.

the corresponding positive baseline effect for CEE. Against this backdrop, robot adoption is associated with employment reductions in both regions, but the magnitude of this relationship differs substantially. In WEU, the negative baseline association between robot density and employment is only modestly offset by a small but statistically significant region–robot interaction. In contrast, the substantially larger and highly significant CEE–robot interaction indicates a much stronger attenuation of robot-related displacement effects in CEE relative to the average relationship, consistent with later adoption stages, lower initial robot penetration and greater adjustment margins in these economies (see Table A2). By comparison, interaction terms between AI exposure and region are statistically insignificant, which likely reflects the time- and country-invariant nature of the AI exposure measure and the resulting limited identifying variation once country and year fixed effects are included, rather than the absence of economically meaningful AI-related adjustment. Overall, these regional differences should be interpreted descriptively rather than causally.

Table 4 reports sector-specific estimates of the effects of automation on employment and economic outcomes across industries, using fixed-effects regressions with employment, wages, output and gross value added as dependent variables. Allowing the estimated effects to vary across sectors highlights substantial heterogeneity in how automation technologies are associated with labor market and production outcomes, consistent with task-based frameworks emphasizing differences in routine intensity and task composition across industries (Autor and Dorn, 2013; Acemoglu and Restrepo, 2020). The results indicate stronger employment declines in routine-intensive sectors such as agriculture and mining, while effects are weaker or insignificant in many service industries. In contrast, knowledge- and skill-intensive sectors, including professional and technical services, communication and finance, exhibit positive associations with wages, output and gross value added, suggesting that automation in these industries is more closely linked to productivity-enhancing complementarities rather than pure labor substitution, consistent with European evidence on sectoral adjustment to automation (Anton et al., 2022).

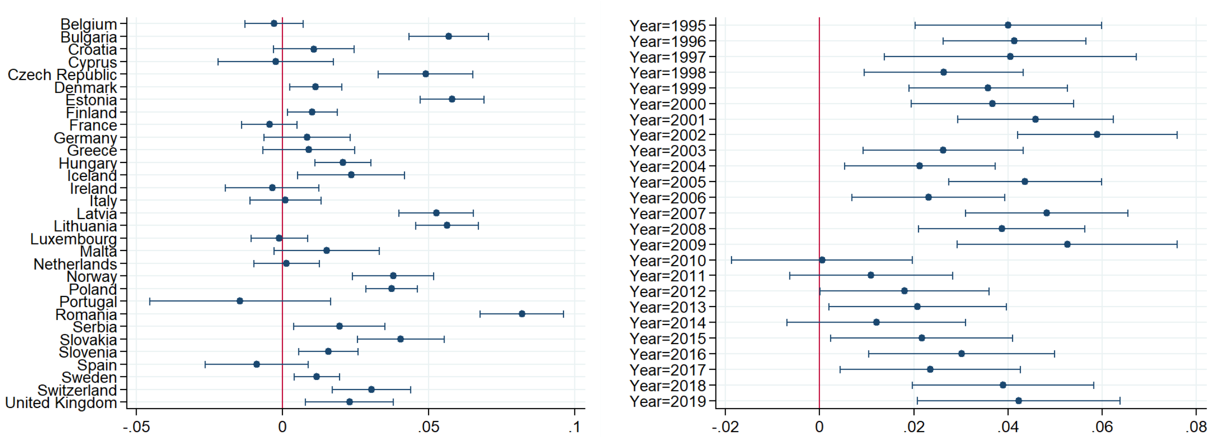
Table 4: Sectoral Heterogeneity in the Effects of Automation on Employment and Economic Outcomes

