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The Impact of Technological Change on Employment: A Composite Indicator Approach

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Abstract

Despite extensive research, a consensus remains elusive regarding the optimal method for measuring the effects of technological change and innovation on employment. This study introduces a Technological Change Composite Indicator (TCI), constructed using Principal Component Analysis (PCA) to synthesize seven firm-level innovation metrics. This methodology mitigates issues associated with multicollinearity in regression analyses involving correlated variables. The proposed TCI serves as a proxy for technological change to examine its association with employment in manufacturing sectors across European Union countries. Applying the TCI to a pooled cross-section of ten European countries and seventeen manufacturing sectors (170 observations) with country fixed effects and a one-year time lag, we find that a one-unit increase in the TCI corresponds to a 0.58% higher employment level. The association is positive and statistically significant, indicating that a multidimensional measure of technological change outperforms traditional single proxies such as R&D expenditure or patent counts. The TCI provides policymakers and industry stakeholders with a novel framework for assessing how a broad portfolio of innovation activities – including machinery acquisitions, external knowledge, intellectual property rights, and both product- and process-oriented efforts – relates to manufacturing employment. By moving beyond narrow indicators, our approach offers a more reliable empirical basis for understanding the employment implications of technological change, including emerging technologies such as AI.

JEL classification

O33, J23, O14, C38

Keywords

composite indicator, latent approach, technological change, employment, manufacturing industry, PCA analysis, regression method

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1. Introduction

Technological developments play a vital role in shaping the quantity and quality of employment in the labor market (Acemoglu et al., 2024; Ayhan & Elal, 2023; Bazylik & Gibbs, 2022; Vivarelli & Arenas Díaz, 2025). The emergence, diffusion, adoption, and application of new technologies such as robotics, the Internet of Things (IoT), and Artificial Intelligence (AI) in automation have profoundly transformed production systems and employment structures across economies (Bruckner et al., 2017; Corrocher et al., 2023). However, the adoption of new technologies varies substantially across industries, sectors, and firms of different sizes. For instance, Acemoglu et al. (2024) report that larger firms are significantly more likely to adopt AI-related technologies than smaller firms (Acemoglu et al., 2024). Similarly, they also document technology-intensive sectors such as machinery, electronics, and automotive manufacturing exhibit substantially higher innovation intensity than traditional manufacturing industries.

While innovation can enhance productivity, concerns persist about its effects on job opportunities (Hötte et al., 2023). This longstanding debate has prompted economists from various schools of thought to examine this relationship through both theoretical frameworks and empirical lenses (Appelbaum & Schettkat, 1995; Bogliacino & Pianta, 2010; K. Marx, 1969; Pigou, 1962; Vivarelli & Pianta, 2000; Wicksell, 1961). From a theoretical perspective, innovation can simultaneously eliminate existing occupations through process innovation and create new ones through product innovation. The dispute endures partly because the literature lacks a unified model or set of variables for evaluating the impact of technological progress. When it comes to the technology-employment nexus, the theoretical landscape is largely shaped by two broad perspectives that pull in opposite directions. On one side, a long line of reasoning-from classical economists to contemporary scholars- holds that process innovation lets a firm produce the same output with fewer workers, leading to what is often called technological unemployment (Coad & Rao, 2011;

Dosi & Mohnen, 2019; Petit, 1995; Sasaki, 2020; Vivarelli, 1995; Vivarelli & Pianta, 2000; Zhu et al., 2021). On the other side, an alternative view argues that the indirect demand-side effects stemming from product innovation can compensate more than for the initial job losses (M. Piva & M. Vivarelli, 2017; Vivarelli, 2014). Economic theory thus offers no conclusive prediction. The relationship is contingent on several elements- such as the level of aggregation (macro, sectoral, or firm level), whether technical change is of embodied or disembodied variety (Calvino & Virgillito, 2018; Pellegrino et al., 2019), and crucially, the inherent difficulty of measuring technological change and innovation. Among these, measurement complexity stands out as particularly relevant.

Measuring technological change is highly complex because it is multidimensional. As Bailey et al. (2003) argue technical change is unobservable and has traditionally been proxied by variables ranging from simple time trends to more sophisticated knowledge stock measures. R&D expenditures typically represent inputs into innovation, while patent numbers serve as outputs indicators (Vivarelli, 2014). Yet, there is no consensus on the optimal proxy. Kromann et al. (2011) argue that the best indicator of technological growth is R&D expenses, whereas Eaton and Kortum (1997) favor patents. Bailey et al. (2003) further complicate the picture by showing that neither R&D expenditure nor patent data significantly explain changes in input–output shares. They suggest that a latent variable presentation of technological change is appropriate, because technological progress occurs in a stochastic manner and is itself biased across production factors. Given these discrepancies, the literature is stuck: scholars agree measurement matters, but no one agrees on what to measure or how. To move past this deadlock, we take a fresh approach. Our main contribution is to construct a composite indicator for technological change (TCI) that combines seven different firm-level innovation metrics using Principal Component Analysis

(PCA). The idea is to capture the multidimensional reality of technological change without forcing a choice of one proxy over another. Once the indicator is built, we apply it to a pooled cross-section of ten European countries and seventeen manufacturing sectors. Using a model with country fixed effects, a one-year time lag (TCI from the CIS 2018 wave, employment and controls from 2019), and controls for wages and value added, we estimate how the TCI relates to employment. Our findings show that, on average, the TCI is positively and significantly associated with manufacturing employment. Country fixed effects reveal substantial differences in employment levels across countries, but the positive association holds across the pooled sample. We acknowledge that defining the appropriate quantity remains a major challenge, because technology-related activities in a business are not always identifiable from company information.

The remainder of this paper is organized as follows. Section 2 reviews the literature background, including theoretical framework and empirical evidence of technology-employment nexus. Section 3 describes the data, the construction of the composite indicator, the empirical model, and the results. Section 4 concludes.

2. Literature Background

2.1. Theoretical Framework

Researchers have long debated how to assess the impact of technological change on the labor market. The connection between technological change and employment has been the focal point of discussion in economic research. Although process innovation is commonly linked with technological unemployment because of its labor-saving nature, economic theory identifies several compensation mechanisms that can counteract the loss of jobs. Moreover, product innovation adds new facets to this connection, as it necessarily creates employment by developing new markets and products.

