MANAGEMENT
2026, Vol. 30, No. 1
www.management-poland.com
DOI: 10.58691/man/220692

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Changing demand across skill levels in EU labor market: when production goes global and assets go intangible

Abstract

Research background and purpose: The ongoing integration of global production networks and the rising significance of intangible assets are fundamentally transforming the competitive landscape and organizational structures of European firms. These changes have heightened concerns about workforce polarization, especially the shrinking opportunities for low-skilled labor, as firms increasingly focus on knowledge, innovation, and participation in global value chains. The literature emphasizes the dual role of intangible assets and offshoring in driving both strategic change and growing employment inequality among different skill groups. This study examines how the internationalization of production and investments in intangible assets affect employment distribution among high-, medium-, and low-skilled workers in enterprises across CEE-11 and EU-15 countries.

Design/methodology/approach: Employment share equations for low-, medium-, and high-skilled labor are estimated using Seemingly Unrelated Regression (SUR) techniques, with model specification derived from the translog cost function. Using a balanced panel dataset for CEE-11 and EU-15 countries, this method allows for the identification of group-specific effects of offshoring and detailed intangible asset investment on skill-specific employment structures.

Findings: The results show that offshoring consistently increases the share of high-skilled labor in both regions, but its displacement effects vary: in CEE-11 countries, offshoring significantly reduces low-skilled employment, while in EU-15 countries, it mainly displaces medium-skilled workers. Intangible capital further speeds up workforce polarization by disadvantaging low-skilled workers and benefiting those with higher skills. These patterns highlight the need for reskilling initiatives and flexible talent management to stay competitive in a changing labor market.

Value added and limitations: These findings highlight the importance of reskilling initiatives and flexible talent management for maintaining competitiveness in a changing labor market. The analysis is limited by using aggregate country group data and available indicators for skills and intangible assets. Future research should address these limitations by investigating sector- and occupation-specific effects and further distinguishing between types of offshoring to gain deeper insights into labor market transformation.

Keywords: *internationalization, offshoring, intangible assets, labor market, skill level, EU*

JEL Classification: F16, J31, O33

Received: 2026-01-14; **Revised:** 2026-02-26; **Accepted:** 2026-04-15

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1. Introduction

Workforce polarization has become a defining feature of labor market adjustment in Europe, with particularly strong manifestations in Central and Eastern European (CEE) economies. Over the past three decades, these countries have undergone rapid integration into global markets, driven by foreign direct investment, export-oriented growth, and deep participation in global value chains. This transformation has fundamentally altered employment structures, making the CEE region a particularly informative context for analyzing how globalization and technological change jointly reshape labor demand across skill levels.

At a deeper analytical level, these labor market developments reflect the aggregated outcomes of firm-level strategic responses to changing competitive conditions. From this perspective, workforce polarization is closely linked to firms' decisions regarding production organization and asset allocation in the era of globalization and digital transformation. Traditional strategic management approaches (Porter, 1978, 1985; Barney, 1991; Grant, 1991) emphasized tangible assets such as production capacity, cost efficiency, and location as the primary sources of competitive advantage. In the context of CEE economies, this logic initially underpinned their integration into European production networks, where comparative advantages were largely based on relatively low labor costs and geographic proximity to Western European markets. These strategic shifts are of particular relevance not only for labor market outcomes, but also for managerial decision-making in firms operating within international production networks.

As European production systems have evolved, however, the basis of competitive advantage has increasingly shifted toward intangible assets, including knowledge, innovation capabilities, organizational capital, and firm-specific know-how. This transition is particularly consequential for CEE countries, whose growth models remain strongly embedded in international production networks and thus highly exposed to changes in firms' global strategies. At the same time, production processes have become more fragmented across borders, with firms offshoring and outsourcing specific stages of value creation within global value chains. While cost considerations continue to matter, access to skilled labor, technological capabilities, and innovation ecosystems has emerged as a key driver of these strategic decisions.

These intertwined developments have direct implications for labor markets in the CEE region. The relocation of routine and standardized production activities constrains employment growth in medium-skilled occupations, while in highly internationalized CEE economies it may also increasingly affect low-skilled labor employed in labor-intensive manufacturing segments. In contrast, rising investment in intangible assets supports increasing demand for highly skilled, knowledge-intensive labor, particularly in engineering, digital, and managerial functions. Workforce polarization in CEE

economies can therefore be understood not only as a macroeconomic outcome of globalization, but also as a micro-level consequence of firms' strategic reorientation within global value chains.

Building on this perspective, the present study examines how production internationalization and intangible investment jointly shape employment structures across European economies. Particular attention is paid to differences between CEE-11 and EU-15 countries, reflecting their distinct positions within European value chains and heterogeneous exposure to global competitive pressures. The primary aim of the study is to assess the impact of these transformations on employment across different skill levels using Seemingly Unrelated Regression (SUR) models, thereby contributing new empirical evidence on the mechanisms underlying workforce polarization in Europe.

The paper is organized as follows. Following the introduction, Section 2 reviews the theoretical background. Section 3 describes the data, while Section 4 outlines the empirical model used to examine the impact of offshoring and changes in intangible assets on employment share. Section 5 presents and discusses the empirical results. Finally, the paper concludes with concluding remarks.

2. Theoretical background

A substantial body of literature has examined how offshoring and investment in intangible assets reshape labor markets, both overall and by skill level.

Technological change, including automation, digitalization, and ICT, has mixed effects. Some studies report negative employment impacts, particularly on routine manual and cognitive tasks (i.e., Acemoglu & Restrepo, 2020), while others find positive or negligible effects (i.e., Graetz & Michaels, 2018). Technology also drives labor market polarization: medium-skilled occupations are most susceptible to displacement, whereas artificial intelligence and advanced technologies may increasingly affect highly skilled workers (i.e., Webb, 2020). Recent analyses for European regions confirm persistent skill-biased shifts and increasing educational mismatches, especially among women (Lovaglio & Riussi, 2025).