	Empl	Empl_male	Empl_female	Wages	Output	GVA
Agriculture	-0.032**	-0.033***	-0.035***	-0.010	-0.020**	-0.033***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.007)	(0.008)
Mining	-0.026***	-0.025***	-0.021	-0.013*	-0.016**	-0.015*
	(0.006)	(0.006)	(0.015)	(0.006)	(0.006)	(0.006)
Utility	-0.009	-0.009	0.013	0.008	0.013	0.017*
	(0.009)	(0.009)	(0.015)	(0.006)	(0.007)	(0.007)
Construction	-0.000	-0.001	0.007	0.010*	0.010*	0.009
	(0.005)	(0.005)	(0.008)	(0.004)	(0.005)	(0.005)
Wholesale trade	-0.007	-0.005	0.006	0.024***	0.013*	0.023***
	(0.009)	(0.008)	(0.014)	(0.005)	(0.006)	(0.007)
Transportation	0.002	0.003	0.019	0.013***	0.016**	0.015**
	(0.006)	(0.006)	(0.010)	(0.003)	(0.005)	(0.005)
Accommodation	0.010	0.014*	0.018	0.033***	0.016**	0.027***
	(0.007)	(0.007)	(0.011)	(0.004)	(0.005)	(0.006)
Communication	0.008	0.025	0.012	0.054**	0.038*	0.065***
	(0.023)	(0.022)	(0.031)	(0.017)	(0.017)	(0.018)
Finance	-0.008	0.006	0.004	0.026	0.023	0.048**
	(0.022)	(0.021)	(0.029)	(0.016)	(0.016)	(0.017)
Real estate	0.010	0.013	0.023	0.042***	0.023*	0.042***
	(0.015)	(0.015)	(0.021)	(0.011)	(0.011)	(0.012)
Professional & Tech	0.107***	0.108***	0.125***	0.055**	0.037*	0.067***
	(0.023)	(0.023)	(0.031)	(0.017)	(0.017)	(0.018)
Support service	0.004	0.006	0.014	0.049***	0.038***	0.045***
	(0.008)	(0.008)	(0.012)	(0.004)	(0.005)	(0.005)
Public admin	-0.008	-0.008	0.015	0.019	0.010	0.032**
	(0.015)	(0.015)	(0.022)	(0.011)	(0.011)	(0.012)
Education	-0.005	-0.001	0.015	0.037*	0.024	0.054**
	(0.022)	(0.021)	(0.030)	(0.017)	(0.017)	(0.018)
Health & social	0.003	0.004	0.018	0.039***	0.028*	0.048***
	(0.015)	(0.015)	(0.021)	(0.010)	(0.011)	(0.012)
Arts & recreation	-0.001	0.002	0.015	0.039**	0.035**	0.053***
	(0.017)	(0.016)	(0.023)	(0.012)	(0.013)	(0.014)
Other service	0.005	0.006	0.018	0.020***	0.011	0.024**
	(0.010)	(0.010)	(0.015)	(0.006)	(0.007)	(0.008)
Constant	-0.014	-0.046	0.015	0.057	0.141*	0.196**
	(0.072)	(0.075)	(0.095)	(0.052)	(0.061)	(0.061)
Observation	13359	12746	12445	12602	12934	12936
R^2	0.584	0.588	0.352	0.639	0.543	0.589
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes

Note: All regressions include fixed effects as indicated. Standard errors in parentheses
Source: Author's estimates based on IFR, Eurostat and PWT data.

Figure 5: Fixed Effects on Wages (baseline: Austria and 1994)

(a) Country dummy (b) Year dummy



Note: Fixed effects are estimated from the fully specified model (Column 4 of Table A1). Error bars represent 95% confidence intervals.
Source: Author's illustration based on IFR and Eurostat.

Figure 5 presents the estimated country and year fixed effects from the wage specification. These fixed effects capture persistent cross-country differences and common temporal patterns in wages after conditioning on robot density, AI exposure, their interaction and other covariates. The country effects reveal substantial heterogeneity across Europe, with both CEE and WEU exhibiting positive and statistically significant conditional wage effects relative to the Austria baseline. Importantly, these differences should not be interpreted as reflecting the causal impact of automation on wages. Instead, they likely capture long-run structural and institutional factors, such as wage-setting regimes, labor market institutions and convergence dynamics, that are not explicitly modeled but absorbed by the fixed effects. The year fixed effects similarly indicate common wage movements over time, consistent with shared macroeconomic conditions rather than sector- or technology-specific shocks.

To assess whether employment displacement is accompanied by broader economic gains, the analysis jointly examines employment, wages, output and gross value added. While robot density is consistently associated with employment reductions, its relationship with production and income outcomes is considerably weaker. In fully saturated specifications with industry, year and country fixed effects, robot adoption is not robustly or statistically significantly associated with higher output or value added at the aggregate industry level. Although point estimates for gross value added are positive and those for output are close to zero, neither is statistically precise, suggesting that productivity gains from robotics are not uniformly detectable at this level of aggregation. This pattern does not rule out productivity improvements at the firm or subsector level, but it indicates that such gains do not systematically translate into higher aggregate output or value added across industries over the sample period (Graetz and Michaels, 2018; Dauth et al., 2021).