2.1.1. Process innovation and employment (Compensation Theory)

Job displacement is a direct consequence of process innovation. By definition, process innovation enables the same level of output with less labor input (Mariacristina Piva and Marco Vivarelli (2017). However, economic theory has long suggested the existence of countervailing economic forces capable of compensating for reduced employment caused by technological advancements. In the first half of the nineteenth century, classical economists established a theory that Marx subsequently dubbed the "compensation theory" (Marx (1961). This framework outlines several mechanisms by which labor-saving technological change (process innovation) can be compensated:

A) **Compensation mechanism "via New Machines"**. The same process innovation that displaces workers in user industries can create jobs in the capital sectors that produce new machines. However, this mechanism's relevance is often questioned today. Marx's critique of this mechanism was very sharp. He believed that "the machine can only be employed profitably if it [...] is the (annual) product of far fewer men than it replaces" (Karl Marx, 1969)

B) **Compensation mechanism "via price reduction".** Process innovations lower production costs, which can lead to lower prices. This, in turn, can stimulate new demand for products and additional production and employment. The mechanism of compensation "via price reduction" has been proposed many times in the history of economic thought by both neoclassical and contemporary economists (Dobbs et al., 1987; Hall & Heffernan, 1985; Nickell & Kong, 1989; Smolny, 1998; Stoneman, 1983). As first mentioned by Malthus (1964), Sismondi (1971), and Mill (1976), the first effect is a shift in labor-saving technology and a reduction in aggregate demand due to the abolition of demand previously associated with laid-off workers. Therefore, the mechanism “via price reduction” becomes effective via a time lag.

C) **The mechanism of compensation “via New Investments”**. Cost reductions from technological change can generate additional profits. If reinvested, these profits can drive the creation of new products, markets, and industries, ultimately generating new employment opportunities to offset job losses caused by technological changes. However, Keynes argued that pessimistic expectations may delay investment decisions, even when profits have accumulated through innovation.

D) **Compensation mechanism “via a Decrease in Wage”.** In this framework, technological unemployment leads to wage reductions, theoretically making labor more cost-effective and potentially slowing the shift toward increased technological adoption. Early economists such as Wicksell (1961), Hicks (1963), and O’Brien (1933) explored this argument. While lower wages may incentivize firms to hire more workers, this mechanism conflicts with Keynesian theory, which stresses the significance of effective demand. Keynesian analysis argues that wage reductions diminish workers' purchasing power and aggregate demand, thereby dampening employers' expectations, thereby deterring employers from hiring and investing. Thus, although wage reductions may temporarily lower costs, they risk perpetuating weak demand and limited job growth.

E) **Compensation mechanism “via an Increase in Incomes”**. Keynes introduced the idea that part of the cost savings from innovation could be redirected to increase incomes, stimulating higher consumption. This rise in demand would, in turn, create additional employment opportunities, offsetting the job losses caused by process innovations (Boyer, 1988; Pasinetti, 1983). However, the effectiveness of this mechanism has waned in modern economies. As Appelbaum and Schettkat (1995) highlight, contemporary labor markets, characterized by intense competition and flexibility, alongside changing patterns of income distribution, have significantly weakened its practical impact. Although the principle remains valid in theory, its practical impact has diminished in today's economic context.

In summary, economic theory does not provide a definitive conclusion regarding the impact of process innovation on employment. While the compensation mechanisms described have the potential to offset direct job losses, their actual efficacy is highly contingent caused by process innovation. However, determining their actual efficacy is challenging since it is contingent on various factors such as competitiveness, demand elasticity, and the way business expectations are built. Compensation, in general, varies according to institutional, social, and economic circumstances, and technological unemployment may be only partially compensated.

2.1.2. Product innovation and employment

Technological change encompasses not only process innovation but also product innovation, which has a distinct and significant potential impact on employment. The theoretical link for product innovation is relatively straightforward: the successful launch of new products and the development of new markets inherently create employment creation (Bogliacino & Pianta, 2010; Vivarelli & Pianta, 2000). Classical economists have underlined the labor-friendly effect of product innovation. It opens the way for the development of new products or serves as the primary point of difference for mature commodities. Nonetheless, the effectiveness of job creation through product innovation can vary significantly, leading to widely disparate employment outcomes across different sectors and innovations.

In conclusion, the theoretical relationship between innovation and employment is multifaceted. Process innovation has a direct labor-saving effect, but its net impact is mediated by the strength of various compensation mechanisms. Conversely, while product innovation is inherently employment-friendly, its effects can vary in scale. Therefore, despite sophisticated theoretical models, economic theory offers no straightforward prediction about the overall impact of technological change on employment. The ultimate effect is contingent upon the balance between process and product innovation, the specific economic parameters at play, the influence of compensation mechanisms, and the broader institutional and social context in which these dynamics unfold.

2.2. Empirical evidence

The empirical literature on technology-employment nexus is quite extensive and, in many ways, fragmented. Further, systematic reviews and survey studies confirm that this link continues to be complicated and highly heterogeneous. Instead of yielding any definite conclusions about the existence or absence of a certain pattern, this literature draws attention to the fact that employment results are highly context dependent with respect to the kind of innovation in question, the level of analysis, sectoral specifics, institutional setting, and choice of indicators. Several survey studies, including the following ones, have summarized what we know about technology-employment nexus with the emphasis on co-existence of labor displacing and labor creating effects of innovation. Thus, Calvino and Virgillito (2018) provide a critical review of both theoretical and empirical findings showing how different levels of analysis (firm versus sector and the type of innovation, process versus product) affect the result. Similarly, Mondolo (2022) surveys the empirical literature on automation, digitalization, and labor demand indicating that technological development does not necessarily generate technological unemployment because its effect depends on the interplay of displacement and compensation processes related to increased productivity, demand, and creation of new markets. In the most recent survey, Montobbio et al. (2024) reviewed the empirical literature about technology, employment and occupations, highlighting some lessons and challenges ahead. Hötte et al. (2023), in their systematic review, classified the body of evidence spanning four decades into five different types of technologies (ICT, robotics, innovation, total factor productivity and other). In terms of meta-analysis evidence, Ugur et al. (2018) synthesized the results from labour-demand models based on different proxies and conclude that there is no relationship between R&D expenditure and employment, ICT-based proxies yielding significantly positive results. On their part, Arenas Diaz et al. (2024), in a meta-analysis study on product vs. process innovation, report that product innovation is generally job-creating, whereas process innovation can be either job-creating or destroying, contingent upon circumstances.

On the level of cross-country analysis, Antonucci and Pianta (2002), analyzing European manufacturing sectors through innovation expenditures and the share of new products in revenues, found that product innovation had a significant positive impact on employment, especially in innovative sectors. Bogliacino and Pianta (2010), relying on a dynamic panel analysis on EU manufacturing sectors, verified that both R&D expenditure and introduction of new product lines increase employment levels, especially among innovative sectors. In contrast, Piva and Vivarelli (2005), working with OECD country data and using R&D expenditure as their main proxy, could not find a consistent employment effect – a result that again points to the sensitivity of findings to the proxy chosen.