Recent management-oriented studies emphasize that automation and digital transformation increasingly affect white-collar and service-sector work by reshaping the nature of office tasks and organizational processes. Rather than leading to immediate job elimination, office automation primarily targets routine and repetitive activities, altering how administrative and support functions are performed. These changes introduce organizational, technical, and human-resource challenges and require employees to adapt to new modes of work and technology use (Remlein et al., 2025). At the aggregate level, such task reallocation contributes to workforce polarization by favoring non-routine, knowledge-intensive activities that are closely

linked to investments in intangible assets, while routine administrative tasks become increasingly automated or reorganized.

The growing share of investment in intangible assets further transforms labor demand and wage structures. Intangible capital disproportionately increases demand for highly skilled workers while reducing opportunities for low- and medium-skilled labor, particularly in routine-intensive sectors (Aldieri et al., 2021; Hijzen et al., 2005). R&D plays a key role, driving knowledge-intensive production and reinforcing the need for retraining and professional education (Rađenović et al., 2023). Intangible assets also contribute to wage polarization: medium-skilled wages often stagnate or decline, while highly skilled workers' earnings rise, and firms with substantial intangible capital can attract top talent with higher pay, widening disparities between firms and their employees (Michaels et al., 2013; Gravina & Foster-McGregor, 2024). This pattern is further supported by evidence that the accumulation of intangibles enhances domestic value-added creation and international competitiveness through innovation, ICT, and the quality of human capital (Ďurčová & Pekarčík, 2023). These dynamics can exacerbate income inequality, as employees in sectors with high concentrations of intangible assets increasingly outperform those in more traditional industries (Antonelli et al., 2025; Roth & Mitra, 2025).

At the firm level, these effects are closely linked to the way organizations manage and integrate knowledge within their processes. Empirical evidence indicates that effective knowledge transfer and integration significantly improve business process performance, highlighting the role of embedded knowledge and organizational routines in shaping firm-level outcomes (Malewska et al., 2025). This micro-level perspective helps explain how investments in intangible assets translate into productivity gains and changing skill requirements within firms.

Offshoring has similarly heterogeneous effects: while its aggregate impact on employment in advanced economies is generally modest (Landesmann & Leitner, 2023), sectoral outcomes differ. Manufacturing offshoring tends to reduce employment, particularly for low- and medium-skilled workers, whereas services offshoring may sometimes generate modest employment gains (Hijzen et al., 2005; Amiti & Wei, 2009). Offshoring to low-income or Central and Eastern European countries is often associated with job losses and higher unemployment rates, whereas offshoring to high-income countries may increase employment (Mion & Zhu, 2013; Egger et al., 2024). Medium- and low-skilled workers remain most vulnerable, but even skilled occupations, including managers and professionals, are increasingly exposed as their tasks become offshorable (Foster-McGregor et al., 2013).

From a globalization perspective, transnational corporations are identified as key actors in shaping the global economy due to their significant international presence and activities. Firms with higher levels of internationalization have a greater influence on global economic processes, as measured by indicators such

as the Transnationality Index, which reflects foreign assets, sales, and employment (Rogaczewski, 2025).

Beyond labor demand and wages, offshoring and intangible assets affect the organization and geography of work. Offshoring and global value chains shift employment and production across borders, increasing firms' reliance on external suppliers and networked production structures (Wright, 2014). Similarly, digitalization and ICT enable remote work, service automation, and platform-based labor, altering the spatial distribution of jobs and potentially widening regional disparities in employment opportunities. Intangible-intensive firms tend to cluster in innovation hubs, creating localized high-skill labor markets. At the same time, regions dominated by routine-intensive industries may experience stagnation or decline, highlighting the spatial dimension of labor-market polarization (Lukic & Vojteski Kljenak, 2017).

In this context, recent evidence indicates that digital work arrangements can also influence how job performance is perceived and evaluated. Differences between traditional on-site work and digitally mediated (e-work) arrangements reflect changes in how employees experience productivity in flexible work environments. In a study of Austrian service professionals, remote work was associated with higher self-reported focus, efficiency, and perceived productivity compared to office-based work, suggesting that the expansion of e-work may alter performance dynamics in service sectors (Beno & Caganova, 2025). Although this evidence does not directly assess changes in skill requirements, it underscores how digital work formats reshape work organization and employee experiences in intangible-intensive activities.

In the post-pandemic context, European labor markets are further challenged by demographic decline, skill shortages, and unequal recovery patterns (Stehrer, 2025; European Commission, 2025).

Although offshoring and technological change, represented as investments in intangible assets, are often discussed, it is difficult to measure their real effects on jobs and wages. Offshoring is sometimes seen as the main driver of slower job growth and wage pressure in developed countries, but research shows these fears are often exaggerated (Harrison, 2025). Therefore, it is essential to examine the evidence on the EU labor market. This paper addresses a significant knowledge gap by examining the combined effects of investments in intangible assets and offshoring, across CEE-11 and EU-15 countries.

Building on the theoretical framework and existing empirical evidence, this study examines how production internationalization and technological change, represented by investment in intangible assets, jointly shape employment structures across European economies. Particular attention is paid to differences between CEE-11 and EU-15 countries, reflecting their distinct positions within European value chains and heterogeneous exposure to global competitive pressures.

Based on the theoretical framework, this study addresses the following research questions:

RQ1: How does offshoring intensity affect employment shares across high-, medium-, and low skilled workers in European economies, and to what extent does it contribute to labor market polarization?
RQ2: How does investment in intangible assets, as a proxy for technological change, influence employment shares across different skill groups, and to what extent does it contribute to labor market polarization?
RQ3: Do the effects of offshoring and intangible investment on employment shares differ between CEE-11 and EU-15 countries?

On the basis of these research questions, the following hypotheses are formulated:

H1. Offshoring intensity is associated with systematic changes in employment shares across high, medium-, and low-skilled workers.
H2. Offshoring intensity contributes to labor market polarization.
H3. Investment intensity in intangible assets, as a proxy for technological change, is associated with systematic changes in employment shares across high-, medium-, and low-skilled workers.
H4. Investment in intangible assets contributes to labor market polarization.
H5. The effects of offshoring and intangible investment on employment shares differ systematically between CEE-11 and EU-15 countries, reflecting their different levels of production internationalization and intangible capital intensity.