The moderating role of AI exposure appears asymmetric across outcomes. While higher AI exposure is associated with attenuated employment losses from robot adoption, this moderation does not extend to wages or production variables. Instead, the interaction between robot density and AI exposure is negative and statistically significant for wages, output and gross value added, indicating that AI-intensive environments may coincide with weaker measured income and productivity responses even as employment effects are partially mitigated. Gender-disaggregated estimates further show that robot-related employment declines are more pronounced for male workers, reflecting their concentration in routine-intensive sectors, whereas effects for female employment are smaller and less precisely estimated, consistent with greater exposure to cognitive automation in clerical and administrative roles (Gmyrek et al., 2023). Wage outcomes display no robust association with robot density, while AI exposure is weakly negatively related to wages in routine cognitive activities, in line with evidence on job polarization and wage compression in mid-skill occupations (Goos and Manning, 2007; Acemoglu and Restrepo, 2018). Taken together, these results suggest that automation, particularly when combined with AI, is more closely associated with task reallocation and structural adjustment than with broad-based gains in aggregate productivity or earnings, highlighting the importance of complementary intangible assets and organizational readiness for translating technological change into measurable economic returns (Domini et al., 2021; Anton et al., 2022).

Across specifications and outcome variables, the control variables display economically plausible signs and stable behavior. The number of persons engaged is positively and strongly associated with employment, wages and production outcomes, capturing scale effects and overall labor market size. Human capital enters with smaller and less precisely estimated coefficients, reflecting its country-level aggregation and limited within-country variation. Trade variables exhibit stronger associations with output, gross value added and wages than with employment, consistent with their closer link to production and income margins. Importantly, the inclusion of these controls does not materially alter the magnitude or statistical significance of the automation-related coefficients, indicating that the main results are robust to alternative conditioning variables.

Overall, the results point to a nuanced pattern of technological change. Industrial robots are consistently associated with reductions in routine employment, while aggregate productivity gains at the industry level remain limited once sectoral and regional heterogeneity is accounted for, particularly in manufacturing (Dinlersoz and Wolf, 2024). AI exposure, by contrast, is more closely linked to a moderation of employment pressures in knowledge- and cognitive-intensive activities, although its effects on aggregate productivity and wages are uneven and highly context-dependent. These findings suggest that automation-driven adjustment primarily operates through task reallocation rather than broad-based productivity expansion. Evidence from non-European contexts documents similar displacement–productivity trade-offs under rising robot adoption, lending external support to the associations identified in this study (Sharfaei and Bittner, 2024; Plumwongrot and Pholphirul, 2023). Emerging forms of AI-enabled virtual agglomeration may further reshape task allocation in services, with potential implications for job quality and spatial employment patterns (Shen and Zhang, 2024).

6. Conclusion

The diffusion of automation technologies across European labor markets reflects a complex and uneven transformation, characterized by pronounced regional, sectoral and demographic heterogeneity. This paper has examined how industrial robotics and AI exposure are associated with employment and productivity outcomes across European industries, highlighting that the effects of automation are highly context-dependent and shaped by task composition, institutional settings and complementary capabilities.

The empirical analysis combines panel regression estimates with descriptive trend evidence, which capture different temporal dimensions of automation-related adjustment. The fixed-effects regressions exploit year-to-year variation in robot adoption and employment within country–industry cells and should therefore be interpreted as reflecting medium-run adjustment dynamics. By contrast, the descriptive figures summarize longer-run structural developments in robot adoption and employment across regions and sectors over the full sample period. Distinguishing these temporal layers helps clarify the scope of the results and avoids conflating short- and medium-run adjustment processes with longer-term structural change.

Overall, the findings are consistent with the routine-biased technological change framework, which emphasizes task routinization, rather than skill level alone, as a key channel through which automation is associated with labor market outcomes (Nedelkoska and Quintini, 2018; Gregory et al., 2022). Employment reductions are more frequently observed in routine-intensive activities, while adjustment processes in some service-oriented sectors appear to generate offsetting effects over time. This pattern points to differentiated adjustment dynamics across tasks and sectors and suggests that policy responses may need to balance short-term adjustment support with longer-term investments in reskilling and task reallocation, recognizing that the effectiveness of such measures is likely to vary across institutional and sectoral contexts (Piva and Vivarelli, 2018; Webb, 2019).