Moving to the firm or detailed sector level, the picture becomes richer but also more tangled. Greenan and Guellec (2000) examined French firms between 1980 and 1990, distinguishing process from product innovation. They found that at the firm level, process innovation was more strongly linked to job creation – a result that seems counter-intuitive at first but may reflect compensation mechanisms operating quickly. At the sectoral level, however, product innovation took the lead. Coad and Rao (2011) studied US high-tech manufacturing firms using patents and

R&D costs, constructing an innovativeness index via principal components. They concluded that innovation contributes more strongly to job creation than previously recognized, especially when accounting for firm size heterogeneity. Dosi et al. (2019) proposed a vertically integrated model linking upstream R&D to downstream employment, finding that R&D and product innovation enhance employment mainly in upstream industries where value added is higher.

A growing number of recent studies have examined the employment effects of emerging technologies such as AI and robotics. Acemoglu et al. (2024), using firm-level data from the 2019 Annual Business Survey in the United States, report that larger firms adopting AI and robotics experience higher productivity and a shift towards skilled labour, but the overall employment effects remain mixed. They estimate that 12 to 64 per cent of US workers are exposed to these technologies, with manufacturing workers at the higher end. This finding underscores that the impact of technological change is not merely a matter of measuring it correctly, but also depends on how technology interacts with firm size, skill composition, and market structure.

What does this body of evidence tell us? First, the choice of proxy is far from neutral: R&D, patents, ICT investment, and newer automation metrics do not always point in the same direction. Second, the level of analysis – macro, sectoral, or firm – matters a great deal. Third, product innovation tends to be more reliably employment-friendly than process innovation, although process innovation can sometimes create jobs through compensation mechanisms. Fourth, the literature clearly needs a more integrated way of measuring technological change, one that does not force researchers to rely on a single indicator such as R&D alone, patents alone, or only one type of innovation. The composite indicator introduced in this paper is designed precisely to fill this gap. Table 1 below summarizes the main studies mentioned above for quick reference.

Table 1. A summary of the key studies related empirical studies.

Level / type	Study	Methodology, data, region	Main findings
Systematic reviews & meta-analyses	Calvino & Virgillito (2018)	Critical survey of theory and empirics	Emphasizes role of aggregation level (firm vs. sector) and innovation type (product vs. process).
	Mondolo (2022)	Survey of composite-indicator approaches	Reviews how different composite measures affect employment.
	Hötte et al. (2023)	Systematic review of four decades, five technology categories	Employment effects depend strongly on technology type and analysis level.
	Montobbio et al. (2024)	Review of empirical literature on technology, employment and occupations	Identifies challenges related to proxy choice, aggregation, and task-based approaches.
	Ugur et al. (2018)	Hierarchical meta-regression of derived labour-demand models	R&D spending has no systematic employment effect; ICT investment shows significant positive impact.
	Arenas Díaz et al. (2024)	Meta-regression on product vs. process innovation	Product innovation is consistently job-creating; process innovation's effect is context-dependent.
Cross-country / macro studies	Antonucci & Pianta (2002)	EU manufacturing sectors, innovation expenditure and new product sales	Positive employment effect of product innovation, especially in high-innovation-intensity sectors.
	Bogliacino & Pianta (2010)	Dynamic panel, EU manufacturing, R&D and new products	Both R&D and new product lines boost employment, particularly in innovative manufacturing sectors.
	Piva & Vivarelli (2005)	Panel data, Italy and OECD countries, R&D expenditure as proxy	No consistent employment effect, highlighting proxy sensitivity.
Firm-level / sectoral studies	Greenan & Guellec (2000)	French firms (1980–1990), product and process innovation	At firm level, process innovation linked to job creation; at sector level, product innovation dominates.
	Coad & Rao (2011)	US high-tech manufacturing, patents	Innovation contributes more strongly to job creation than

		and R&D costs, principal components index	previously recognized, accounting for firm size.
	Dosi et al. (2019)	Vertically integrated model, EU sectors, R&D and product innovation	R&D and product innovation increase employment mainly in upstream industries with higher value added.
Recent AI / robotics studies	Acemoglu et al. (2024)	US firm-level data (2019 Annual Business Survey), AI, robotics, software	Large adopters see productivity gains (+11.4%) and skill upgrading; overall employment effects mixed.

3. Data, methodology and the model

3.1. Data

For empirical analysis, we use the last released Eurostat and the Community Innovation Survey CIS 2018 wave, which covers the reference period 2016–2018. To construct the Technological Change Composite Indicator (TCI) we used seven innovation indicators including: acquisitions of machinery and equipment, acquisitions of external knowledge, intellectual property rights, patents, trademarks, product-only innovators, and process-only innovators –that are extracted from this wave at the two-digit NACE Rev. 2 sector level and aggregated by country. Moreover, data on employment, wages, and value added are taken from Eurostat's Structural Business Statistics (SBS) and the Labor Force Survey (LFS), with the year 2019 as the reference.

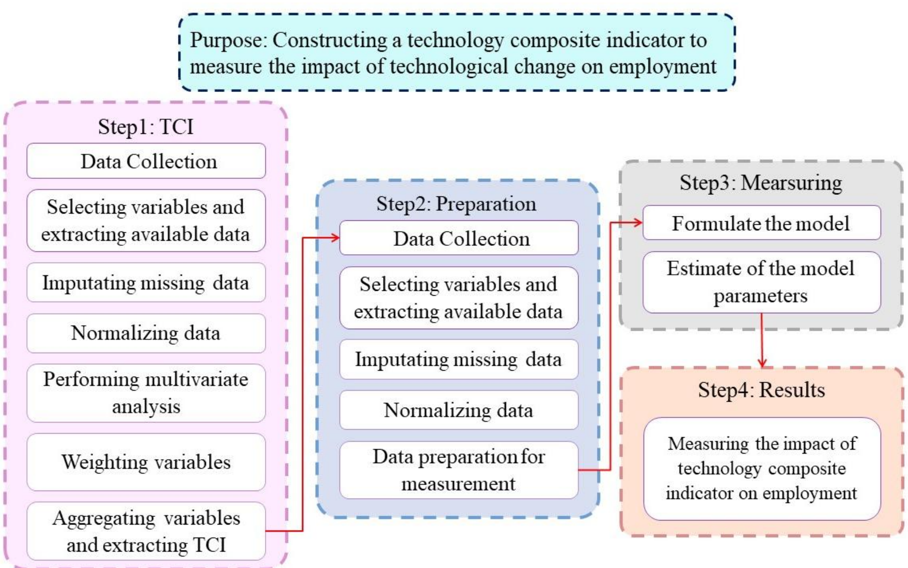
Due to data availability constraints, the study only covers ten European countries-Austria, Italy, France, Germany, Hungary, Portugal, Serbia, Slovakia, Norway, and Estonia-and seventeen two-digit manufacturing industries aggregated according to the ISIC Rev. 3 classification. These industries include: (1) Food, beverages, and tobacco; (2) Textiles; (3) Wood and wood products (excluding furniture); (4) Articles of straw and plaiting materials; (5) paper and paper products; (6) Printing and reproduction of recorded media; (7) Rubber and plastic products; (8) other non-metallic mineral products; (9) Basic metals; (10) Manufacture of fabricated metal products (excluding machinery and equipment); (11) Computer, electronic and optical products; (12)

Electrical equipment; (13) Machinery and equipment n.e.c.; (14) Motor vehicles, trailers, and semi-trailers; (15) Other transport equipment; (16) Furniture; (17) MontobbioRepair and installation of machinery and equipment.