3. Data

The analysis relies primarily on two key data sources. The first is the EUKLEMS & INTANProd database. This database provides comprehensive information on labor, capital, and various intangible assets. It supplies detailed figures on employment shares by skill level (low-, medium-, and high-skilled), gross output, hourly wages, capital stock, and expenditures on intangible assets. These assets include computer software and databases, research and development (R&D), economic competencies, branding, organizational capital, and training. Hourly wages are defined as labor costs per type of labor relative to total hours worked. The intensities of computer software and databases, R&D, and economic competencies are calculated as ratios to total hours worked, measured in millions of hours (Gravina & Foster-McGregor, 2024). Additionally, data from the OECD TiVA database are used to calculate international production, also known as offshoring. These data facilitate the measurement of intermediate inputs when assessing the effects of offshoring and domestic outsourcing.

Following Feenstra and Hanson (1999), we distinguish between narrow and broad offshoring. Narrow offshoring accounts only for imports of intermediates from the same industry, whereas broad offshoring includes imports of intermediates from all industries. Narrow offshoring more accurately reflects the nature of international production fragmentation, which occurs within industries. However, due to data availability, we adopt the broad definition of offshoring, where IIM represents imported intermediates from a given industry, n denotes the industry index, and VA stands for value added:

$$OFF = \frac{\sum IIM_n}{\sum VA_n} \tag{1}$$

For further analysis, it is also necessary to calculate domestic outsourcing, which is determined in a similar manner:

$$DO = \frac{\sum TIM_n - \sum IIM_n}{\sum VA_n} \tag{2}$$

where *TIM* represents the value of total intermediate inputs, *IIM* denotes imported intermediates from the given industry, n is the industry index, and VA stands for value added.

Then, according to ISCED classification, labor data are divided into three skill categories (low-, medium-, and high-skilled). A detailed description of the variables and data sources is provided in Table 1.

Table 1. **Description of the variables and data sources**

Variable	Explanations	Data source
E	Employment shares of low-, medium- and high-skilled labor	EUKLEMS & INTANProd
W	Hourly wage of low-, medium- and high-skilled labor. Calculated as the labor cost for each labor type relative to the total hours worked.	EUKLEMS & INTANProd
W_{II}	Imported intermediate inputs	EUKLEMS & INTANProd
OFF	Imported intermediate inputs from all industries over value-added	OECD TiVA
DO	Total intermediate input from all industries minus imported intermediates from all industries over value-added	OECD TiVA

Y	Gross output	EUKLEMS & INTANProd
K	All assets capital over total hours worked	EUKLEMS & INTANProd
SoftDB	Computer software and databases over total hours worked	EUKLEMS & INTANProd
RD	R&D expenditure over total hours worked	EUKLEMS & INTANProd
EconComp	Economic competences over total hours worked	EUKLEMS & INTANProd
Brand	Brand expenditure over total hours worked	EUKLEMS & INTANProd
OrgCap	Organizational capital expenditure over total hours worked	EUKLEMS & INTANProd
Train	Training expenditure over total hours worked	EUKLEMS & INTANProd

Source: own study

Table 2 presents the levels of offshoring intensity across EU-27 countries in 2020, alongside the corresponding growth rates over 2008–2020. The period is determined by data availability, as the OECD TiVA database reports comparable data only until 2020. The value of offshoring is measured using data on imported intermediate inputs and value-added obtained from the OECD TiVA database. The data highlight notable cross-country variation, with significantly higher offshoring intensities observed in smaller, more open economies such as Luxembourg, Malta, and Cyprus, as well as in Eastern Europe. These countries exhibit stronger international production linkages, which are consistent with their integration into global supply chains. In contrast, larger or more domestically oriented economies - including France (0.169) or Italy (0.160) - report comparatively lower levels of offshoring activity.

Table 2. **Offshoring intensity and its growth across EU-27 countries**

	Value 2020	Growth rate (2008–2020)
CEE - 11		
HU	0.533	0.003
SK	0.506	0.010
EE	0.411	0.013
CZ	0.388	0.003
SI	0.340	-0.007
LT	0.332	0.019
BG	0.331	-0.012

PL	0.291	0.021
HR	0.236	0.004
RO	0.213	0.014
EU-15 (without UK)		
LU	1.459	0.034
IE	0.654	0.022
CY	0.504	0.045
BE	0.372	-0.005
NL	0.306	0.023
DK	0.295	0.001
AT	0.276	0.012
FI	0.261	-0.001
PT	0.251	0.010
SE	0.210	-0.013
DE	0.188	0.001
ES	0.175	-0.001
FR	0.169	-0.005
IT	0.160	-0.006

Source: own elaboration based on OECD TiVA data

Interestingly, several Central and Eastern European countries - namely Hungary, Slovakia, and the Czech Republic - also demonstrate above-average offshoring values, reinforcing findings from previous studies (e.g., Foster-McGregor et al., 2013) that highlight the region's specialization in international manufacturing networks.

According to Figure 1, the employment structure across EU-27 countries has undergone notable changes between 2008 and 2020. The most striking trend is the decline in the share of medium- and low-skilled workers, observed in nearly all member states. This shift is often linked to automation and the offshoring of routine tasks. Conversely, the share of high-skilled labor in total employment increased in all analyzed countries. Taken together, these patterns signal a growing polarization of the labor market.

In addition to offshoring, skill upgrading and changes in labor demand are associated with structural technological change. We can measure these changes through investments in intangibles. Intangible assets can be categorized into several groups, as discussed in Corrado et al. (2017) and Bontadini et al. (2023). For the purposes of our analysis, we focus on the

following categories: computer software and databases (SoftDB), research and development (R&D, representing the core of innovation property), and economic competencies. The SoftDB category encompasses all knowledge embedded in computer programs and databases and is commonly referred to as ICT-related intangible assets. Economic competencies are further divided into brand, organizational capital, and training.