Sectoral characteristics provide additional insight into this heterogeneity. Capital-intensive manufacturing industries, such as automotive and machinery, tend to exhibit stronger substitution patterns as robots are adopted in routine manual tasks. In contrast, service-oriented and knowledge-intensive sectors, including education, health and professional services, display indications of complementarity, where AI and digital technologies are associated with changes in task composition rather than outright labor replacement. Differences in workforce composition further shape these outcomes, as routine-intensive low- and medium-skill occupations appear more exposed to displacement risks, while high-skill analytical and interactive roles are more likely to benefit from technological augmentation (Filippi et al., 2023; McGuinness et al., 2023; Plumwongrot and Pholphirul, 2023). These patterns should be interpreted as suggestive of task reallocation processes rather than as direct evidence of specific adjustment mechanisms. While the analysis exploits rich panel variation, the findings should be interpreted in light of the time-invariant nature of AI exposure and the industry-level aggregation, which may mask firm-level adjustment dynamics.

Automation-related outcomes also diverge across regions. In WEU economies, capital-intensive manufacturing sectors appear better positioned to absorb robotics within existing institutional and technological frameworks, exhibiting adjustment patterns more consistent with productivity-oriented reallocation despite associated employment pressures. In contrast, CEE countries, which remain more reliant on routine-intensive production structures, tend to face potentially larger adjustment needs as adoption accelerates. This contrast underscores that automation's economic effects are not automatic but contingent on absorptive capacity, institutional quality and complementary investments. Placing these findings in a broader international perspective, evidence from North America and East Asia suggests that robot adoption has often been associated with sharper local employment displacement, particularly in manufacturing-intensive regions (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). By contrast, the comparatively more muted average employment responses observed in the European context may reflect the role of stronger labor protections, coordinated wage-setting institutions, and well-developed vocational training systems, which can facilitate worker reallocation and dampen short-run adjustment costs. While the present analysis does not formally test cross-regional institutional effects, this comparison highlights how institutional environments may condition automation–employment relationships across advanced economies.

Cross-country differences further condition these relationships. WEU economies typically combine higher robot penetration with relatively flexible labor markets and more developed vocational training systems, factors that may facilitate worker reallocation and the absorption of automation-related shocks. Many CEE countries, by contrast, face slower diffusion of retraining programs, weaker labor market institutions and a higher concentration in routine-intensive industries (Cséfalvay and Gkotsis, 2022; Albanesi et al., 2025). Within the limits of the fixed-effects framework employed, automation in WEU is more often associated with productivity-enhancing adjustment patterns, whereas in CEE it is more frequently linked to employment pressures. Differences in wage-setting institutions may also play a role, as more flexible regimes, such as those observed in Nordic countries, are generally associated with smoother occupational adjustment, while more rigid systems may slow reallocation (Nedelkoska and Quintini, 2018; McGuinness et al., 2023). Taken together, these institutional and structural features reinforce the context-dependent nature of automation–employment relationships (Filippi et al., 2023). These contrasts should be interpreted as descriptive patterns rather than causal estimates, reflecting differences in industrial structure and institutional environments.

The sectoral analysis further illustrates that robotics and AI operate along distinct margins. While robot adoption is associated with labor displacement in codifiable and routine tasks, particularly in manufacturing and logistics, AI exposure is more closely linked to task restructuring in high-skill, knowledge-intensive services, such as ICT, finance and professional activities. At the same time, the productivity effects of AI appear more muted at the aggregate level, likely reflecting the greater organizational complexity of AI adoption and its dependence on complementary intangible assets, managerial capacity and organizational change.

Automation also reshapes labor market outcomes along gender lines. Male workers, who are overrepresented in manufacturing and transport-related sectors, face higher exposure to robot-related displacement risks. Female workers, often concentrated in routine cognitive and administrative occupations, appear more exposed to AI-related restructuring. These asymmetric exposures highlight the importance of gender-sensitive policy frameworks that prioritize inclusive digital upskilling and account for potential biases in AI deployment.