3.2. Empirical Strategy

Our analytical strategy consists of three main stages. First, we construct the TCI using PCA, following OECD guidelines for composite indicator design. This involves selecting innovation measures, normalizing data, conducting multivariate analysis, and aggregating variables to derive TCI values for each country and sector. Second, we specify the regression model, define dependent and independent variables, and extract relevant data. The dependent variable is sectoral employment, while the independent variables include the lagged TCI, wages, value added, and country fixed effects. Third, we estimate the model using ordinary least squares (OLS) with robust standard errors. The study's conceptual framework is presented in Figure 1.

Figure 1. The Road map of the research design discussed in this study.



3.2.1. Constructing a composite indicator

A *composite indicator*-a mathematical aggregation of several indicators representing different dimensions of a phenomenon-provides a synthetic measure of complex concepts (Saisana &

Tarantola, 2002). Such indices are used when single variables are unreliable or insufficiently representative, and when there is no straightforward weighting method. Composite indicators are increasingly common in socio-economic research. Examples include the Human Development Index (UNDP), the Doing Business Indicators (World Bank), the Index of Economic Freedom (Heritage Foundation), the World Competitiveness Index (IMD), and the Human Tourism Index (WTTC).

I. Selected variables and descriptions

The reliability of a composite indicator depends largely on the quality and relevance of its underlying variables. Ideally, these variables should be selected according to their theoretical relevance, analytical accuracy, timeliness, and data availability. While a conceptual framework guides the process, indicator selection can still be subjective, as no universally accepted list exists. Each variable should match the phenomenon being measured and collectively reflect its multidimensional nature. Composite indicators can include both input and output measures. For instance, an innovation index might combine R&D expenditure (input) with the number of new products (output). However, if the goal is to measure innovation performance, output-oriented indicators should receive greater weight. Poor data quality inevitably leads to poor results; hence, variable selection must be deliberate and theoretically grounded. Drawing upon previous studies, we include the following seven base variables for constructing the TCI:

i) Number of acquisitions of machinery, equipment, buildings, and software. This innovation activity refers to goods that have been purchased specifically for use in the product and process innovation activities of the company. It includes acquiring land and buildings (including overhauls, upgrades, enhancements), machinery, tools, equipment (including computer hardware), and computer software. This group only comprises the acquisition of capital goods for innovation that are not included in R&D activities.

ii) Number of acquisitions of existing knowledge from other enterprises or organizations. Acquisition of technology and knowledge involves purchasing foreign knowledge and technology without active cooperation with the source. This external knowledge can be machinery or equipment that incorporates this knowledge. It can also include hiring staff with new knowledge or using research and consulting services.

iii) Number of intellectual property rights (IPRs). Intellectual Property Rights (IPRs) are legal rights that protect productions or inventions resulting from intellectual activity in the industrial, scientific, literary, or artistic fields. The most common IPRs include patents, copyrights, marks, and trade secrets.

iv) Number of patents. A patent is a legal property granted by a national patent office. A patent gives its owner only the right (for a certain period) to invent the patented idea. Patent statistics are increasingly used as an output indicator of research activities. The number of patents issued to a particular company or country may indicate the dynamics of its technology. Many innovations have not been patented, and some have been covered by several patents. Many patents have no technical or economic value, while some are highly valued.

v) Number of trademarks. Trademarks help differentiate products in legal and commercial systems for consumers. They are used to identify and protect design words and elements that identify the source, owner, or developer of a product or a service. They can be the logo, motto, or brand of a company's product.

vi) Number of product innovative enterprises only. Innovative companies are the product of companies that have improved new goods or services according to their capabilities, whether user-friendly components or subsystems.

vii) Number of process innovative enterprises only. Innovative process companies are firms that provide significant improvements in the production process, distribution method, or operations.

II. Normalization of data

Parametric statistical analyses generally assume normally distributed variables. To enhance comparability and statistical robustness, the selected indicators were normalized to a [0, 1] scale by subtracting the minimum value and dividing by the range of observed values. This process standardizes the measurement units of variables and increases the interpretability of results.

$$I_i = \frac{x_i - min(x_i)}{max(x_i) - min(x_i)} \tag{1}$$

III. Multivariate analysis

Multivariate analysis examines how variables interrelate and how much of the variance in the dataset can be captured by a smaller set of uncorrelated components. In PCA, the goal is to explain the maximum variance through a limited number of linear combinations of the original variables—known as principal components. While there are Q variables, $X_1, X_2, \ldots\ldots, X_Q$, much of the data's variation can often be accounted for by a small number of variables, that is, principal components or linear relations of the original data, $z_1, z_2, \ldots\ldots, z_Q$, which are uncorrelated. At this point, there are still Q principal components, i.e., as many as the variables. The next step is to select the first, e.g., P <Q principal components that preserve a "high" degree of the cumulative variance of the original data.

$$\begin{aligned} z_i &= a_{11}x_1 + a_{12}x_2 + \ldots\ldots + a_{1Q}x_i \\ z_2 &= a_{21}x_1 + a_{22}x_2 + \ldots\ldots + a_{2Q}x_Q \\ &\ldots\ldots. \\ z_Q &= a_{Q1}x_1 + a_{Q2}x_2 + \ldots\ldots + a_{QQ}x_Q \end{aligned} \tag{2}$$

A lack of correlation between the principal components is a useful property. It indicates that the principal components measure different "statistical dimensions" in the data. The new variables are linear combinations of the original ones. It must be stressed that PCA cannot always reduce a large number of original variables to a small number of transformed variables. Indeed, if the original variables are uncorrelated, the analysis is of no value. On the other hand, a significant reduction can be obtained when the original variables are highly correlated, positively or negatively.