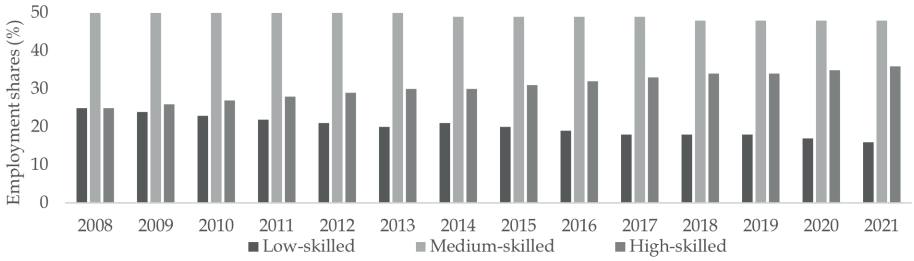

Figure 1. **Employment shares in EU-27 countries in 2008-2020**

Source: own elaboration based on EUKLEMS & INTANProd data

The growing importance of these assets is also reflected in the evolution of aggregate investment patterns. Across the 27 economies in our sample, intangible investment has persistently outpaced tangible investment over time (Figure 2). Using 2008 as the index baseline, intangible investment rose to about 160 by 2020, an increase of just over 60 percent. Over the same period, tangible investment reached roughly 129, corresponding to growth of about 30 percent. From 2008 onward, the pace of intangible investment accelerated, resulting in growth more than twice as fast as that of tangible investment between 2008 and 2020. This divergence underscores the gradual shift from a capital structure dominated by physical assets toward one increasingly driven by knowledge-based capital.

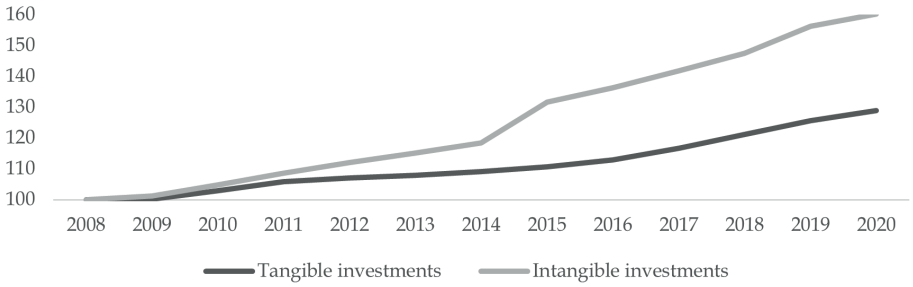

Figure 2. **Investment in tangible and intangible assets in 2008-2020 (2008=100)**

Source: own elaboration based on EUKLEMS & INTANProd data

A closer look at the composition of intangible assets further illustrates this shift. According to Figure 3, Research and Development (R&D) clearly dominates the intangible asset landscape in the EU-27, accounting for approximately 36 percent of total intangible investment. R&D captures the systematic efforts of firms to generate new knowledge, technologies, and products, playing a central role in sustaining long-term productivity growth and competitiveness within the European economy. This is followed by design, which represents about 18 percent of total investment, and organizational capital at around 16 percent. Organizational capital refers to the internal know-how involved in managing and structuring a firm's operations, where robust internal processes and effective management practices serve to boost productivity and drive innovation from within. Software and databases account for roughly 11 percent of the total, reflecting the increasing importance of digital infrastructure and data-driven processes. Finally, smaller shares are observed for brands, training, and other intangibles, with each category contributing between 6 and 7 percent of the total intangible investment.

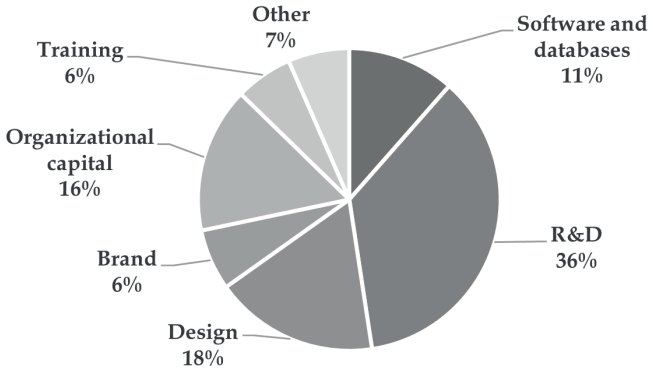

Figure 3. **Share of intangible investment by asset type (%), EU-27**

Notes: Intangible investment by asset type is aggregated across the EU-27 sample countries for 2020. The "Other" category denotes new financial products and entertainment, artistic and literary originals plus mineral explorations.

Source: own elaboration based on EUKLEMS & INTANProd data

The cross-country perspective in Figure 4 shows how these patterns translate into differences in investment intensity. This figure illustrates the share of intangible investment in GDP across EU countries in 2008 and 2020. In 2020, intangible investment as a share of GDP exceeded 15 percent in several European economies, most notably Ireland (36.9%), Malta (19.5%), and Estonia (18.0%). These countries stand

out as highly intangible-intensive, reflecting their strong orientation toward digital services, multinational firm presence, and investment in knowledge-based assets. Most countries recorded modest growth in the share of intangibles over the period, with some of the most dynamic increases observed in Ireland (+26.6 p.p.), Estonia (+8.3 p.p.), and Malta (+1.3 p.p.). Countries like France (15.6%), Sweden (17.4%), and Finland (15.6%) also maintain high levels of intangible investment intensity, consistent with their advanced innovation ecosystems. In contrast, Southern and Eastern European countries such as Greece (7.2%), Bulgaria (8.3%), and Romania (9.4%) remain below the EU average.