Taken together, these findings point to the need for anticipatory and multi-level policy strategies. At the regional level, CEE countries may benefit from targeted investment in digital infrastructure, adult retraining and institutional capacity to mitigate displacement risks and support technological convergence. European cohesion instruments, including the Just Transition Fund and the Digital Europe Programme, could play a role in supporting automation-sensitive regions and facilitating more equitable adjustment.

At the sectoral level, policy responses need to be dual-pronged, supporting adjustment and job transformation in routine-intensive activities while fostering innovation and skill formation in AI-intensive services. This includes expanding modular training pathways, strengthening public–private partnerships in skill development and integrating AI literacy into vocational and lifelong learning systems. Gender equity considerations should be embedded in these strategies to ensure equal access to reskilling opportunities and emerging job roles.

Ultimately, automation should be understood not as a monolithic force but as a task-based transformation, with its consequences shaped by sectoral routines, regional institutions and technological complementarities. Effective governance of this transition requires a coordinated policy mix that links labor market resilience with innovation capacity. Only through such differentiated and inclusive approaches can Europe harness the potential benefits of automation while supporting equitable growth and social cohesion.

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Table A1: Automation and Economic Outcomes Across Dependent Variables

	Empl	Empl_male	Empl_female	Wages	Output	GVA
Robot Density	-0.208***	-0.170**	-0.173	-0.004	-0.001	0.037
	(0.058)	(0.053)	(0.094)	(0.018)	(0.032)	(0.038)
AI Exposure	0.009	-0.000	0.001	-0.017	-0.008	-0.033*
	(0.020)	(0.020)	(0.024)	(0.017)	(0.015)	(0.016)
RD_AI interaction	0.265**	0.209**	0.034	-0.142**	-0.177*	-0.238*
	(0.102)	(0.072)	(0.174)	(0.047)	(0.082)	(0.096)
Person engaged	0.958***	0.854***	1.126***	0.750***	0.646***	0.667***
	(0.102)	(0.112)	(0.124)	(0.080)	(0.077)	(0.083)
Human capital	0.003	0.016	-0.016	-0.032	-0.052**	-0.072***
	(0.023)	(0.025)	(0.030)	(0.017)	(0.020)	(0.020)
Export	0.042	0.007	0.053	-0.182***	-0.022	0.063
	(0.036)	(0.045)	(0.046)	(0.043)	(0.032)	(0.038)
Import	-0.053	-0.017	-0.063	0.460***	0.383***	0.269***
	(0.037)	(0.046)	(0.047)	(0.047)	(0.035)	(0.037)
Constant	-0.014	-0.046	0.015	0.057	0.141*	0.196**
	(0.072)	(0.075)	(0.095)	(0.052)	(0.061)	(0.061)
Observation	13359	12746	12445	12602	12934	12936
R^2	0.584	0.588	0.352	0.639	0.543	0.589
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes

Note: All regressions include fixed effects as indicated. Standard errors in parentheses
Source: Author's estimates based on IFR, Eurostat and PWT data.

Table A2: Regional Heterogeneity in the Employment Effects of Automation

	WEU interactions	CEE interactions
	Empl	Empl
Robot Density	-0.217***	-0.226***
	(0.057)	(0.058)
AI Exposure	-0.009	0.004
	(0.022)	(0.020)
RD_AI interaction	0.260**	0.263**
	(0.098)	(0.102)
Person engaged	0.944***	0.932***
	(0.091)	(0.091)
Human capital	-0.009**	-0.009**
	(0.003)	(0.003)
Export	0.043	0.043
	(0.035)	(0.035)
Import	-0.054	-0.053
	(0.036)	(0.036)
WEU (Region Dummy)	-0.006**	
	(0.002)	
Robot Density × WEU	0.010*	
	(0.004)	
AI Exposure × WEU	0.006	
	(0.005)	
CEE (Region Dummy)		0.004*
		(0.002)
Robot Density × CEE		0.029***
		(0.005)
AI Exposure × CEE		-0.003
		(0.005)
Constant	0.018	0.017
	(0.015)	(0.015)
Observations	13359	13359
R^2	0.559	0.559
Industry dummy	Yes	Yes
Year dummy	Yes	Yes

Note: All regressions include fixed effects as indicated. Standard errors in parentheses
Source: Author's estimates based on IFR, Eurostat and PWT data.