The weights $\boldsymbol{a_{ij}}$ (also called component or factor loadings) applied to the variables $\boldsymbol{x_j}$in equation 3 are selected so that the principal components $\boldsymbol{z_i}$satisfy the following conditions:

i) They are uncorrelated.

ii) The first principal component accounts for the maximum possible proportion of the variance of the set x_s, and the second principal component accounts for the maximum of the remaining variance. This process continues until the last principal component absorbs all the remaining variance not accounted for by the preceding components, and where a_{ij} are the factor loadings, $x_1, x_2, \ldots, x_Q$ are the variables (indicators), and Q the number of variables.

$$a_{i1}^2 + a_{i2}^2 + \ldots + a_{iQ}^2 = 1, i = 1,2,\ldots,Q \qquad (3)$$

PCA involves finding the eigenvalues $\lambda_j, j = 1,\ldots,Q$ of the sample covariance matrix CM,

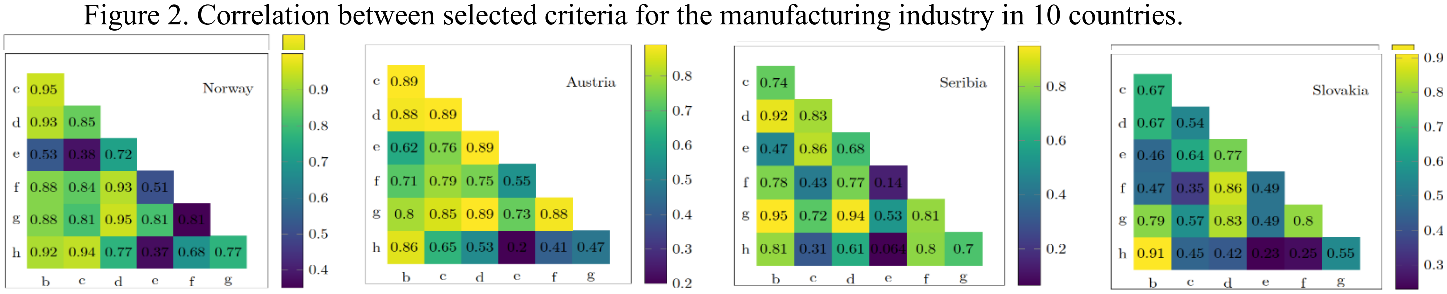
$$CM = \begin{pmatrix} \mathrm{cm}_{11} & \mathrm{cm}_{12}\ldots & \mathrm{cm}_{1Q} \\ \mathrm{cm}_{21} & \mathrm{cm}_{22}\ldots & \mathrm{cm}_{2Q} \\ \ldots\ldots & & \\ \mathrm{cm}_{Q1} & \mathrm{cm}_{Q2}\ldots & \mathrm{cm}_{QQ} \end{pmatrix} \qquad (4)$$

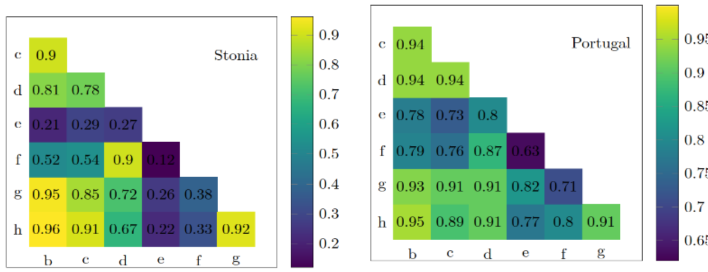
where the diagonal element cm_{ii} is the variance of x_i and cm_{ij} is the covariance of variables x_i and x_j. The eigenvalues of the matrix CM are the variances of the principal components. They can be found by solving the characteristic equation $|CM - \lambda I| = 0$, where (I) is the identity matrix with the same order as CM, and λ is the vector of eigenvalues. There are Q eigenvalues, some of which may be negligible. Negative eigenvalues are not possible for a covariance matrix. An important property of the eigenvalues is that they add up to the sum of the diagonal elements of CM. That is, the sum of the variances of the principal components is equal to the sum of the variances of the original variables.

$$\lambda_1 + \lambda_2 + \ldots + \lambda_Q = \mathrm{cm}_{11} + \mathrm{cm}_{12} + \ldots + \mathrm{cm}_{QQ} \qquad (5)$$

If the original variables are uncorrelated, PCA yields little benefit; conversely, when strong correlations exist, PCA effectively reduces dimensionality and mitigates multicollinearity. In our dataset, correlations between variables ranged from 0.5 to 0.9, indicating suitability for PCA. As illustrated in Figure 2, lighter colors in the heatmaps represent stronger positive correlations, confirming that the chosen indicators are sufficiently interrelated to justify the method.

Figure 2. Correlation between selected criteria for the manufacturing industry in 10 countries.





Source: Research findings

According to the heatmap graphs drawn for 10 countries in Figure 2, the selected variables have a high correlation with each other (the lighter the color of the heatmap graph, the stronger the dependence, and the darker the graph, the less the dependence between variables). For example, the correlation between variable II and variable III in Germany is 0.96. These findings illustrate a strong correlation between included variables, therefore PCA is appropriate.

IV. Weighting variables

The weighting and aggregation of indicators are critical in combining them meaningfully into a single index. We derive weights from PCA loadings and employ linear aggregation. Typically, only the first few principal components are retained-those explaining the largest share of total variance. Three main criteria guided component selection:

1- Scree test: Visual inspection of eigenvalues identifies a point beyond which additional components contribute marginal explanatory power (Figure 3).

2- Eigenvalue rule: Components with eigenvalues ≥ 1 are retained (Table 2).

3- Cumulative variance: Components capturing approximately 95–96 % of total variance is considered sufficient (Table 3).