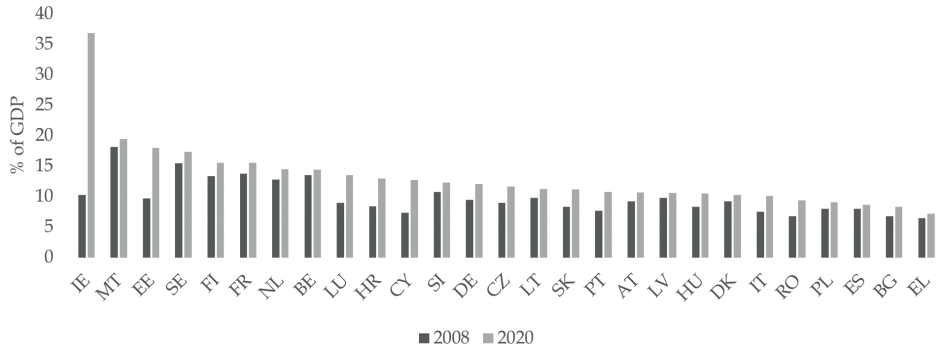

Figure 4. **Investment in intangible assets as a % of GDP (2008 versus 2020)**

Source: own elaboration based on EUKLEMS & INTANProd

Table 3 provide summary descriptive statistics for the CEE-11 and EU-15 country groups. The findings indicate significant structural differences between these regions in labor market composition, production capacity, and the significance of intangible assets. In CEE-11 countries, employment is concentrated in medium-skilled occupations, followed by high-skilled, with low-skilled employment remaining much lower. In contrast, EU-15 countries exhibit higher employment levels across all skill groups, particularly among high-skilled labor, and a more balanced distribution of low-skilled employment. These findings suggest that EU-15 labor markets operate on a larger scale and possess a more diversified skill structure. Wage differentials further reinforce this pattern.

Table 3. **Descriptive statistics of variables (2008-2020)**

Variable	Mean	Std. Dev.	Minimum	Maximum
CEE-11				
ln E_{HS}	3.377	0.270	2.696	3.864
ln E_{MS}	3.994	0.234	3.371	4.363
ln E_{LS}	2.402	0.679	1.321	3.935
ln W_{HS}	2.521	0.356	1.535	3.359
ln W_{MS}	1.988	0.417	0.815	2.751
ln W_{LS}	1.794	0.441	0.655	2.697
ln W_{II}	2.897	0.348	2.183	3.760
ln OFF	-1.053	0.443	-1.838	0.137
ln DO	−0.289	0.346	−2.107	0.181
ln Y	3.502	0.320	2.850	4.221
ln K	4.019	0.401	2.767	4.623
ln SoftDB	−1.858	0.811	−4.905	0.532
ln RD	−2.017	0.631	−3.401	−0.508
ln EconComp	−0.182	0.439	−1.160	1.169
ln Brand	−1.361	0.580	−2.634	0.429
ln OrgCap	−0.812	0.477	−1.812	0.451
ln Train	−2.394	0.664	−3.616	−0.570
EU-15				
ln E_{HS}	3.525	0.280	2.706	3.949
ln E_{MS}	3.704	0.284	2.718	4.150
ln E_{LS}	3.014	0.448	2.150	4.247
ln W_{HS}	3.593	0.295	2.864	4.150
ln W_{MS}	3.233	0.321	2.267	3.682
ln W_{LS}	2.992	0.338	2.045	3.517
ln W_{II}	3.937	0.468	2.923	5.357

ln OFF	−1.266	0.520	−1.963	0.290
ln DO	−0.229	0.193	−1.391	0.203
ln Y	4.567	0.410	3.604	5.671
ln K	5.059	0.260	4.299	5.719
ln SoftDB	−0.359	0.579	−1.687	0.642
ln RD	0.093	0.806	−1.339	3.519
ln EconComp	0.830	0.501	−0.079	1.708
ln Brand	−0.307	0.412	−1.123	0.964
ln OrgCap	0.044	0.655	−1.107	0.883
ln Train	-0.832	0.582	-2.310	-0.038

Source: own study

Within the CEE-11 group, high-skilled workers earn the highest average wages, while low-skilled wages are significantly lower. Wage dispersion is especially pronounced among low-skilled workers, indicating uneven development across countries. In contrast, EU-15 economies display substantially higher wage levels for all skill groups, particularly for high-skilled labor, along with more moderate variability, which reflects greater labor market stability. Production indicators further emphasize the development gap between the two regions. Both capital stock and gross output are considerably higher in EU-15 economies compared to CEE-11, confirming the stronger productive base of Western European economies. Although the degree of offshoring remains negative in both regions, CEE-11 countries show slightly higher average levels than EU-15 countries, indicating more intensive integration of the CEE-11 region into international production networks. Domestic outsourcing exhibits similar patterns across both groups. The most pronounced contrast appears in the domain of intangible assets. EU-15 economies report substantially higher levels of R&D, economic competencies, organizational capital, and training. These disparities highlight the knowledge-intensive and innovation-driven character of EU-15 economies, whereas CEE-11 countries remain more dependent on tangible production factors. In summary, the descriptive evidence identifies two distinct economic models: the EU-15, defined by high-value-added, skill-intensive, and knowledge-driven production structures, and the CEE-11 group, characterized by a more cost-competitive, manufacturing-oriented model with lower accumulation of intangible capital. This structural divergence provides essential context for interpreting the econometric results presented in the following sections.

4. Methods

This analysis utilizes the translog cost function, a standard method for examining labor demand. Consistent with Foster-McGregor et al. (2013), it is more practical to estimate a system of cost-share equations derived from the translog cost function than to estimate the function directly. Defining as a total variable cost, as wages for different skills and material prices that are chosen for, as fixed input capital and gross output, as proxies for investments in intangible assets. The translog cost function can be written as follows:

$$\begin{aligned} \ln C = {} & \alpha_0 + \sum_{i=1}^{M} \alpha_i \ln w_i + \sum_{k=1}^{K} \beta_k \ln x_k + \sum_{y=1}^{Y} \gamma_y z_y + + \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{M} \gamma_{ij} \ln w_i \ln w_j + \\ & \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \delta_{kl} \ln x_k \ln x_l + \frac{1}{2}\sum_{y=1}^{Y}\sum_{p=1}^{R} \gamma_{yp} z_y z_p + \frac{1}{2}\sum_{i=1}^{M}\sum_{k=1}^{K} \theta_{ik} \ln w_i \ln x_k + \\ & \frac{1}{2}\sum_{i=1}^{M}\sum_{y=1}^{Y} \delta_{iy} \ln w_i z_y + \frac{1}{2}\sum_{k=1}^{K}\sum_{y=1}^{Y} \delta_{ky} \ln x_k z_y. \end{aligned} \tag{3}$$