Figure 2. Screening plot of selected variables in 10 countries

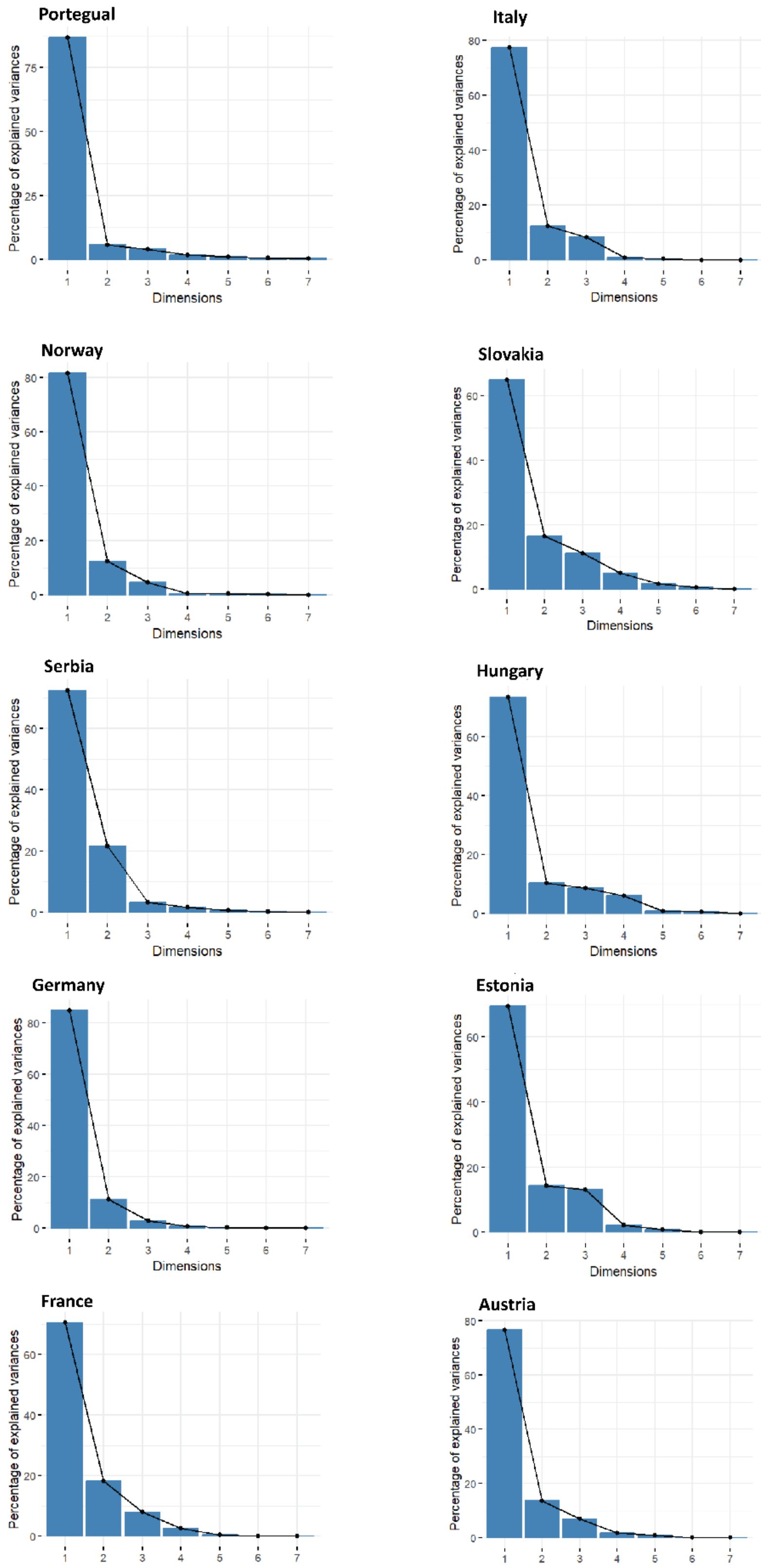


Table 2. Eigenvalues for each sector in each country

	Germany	*Austria*	*France*	*Hungary*	*Italy*	*Norway*	*Portugal*	*Serbia*	*Slovakia*	*Estonia*
1	2.433	2.315	2.221	2.264	2.328	2.387	2.463	2.25	2.132	2.202
2	0.888	0.977	1.129	0.852	0.937	0.931	0.629	1.232	1.071	1.001
3	0.447	0.695	0.746	0.783	0.763	0.566	0.53	0.476	0.884	0.958
4	0.249	0.384	0.428	0.646	0.258	0.202	0.34	0.353	0.592	0.388
5	0.146	0.257	0.199	0.24	0.199	0.196	0.262	0.206	0.342	0.242
6	0.076	0.102	0.091	0.218	0.077	0.141	0.202	0.136	0.207	0.109
7	0.054	0.075	0.055	0.094	0.059	0.102	0.159	0.085	0.105	0.094

Table 3. Eigenvalues of the indicator set in 10 countries

		1	*2*	*3*	*4*	*5*	*6*	*7*	*Cumulative Proportion*
Germany	PC1	-0.3855	-0.3972	-0.4051	-0.3824	-0.3822	-0.3854	-0.2979	0.8458
	PC2	0.36799	-0.1617	0.03615	-0.3225	-0.3135	-0.204	0.7702	0.9583
Austria	PC1	-0.406593	-0.414593	-0.415211	-0.340857	-0.363785	-0.400339	-0.285654	0.7657
	PC2	-0.31655	-0.022546	0.167438	0.502641	0.121991	0.172886	-0.757518	0.902
	PC3	-0.122648	-0.05295	-0.23443	-0.522191	0.727789	0.317058	-0.155918	0.97097
France	PC1	-0.3999	-0.3751	-0.4151	-0.3265	-0.3572	-0.4119	-0.351	0.7046
	PC2	0.39832	-0.143	0.17711	-0.577	-0.4132	-0.0708	0.52996	0.8869
	PC3	0.0246	0.64597	-0.4225	-0.1961	0.28128	-0.4785	0.23891	0.9664
Hungary	PC1	-0.41803	-0.31172	-0.43086	-0.33015	-0.36564	-0.42433	-0.34596	0.7325
	PC2	0.334715	0.129907	-0.02053	-0.48517	-0.45935	-0.14816	0.634292	0.8364
	PC3	0.134828	-0.88365	-0.08699	-0.0193	0.275453	0.121345	0.320075	0.924
	PC4	0.037841	-0.10867	-0.09869	0.803175	-0.48032	-0.23926	0.209708	0.9837
Italy	PC1	-0.39567	-0.41868	-0.41837	-0.35367	-0.3231	-0.40707	-0.31291	0.7745
	PC2	0.40536	-0.10521	-0.18624	-0.47708	-0.1624	-0.1076	0.72412	0.9001
	PC3	-0.03138	-0.11026	0.170907	-0.41648	0.838512	-0.27289	-0.08138	0.9833
Norway	PC1	-0.40832	-0.38798	-0.40895	-0.27923	-0.37892	-0.39921	-0.36683	0.8145
	PC2	-0.17966	-0.36476	0.132163	0.777008	-0.04676	0.25512	-0.38234	0.9384
	PC3	-0.04057	-0.07207	0.243169	-0.25994	0.737035	-0.15188	-0.54787	0.9842
Portugal	PC1	-0.39467	-0.3852	-0.39706	-0.34358	-0.34544	-0.3865	-0.38912	0.8671
	PC2	0.003048	-0.03021	-0.13069	0.642529	-0.70451	0.265913	-0.04585	0.9236
	PC3	0.25954	0.410159	-0.03392	-0.64427	-0.51615	0.242371	0.15169	0.9638
Serbia	PC1	-0.43122	-0.36273	-0.43369	-0.262	-0.36365	-0.43161	-0.3274	0.7232
	PC2	0.094756	-0.41602	-0.10264	-0.6465	0.357498	0.0644	0.507443	0.94
	PC3	-0.35458	-0.20917	0.226212	0.074331	0.735017	0.004928	-0.48327	0.9723
Slovakia	PC1	-0.41376	-0.34782	-0.4281	-0.33946	-0.35982	-0.42583	-0.31383	0.6495
	PC2	0.425762	0.113881	-0.30835	-0.33387	-0.42458	-0.04754	0.645505	0.8136
	PC3	-0.04926	0.603301	-0.09886	0.5582	-0.44129	-0.31035	-0.14556	0.9255
	PC4	0.057253	-0.6346	0.260665	0.519284	-0.1496	-0.34029	0.343837	0.9755

Estonia	PC1	-0.44023	-0.42868	-0.40851	-0.14653	-0.29687	-0.41699	-0.41477	0.6928
	PC2	-0.13048	-0.09694	0.409188	-0.26403	0.743932	-0.2714	-0.33066	0.836
	PC3	-0.15935	-0.04553	0.101113	0.948242	0.121255	-0.12011	-0.18443	0.9672

Source: Research findings

V. Aggregation variables and TCI extraction

The TCI value in Section (c) is calculated from Equation 6 (Seidel et al., 2019), and the results are presented in Table 4,

$$TCI_c = \frac{\sum_{l=1}^{n} \alpha_l . ICI_{lc}}{\underset{c=1}{\overset{24}{Max}}\left(\sum_{l=1}^{n} \alpha_l . ICI_{lc}\right)} \tag{6}$$

Table 4 displays significant variation in the intensity of innovation across manufacturing industries in the ten selected European countries as measured by TCI that ranges between 0 and 1. For Germany, Sector 12 (Machinery) records the highest TCI value of 1.00, indicating its dominance in high-tech manufacturing technologies and innovation-driven industries. Similarly, for France, Sector 9 (Electrical and Precision Equipment) achieves the highest TCI value of 1.00, reflecting its prominence in high-tech and innovation-driven manufacturing. These variations illustrate how industrial and economic structures influence the distribution of innovation intensity across sectors, with countries like Germany and France showing strong alignment between technological change and their established manufacturing strengths.

Table 4 .TCI values for 17 manufacturing sectors in 10 countries

	Germany	*Austria*	*France*	*Hungary*	*Italy*	*Norway*	*Portugal*	*Serbia*	*Slovakia*	*Estonia*
1	0.418729	0.808459	0.890629	1	0.390799	1	1	1	1	0.591965
2	0.077389	0.153348	0.214346	0.066669	0.138056	0.105024	0.414409	0.061468	0.121518	0.153738
3	0.097563	0.301571	0.226625	0.102527	0.07154	0.389048	0.354033	0.154418	0.08592	0.858364
4	0.072219	0.102847	0.196864	0.096384	0.082542	0.025134	0.176669	0.121601	0.046412	0.060636
5	0.133647	0.182079	0.171784	0.111791	0.102609	0.150684	0.245126	0.212836	0.050331	0.178783
6	0.41036	0.370583	0.589273	0.36012	0.274466	0.194185	0.346415	0.275705	0.402139	0.294741
7	0.2122	0.328312	0.310879	0.208688	0.204115	0.158569	0.407444	0.134852	0.351693	0.261959
8	0.097434	0.180308	0.17927	0.074703	0.048554	0.082808	0.10554	0.05165	0.156716	0.047344
9	0.928346	1	1	0.629272	0.645591	0.615542	0.880585	0.351172	0.667414	1
10	0.444171	0.34291	0.483005	0.27231	0.175114	0.166758	0.08126	0.741345	0.180948	0.151898
11	0.367729	0.338779	0.348105	0.299072	0.221522	0.117492	0.185761	0.416421	0.383862	0.181073
12	1	0.906855	0.991078	0.333849	1	0.490617	0.361775	0.396065	0.470702	0.320205
13	0.146508	0.156044	0.249891	0.280598	0.07319	0.081348	0.117056	0.114395	0.203878	0.117141
14	0.064723	0.038202	0.124399	0.048678	0.056189	0.236704	0.066224	0.027852	0.069574	0.059004
15	0.142554	0.430151	0.143743	0.158804	0.157551	0.107329	0.407324	0.145348	0.154048	0.461268
16	0.298027	0.228967	0.345236	0.199631	0.148783	0.130217	0.194739	0.088833	0.050327	0.101897
17	0.215881	0.158041	0.327559	0.177411	0.155876	0.24611	0.184489	0.059718	0.225381	0.139168

Source: Research findings

In contrast, countries with less diversified industrial structures, such as Slovakia and Estonia, show lower TCI values in many sectors, revealing challenges in driving overall innovation. The findings highlight the need for targeted innovation policies, such as higher investment in research and development and employee education, to enhance technological absorption and increase sectoral competitiveness in underperforming regions.

3.3. Measuring the impact of technological change on employment

3.3.1. Empirical model specification

After constructing the composite indicator for sample countries (TCI) as a multidimensional proxy for innovation, we try to estimate the effect of the TCI as a latent variable for technological change and other independent variables in ten European countries. Following the recommendations of recent systematic reviews (Calvino & Virgillito, 2018; Mondolo, 2022; Montobbio et al., 2024) we adopt a pooled cross-sectional specification with country fixed effects. This approach increases statistical power (170 observations instead of 17 per country) and accounts for unobserved cross-country heterogeneity.

$$lnE_{ic} = \beta_0 + \beta_1 lnW_{ic} + \beta_2 TCI_{ic,t-1} + \beta_3 lnVA_{ic} + \sum_{c}^{c-1} \gamma_c Country_c + \varepsilon_{ic} \tag{7}$$

where E_{ic} is employment (number of employees) in manufacturing industry i (two-digit NACE Rev. 2) and country c; W_{ic} is the average annual wage per employee; $TC_{ic(t-1)}$ is the Technological Change Composite Indicator (constructed in Section 3.2); VA_{ic} is value added at factor cost; γ_c are country fixed effects (with Austria as the reference category); and ε_{ic} is error term. All continuous variables except TCI are log-transformed to allow elasticity interpretation. The model is estimated via Ordinary Least Squares (OLS) with robust standard errors.

A crucial point concerns timing. Although our data are cross-sectional, the TCI is based on the CIS 2018 wave, while employment, wage, and value-added data refer to 2019 (Eurostat SBS and LFS). Thus, a one-year time gap is implicitly present between the measurement of innovation inputs/outputs and the observed employment outcomes, which partially mitigates reverse causality concerns (Piva and Vivarelli, 2005; Vivarelli, 2014). Nevertheless, we acknowledge that endogeneity cannot be fully eliminated with cross-sectional data; therefore, we interpret our findings as associations rather than causal effects.