We can express $\frac{\delta \ln C}{\delta \ln w_i} = \left(\frac{\delta \ln C}{\delta \ln w_i}\right)\left(\frac{w_i}{C}\right)$, where $\frac{\delta C}{\delta w_i}$ represents the input demand derived from the first-order derivatives of the cost function with respect to wages and material prices:

$$s_i = \alpha_i + \frac{1}{2}\sum_{j=1}^{M} \gamma_{ij} \ln w_j + \frac{1}{2}\sum_{k=1}^{K} \theta_{ik} \ln x_k + \frac{1}{2}\sum_{y=1}^{Y} \delta_{iy} \ln z_y. \qquad I = 1, \ldots, M \tag{4}$$

The equations for the wage shares of labor by skill level and for materials in different industries n=1….N are reformulated by computing the changes between two periods:

$$\triangle s_i = \alpha_0 + \sum_{j=1}^{M} \gamma_{ij} \triangle \ln w_j + \theta_K \triangle \ln K + \theta_Y \triangle \ln Y + \delta_{OFF} \triangle \ln OFF + \delta_{DO} \triangle \ln DO + \varepsilon_i. \tag{5}$$

The standard translog cost function is extended by incorporating offshoring and domestic outsourcing. Moreover, we examine the impact of technological change on the labor market by distinguishing three groups of intangible assets: computer software and databases, R&D, and economic competencies. Economic competencies are further subdivided into brand, organizational capital, and training, providing a more detailed representation of intangible capital components. Labor is categorized into low-, medium-, and high-skilled groups, and cost shares are replaced with employment shares. As noted by Hertveldt & Michel (2013), substituting cost shares for employment shares reduces the risk of endogeneity arising from the presence of hourly wages on the right-hand side

of the equations, which could otherwise lead to inconsistent estimators. Furthermore, we differentiate between the 'old' EU member states (EU-15) and the Central and Eastern European countries (CEE-11) to more clearly capture cross-country differences in the effects of offshoring and technological change on employment. Then, denoting the employment shares of low-, medium- and high- skilled labor as EMPi, computer software and databases as SoftDB, R&D as RD, economic competencies as EconComp, brand as Brand, organizational capital as OrgCap, training as Train:

$$\triangle \mathrm{EMP_i} = \alpha_0 + \sum_{j=1}^{M} \gamma_{ij} \ln w_j + \delta_{OFF} \triangle \ln OFF + \delta_{DO} \triangle \ln DO + \theta_Y \triangle \ln Y + \theta_K \triangle \ln K + \varepsilon_i. \quad (6)$$

$$\triangle \mathrm{EMP_i} = \alpha_0 + \sum_{j=1}^{M} \gamma_{ij} \ln w_j + \delta_{OFF} \triangle \ln OFF + \delta_{DO} \triangle \ln DO + \theta_Y \triangle \ln Y + \theta_{DB} \triangle \ln Soft_{DB} + \quad (7)$$
$$+\theta_{RD} \triangle \ln RD + \theta_{EC} \triangle \ln EconComp + \varepsilon_i.$$

$$\triangle \mathrm{EMP_i} = \alpha_0 + \sum_{j=1}^{M} \gamma_{ij} \ln w_j + \delta_{OFF} \triangle \ln OFF + \delta_{DO} \triangle \ln DO + \theta_Y \triangle \ln Y + \theta_{DB} \triangle \ln Soft_{DB} + \theta_{RD} \triangle \quad (8)$$
$$\ln RD + \theta_B \triangle \ln Brand + \theta_T \triangle \ln Train + V + \varepsilon_i.$$

As is common in literature, we treat capital as quasi-fixed. Our model is then closely specified following the approaches of Hertveldt & Michel (2013) and Foster-McGregor et al. (2013).

The three employment share equations (6), (7), and (8) are estimated simultaneously using the Seemingly Unrelated Regressions (SUR) technique to account for potential correlation of the error terms across equations.

5. Results and discussion

As previously noted, the primary goal of our analysis is to examine how the internationalization of production and investments in intangible assets affect the labor market, particularly the employment distribution across different skill levels in CEE-11 and EU-15 countries.

As shown in Table 2, offshoring intensity is significantly higher in CEE-11 countries, reflecting their stronger integration into global production networks. Meanwhile, EU-15 countries invest more in intangible assets, with CEE-11 falling behind in this area (Figure 2). These structural differences imply that the labor-market effects of offshoring and intangible capital may vary between the two groups. By allowing the coefficients to differ across these country groups, we seek better to capture the heterogeneity in labor market responses within the EU.

Table 4 and Table 5 present the regression estimates from Equations (6), (7), and (8) using Seemingly Unrelated Regression (SUR) techniques for each employment share. Results are shown in Table 4 for CEE-11 countries and Table 5 for EU-15 countries. Our analysis confirms distinct patterns in how offshoring and capital investments affect employment structures across the CEE-11 and EU-15. One of the most striking differences lies in the impact of offshoring. In the EU-15 countries, offshoring has a negative, statistically significant effect on medium-skilled employment; in the CEE-11 countries, the negative impact is concentrated on low-skilled employment. The decline in low-skilled employment in the CEE-11 countries is due to their specialization in labor-intensive and medium-tech manufacturing, where increasing automation and technological upgrading reduce the demand for low-skilled labor. On the other hand, we confirmed a strong, positive relationship between offshoring and the employment share of high-skilled labor in both groups of countries. Hereby, our findings provide a direct empirical answer to the first research question (RQ1). Offshoring is not neutral with respect to skill composition; rather, it is systematically associated with shifts in employment shares across skill groups. In line with the first hypothesis (H1), the results demonstrate a structured reallocation of employment toward high-skilled labor. Moreover, the simultaneous contraction of medium-skilled employment in EU-15 countries and low-skilled employment in CEE-11 economies indicates polarization dynamics, thereby providing strong support for the second hypothesis (H2).

Furthermore, for the CEE-11 countries, we confirm a negative and statistically significant relationship between the employment share of high-skilled labor and investment in software and databases (SoftDB). In contrast, other intangible capital categories - R&D, training, brand, and organizational capital-positively and significantly impact high-skilled labor. For medium-skilled labor, the findings are mixed. We observe a negative relationship with organizational capital, suggesting potential substitution effects. However, there is a positive, statistically significant relationship among R&D, training, and brand, while the effect of SoftDB is statistically insignificant. These results indicate that medium-skilled workers may benefit from investments in certain intangibles, particularly those that enhance processes and product differentiation, though their adaptability may be limited. Regarding low-skilled labor, we observe a consistent pattern of negative coefficients for R&D, brand, and organizational capital. This indicates that investments in these intangible assets are associated with a decline in the share of low-skilled labor, supporting the argument that intangible capital – especially that linked to innovation and firm-specific capabilities – tends to favor higher skill levels and contributes to labor market polarization in the CEE-11 region. These results align with Gravina & Foster-McGregor (2024). Taken together, these results provide a clear response to the second research question (RQ2). Investments in intangible assets – particularly those linked to innovation, branding, and organizational restructuring –

are systematically associated with changes in employment shares. Therefore, the third hypothesis (H3) is confirmed. The persistent negative associations with low-skilled employment further reinforce the presence of polarization effects, lending additional support to the fourth hypothesis (H4).

Table 4. **Regression results on the relationship between offshoring and intangible investments, and employment shares in CEE-11 countries**

	Panel I			Panel II			Panel III		
	(a) ln E_{HS}	(b) ln E_{MS}	(c) ln E_{LS}	(a) ln E_{HS}	(b) ln E_{MS}	(c) ln E_{LS}	(a) ln E_{HS}	(b) ln E_{MS}	(c) ln E_{LS}
ln W_{HS}	-0.091 (0.079)			-0.302 (0.080)***			-0.348 (0.073)***		
ln W_{MS}		0.102 (0.059)*			-0.044 (0.063)				
ln W_{LS}			0.505 (0.175)**			0.545 (0.202)***		0.505 (0.175)**	
ln W_{II}	-3.876 (0.444)***	0.512 (0.312)	4.148 (1.195)***	-4.332 (0.435)***	0.955 (0.328) ***	3.579 (1.253)***	-4.110 (0.414)***	0.582 (0.301)*	5.494 (1.054)***
ln OFF	0.523 (0.101)***	0.110 (0.072)	-0.858 (0.280)***	0.599 (0.100)***	0.007 (0.077)	-0.794 (0.301)***	0.491 (0.095)***	0.032 (0.070)	-0.873 (0.252)***
ln DO	0.473 (0.089)***	0.492 (0.064)***	-1.589 (0.251)***	0.624 (0.093)***	0.349 (0.073)***	-1.596 (0.282)***	0.610 (0.087)***	0.373 (0.065)***	-1.731 (0.231)***
ln Y	4.156 (0.441)***	-0.954 (0.320)***	-4.644 (1.199)***	4.258 (0.439)***	-1.368 (0.339)***	-3.070 (1.272)**	3.893 (0.418)***	-0.860 (0.316)**	-5.026 (1.083)***
ln K	-0.157 (0.053)***	0.115 (0.037)***						0.124 (0.141)	
ln SoftDB				-0.076 (0.026)***	0.021 (0.020)	-0.014 (0.075)	-0.064 (0.024)***	0.015 (0.018)	0.022 (0.062)
ln RD				0.059 (0.037)	0.116 (0.027)***	-0.267 (0.105)**	0.077 (0.034)**	0.103 (0.025)***	-0.306 (0.087)***
ln Econ-Comp				0.401 (0.070)***	-0.038 (0.053)	-0.501 (0.205)**			
ln Brand							0.143 (0.050)***	0.109 (0.036)***	-1.174 (0.127)***
ln Org-Cap							0.352 (0.063)***	-0.189 (0.046)***	0.624 (0.160)***

ln Train							0.088 (0.028)***	0.040 (0.020)**	-0.052 (0.071)
Breusch-Pagan test		137.7701			137.266			136.712	
R-squared	0.364	0.630	0.355	0.490	0.655	0.392	0.567	0.724	0.591

Note: Standard errors reported in parentheses: Reported significance levels $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: own study

The findings for the EU-15 countries (Table 5) are generally consistent with those from the CEE-11, but with a few notable exceptions. For high-skilled labor, the relationship is negative and statistically significant with SoftDB and training, while brand and organizational capital maintain their positive impact. We observe positive effects from SoftDB, R&D, and training for medium-skilled workers, but a negative relationship with brand capital. As for low-skilled labor, R&D and organizational capital again show a significant negative relationship, confirming that technological advancements and firm restructuring reduce the demand for less-skilled labor. The comparison between CEE-11 and EU-15 countries provides a structured answer to the third research question (RQ3). The differing transmission channels – medium-skilled contraction in EU-15 versus low-skilled contraction in CEE-11, as well as variation in the role of specific intangible assets – highlight meaningful heterogeneity in labor-market adjustment processes. These cross-regional differences confirm the fifth hypothesis (H5) and underscore the importance of countries' positions within European value chains and their respective levels of intangible capital intensity.

Table 5. **Regression results on the relationship between offshoring and intangible investments, and employment shares in EU-15 countries**

	Panel I			**Panel II**			**Panel III**		
	(a) ln E_{HS}	**(b) ln E_{MS}**	**(c) ln E_{LS}**	**(a) ln E_{HS}**	**(b) ln E_{MS}**	**(c) ln E_{LS}**	**(a) ln E_{HS}**	**(b) ln E_{MS}**	**(c) ln E_{LS}**
ln W_{HS}	-0.242 (0.073)**			-0.574 (0.098)***			-0.253 (0.097)**		
ln W_{MS}		0.424 (0.082)**			2.407 (0.714)***			0.034 (0.123)	