The selection of control variables follows the empirical innovation-employment literature (Antonucci & Pianta, 2002; Bogliacino & Pianta, 2010; Dosi et al., 2019). Wages (W_{ic}) capture labor cost effects and, in a cross-sectional setting, also reflect skill intensity and industry heterogeneity. Value added (VA_{ic}) controls for industry size and scale effects. Country fixed effects absorb time-invariant institutional, policy, and macroeconomic differences across countries – such as labor market regulations, R&D subsidies, and educational systems – as recommended by Bogliacino and Pianta (2010) and supported by meta-regression evidence (Ugur et al., 2018; Arenas Díaz et al., 2024).

3.3.2. Regression results

After constructing the composite indicator, we used OLS regression methods to estimate the relationship between technological changes and employment based on equation 7. Table 5 reports the OLS estimation results. The model accounts for a large proportion of the variance in manufacturing employment (adjusted $R^2 = 0.9525$), and the F-statistic confirms the joint significance of all regressors ($F(12,157) = 283.2$, $p < 0.001$).

Table 5. Results of OLS regression.

	Variables	β (Sd)	*P-value*
	Intercept	-5.981*** (1.381)	*<0.001*
	Ln (Wage)	0.291 ** (0.105)	0.006
	TCI	0.585** (0.253)	0.022
	Ln (Value Added)	0.491*** (0.104)	<0.001
γ_c (Sd)	*Germany*	0.431** (0.135)	0.002
	France	`0.478*** (0.117)	<0.001

(ref.= Austria)	*Hungary*	1.231*** (0.125)	<0.001
	Italy	0.688*** (0.122)	<0.001
	Norway	-0.405*** (0.116)	<0.001
	Portugal	0.842*** (0.124)	<0.001
	Serbia	1.482*** (0.145)	<0.001
	Slovakia	1.053*** (0.126)	<0.001
	Estonia	0.565*** (0.148)	<0.001
N = 170	R^2=0.956	F (12,157) = 283.2 p < 0.001	

Note: Significance levels are denoted by ***, **, and *, indicating significance at the 1 %, 5 % and 10 % levels, respectively. Robust standard errors are reported in parentheses.

The findings presented in Table 5 show a positive and statistically significant at the 5% level (β=0.5848, p = 0.022) between the Technological Change Composite Indicator (TCI) and employment in sample countries. Because TCI is already bounded between 0 and 1 (by construction), a one-unit increase corresponds to moving from the minimum to the maximum observed innovation intensity. This finding suggests that, on average across European manufacturing sectors, a multidimensional measure of technological change is positively correlated with employment levels. The result is consistent with compensation mechanisms discussed in Section 2.1 – especially demand-side effects from product innovation (Vivarelli, 2014) – and with meta-analyses reporting positive employment elasticities for ICT-based innovation measures (Ugur et al., 2018; Arenas Díaz et al., 2024).

Moreover, the wage coefficient is positive and significant. At first glance, this appears to contradict standard labor demand theory. However, in a cross-sectional setting across industries, a positive coefficient reflects that high-wage sectors (e.g., machinery, electronics, and automotive manufacturing) also tend to have larger employment levels because they are more capital-intensive, generate higher value added per worker, and operate at larger scale. Similar positive wage-employment associations have been documented in sector-level studies (Bogliacino and Pianta, 2010; Dosi et al., 2019). Thus, the coefficient should not be interpreted as a labor demand elasticity but rather as a descriptive association driven by industry heterogeneity.

Value added has a positive and highly significant coefficient, indicating that industries with higher output systematically employ more workers. The elasticity is below unity (0.49), which suggests that a 1% increase in value added is associated with a 0.49% increase in employment – implying mild productivity gains as scale expands. This is typical for manufacturing sectors where automation and process innovation may partially offset labor demand.

The country dummies capture differences in employment levels after controlling for industry composition, innovation, wages, and value added. Relative to Austria (the reference), most countries exhibit significantly higher employment. The largest positive differentials are observed for Serbia (1.48), Hungary (1.23), and Slovakia (1.05) – reflecting either larger manufacturing bases or different industrial structures. Norway stands out with a negative coefficient (−0.41). This may be due to Norway's smaller manufacturing sector (its economy is dominated by oil, gas, and services) or a higher degree of automation in the remaining industries. These cross-country differences underscore the role of national innovation systems, labor market institutions, and industrial policies, as highlighted by Calvino and Virgillito (2018) and Montobbio et al. (2024).

4. Conclusion

Our paper contributes to the literature on the relationship between technological change and employment by introducing a novel composite indicator. Previous studies have struggled to measure technological change precisely, largely due to the absence of a unified metric. To address this gap, we first developed the *Technological Change Composite Indicator* (TCI) using Principal Component Analysis (PCA), which mitigates multicollinearity and allows for a more comprehensive representation of technological dynamics.

The composite indicator of technological change (TCI) varies considerably across countries and industries. Germany and France display the highest innovation intensity in sectors such as machinery and electrical equipment, with TCI values reaching 1.00, reflecting their strong technological specialization in high-value-added manufacturing. In contrast, countries with less diversified industrial structures – such as Slovakia and Estonia – show consistently lower TCI values across most sectors. This cross-country and cross-sectoral variation in the TCI suggests that innovation is not evenly distributed. It tends to concentrate in economies with advanced industrial bases and in sectors that are R&D-intensive.

Our findings support that technological change and innovation has a positive and significant effect on the manufacturing employment across ten European countries. A one unit increase in TCI – from the lowest to the highest observed innovation intensity – corresponds to a 0.58% higher employment level (β = 0.5848, p = 0.022). This finding closes the long-standing knowledge gap caused by the field's overreliance on single proxies such as R&D expenditure or patent counts, and it advances the measurement of innovation employment linkages by introducing a multidimensional, PCA based composite indicator that captures the full range of firm level innovation activities. From a policy perspective, fostering a broad portfolio of innovation inputs – including machinery acquisitions, external knowledge, intellectual property rights, and both product and process-oriented activities – can sustain manufacturing employment without forcing a trade-off between technological upgrading and job preservation, though the strength of this association depends on national industrial structures and innovation systems. Nevertheless, several limitations must be acknowledged. The cross-sectional design, even with a one-year time lag, cannot fully rule out endogeneity or reverse causality. The sample is restricted to 17 manufacturing sectors in ten European countries due to missing data. The CIS survey is only available up to 2018 with questionnaire changes that prevent pooling multiple waves. Future research should therefore employ panel data and harmonized innovation surveys to separately identify the employment effects of product versus process innovation, and to test whether the TCI employment link varies systematically across national contexts. By demonstrating that a multidimensional composite indicator outperforms traditional proxies, our work provides a robust methodological foundation for evidence-based innovation policy.

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