ln W_{LS}			0.315 (0.082)***			0.623 (0.096)***			0.578 (0.089)***
ln W_{II}	-6.474 (1.097)***	2.252 (1.001)*	2.437 (1.617)	-5.189 (1.018)***	1.473 (0.925)	2.964 (1.190)*	-7.330 (1.047)***	3.395 (0.939)***	3.731 (1.414)**
ln OFF	0.659 (0.131)***	-0.499 (0.120)***	-0.057 (0.194)	0.586 (0.122)***	-0.452 (0.112)***	0.071 (0.149)	0.642 (0.125)***	-0.468 (0.113)***	-0.058 (0.172)
ln DO	1.005 (0.245)***	-0.380 (0.228).	-0.496 (0.360)	0.684 (0.256)**	0.343 (0.248)	-1.648 (0.306)***	0.987 (0.281)***	0.269 (0.255)	-1.958 (0.381)***
ln Y	7.493 (1.222)***	-2.234 (1.109)*	-2.967 (1.793).	5.848 (1.085)***	-1.377 (0.989)	-3.719 (1.247)**	8.324 (1.125)***	-3.561 (1.002)***	-4.514 (1.511)**
ln K	-0.523 (0.227)*	0.336 (0.217)	-1.095 (0.339)**						
ln Soft-DB				-0.088 (0.045)*	-0.033 (0.039)	-0.019 (0.050)	-0.193 (0.044)***	0.186 (0.049)***	-0.017 (0.058)
ln RD				-0.088 (0.040)**	0.242 (0.037)***	-0.519 (0.048)***	-0.027 (0.039)	0.254 (0.035)***	-0.550 (0.052)***
ln Econ-Comp				0.358 (0.060)***	-0.092 (0.050)*	-0.146 (0.069)*			
ln Brand							0.432 (0.073)***	-0.381 (0.067)**	0.078 (0.101)
ln Org-Cap							0.087 (0.036)**	-0.046 (0.033)	-0.102 (0.045)**
ln Train							-0.340 (0.058)***	0.353 (0.057)***	0.009 (0.072)
Breusch-Pagan test		103.386			86.227			86.717	
R-squared	0.513	0.593	0.587	0.604	0.680	0.772	0.690	0.753	0.771

Note: Standard errors reported in parentheses: Reported significance levels $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: own study

From a strategic management perspective, our findings suggest that firms must rethink how they build and sustain competitive advantage in an economy shaped by globalization and rapid technological change. The increasing reliance on R&D, brand, and organizational capital suggests that future competitiveness will depend on how

effectively firms integrate knowledge, innovation, and human capital development into their core strategies.

At the same time, technological upgrading, automation, and the international reorganization of production are transforming the demand for skills. Managers and policymakers, therefore, need to anticipate how these transformations affect different groups of workers and respond by fostering continuous reskilling and knowledge sharing. In this way, strategic management can evolve beyond efficiency-based competition toward a model that combines technological progress with workforce adaptability, transforming innovation and globalization into sources of sustainable, inclusive growth.

6. Conclusions

The integration of global production networks and increased investment in intangible assets are transforming European firms and labor markets, leading to workforce polarization and changes in employment across skill levels in CEE-11 and EU-15 countries. In this context, the present study offers comprehensive empirical evidence on how the internationalization of production and investments in intangible assets reshape labor market outcomes in these regions. This research advances the literature on globalization, technological change, and labor markets in several key ways. First, it develops an integrated empirical framework that incorporates both offshoring and intangible asset measures, enabling a more thorough assessment of the mechanisms by which global production restructuring affects employment structures. Second, by explicitly distinguishing between the CEE-11 and EU-15 country groups, the analysis captures significant regional heterogeneity within the European Union, which would otherwise remain hidden in pooled estimations.

Empirical results indicate that global production integration and intangible capital accumulation are primary drivers of employment restructuring across Europe. Offshoring consistently increases the employment share of high-skilled workers, but its displacement effects differ significantly by region. In CEE-11 countries, offshoring primarily reduces low-skilled employment, while in the EU-15 it mainly affects medium-skilled workers. These divergent outcomes reflect underlying differences in production specialization: CEE-11 economies are more involved in labor-intensive manufacturing, whereas EU-15 economies are more engaged in routine-based and knowledge-intensive segments of global value chains. Intangible capital plays a decisive role in reinforcing these structural transformations. Investments in R&D, brand, and organizational capital systematically reduce low-skilled employment while generally benefiting higher-skilled groups, thereby contributing to labor market polarization. Although the effects on medium-skilled workers are more heterogeneous, the overall pattern indicates a sustained increase in demand

for adaptable, knowledge-intensive competencies alongside declining employment opportunities for routine labor. These findings have important implications for economic policy and corporate strategy. As technological change and offshoring continue to reshape skill requirements, strategic human resource management should prioritize continuous reskilling, flexible talent deployment, and the systematic integration of innovation strategies with workforce development. At the macroeconomic level, education systems and labor-market institutions must evolve to ensure that the gains from globalization and technological progress are translated into inclusive and sustainable economic growth. Moreover, the documented shift in labor demand toward high-skilled and adaptable workers highlights the growing importance of flexible, practice-oriented education models that support continuous competence development and lifelong learning.

Despite its contributions, this study is subject to several limitations. The analysis relies on aggregated country- and industry-level data, which does not allow for capturing firm-level and individual-level heterogeneity in employment adjustments. Consequently, it is not possible to directly observe how specific firms or workers respond to offshoring and investment in intangible assets. Furthermore, both offshoring and technological change are measured using proxy indicators, which may not fully reflect firms' strategic decisions regarding international production organization and intangible capital accumulation. In addition, the classification of labor into broad skill groups based on educational attainment may obscure important differences across occupational categories.

Future research could extend this analysis by examining occupation- and sector-specific effects and by differentiating between types of offshoring in order to provide a more detailed understanding of labor market dynamics in the context of globalization and technological change. In particular, further studies may focus on specific occupational groups, such as managers, clerks, craft workers, and manual workers, to generate more nuanced insights into employment restructuring.

Authors' contribution

K.S..: article conception, research methods applied, data collection, analysis and interpretation of results, draft manuscript preparation. **J.D**: article conception, theoretical content of the article, conducting the research, analysis and interpretation of results.

Acknowledgment

This paper is part of the results of research on project KEGA 072TUKE-4/2024.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Chat GPT in order to check references and Grammarly in order to check grammar. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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