ISSN: 2029-4913 / eISSN: 2029-4921

Article in press

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

https://doi.org/10.3846/tede.2026.28598

THE ASSESSMENT OF THE TECHNOLOGICAL CONVERGENCE OF THE EU-27 ECONOMIES IN 2007–2023

Ewa GRUSZEWSKA [1], Mateusz BORKOWSKI [2]✉

[1,2] *Department of Political Economics, Faculty of Economics and Finance, University of Bialystok, Bialystok, Poland*

Article History:

- received 4 August 2025
- accepted 20 August 2026
- first published online 23 October 2026

Abstract. The purpose of the article is to measure the technological level of EU-27 economies and assess the degree and direction of technological convergence among these countries. The paper applies the dynamic TOPSIS technique (which utilizes Weber median) and σ- and β-convergence methods. The analysis covered the years from 2007 to 2023. Based on the empirical analysis, it was possible to conclude that technological convergence among the EU-27 economies is progressing, although the economic shocks from 2020 have significantly slowed its pace. The results obtained are consistent with those of other studies. The paper contributes to understanding technological change. The article's added value lies in its development of a synthetic, dynamic measure of the technological level of EU-27 economies and its proposal of an analysis of technological convergence among these countries.

Keywords: technological level of the economy, technological convergence, TOPSIS, L1 median, σ-convergence, β-convergence, EU-27 economies.

JEL Classification: C38, O33, O47, O52.

✉Corresponding author. E-mail: ***m.borkowski@uwb.edu.pl***

1. Introduction

Technological change is a sign of contemporary times. Technology, which serves as the basis for manufacturing products, and its long-term evolution are among the primary driving forces behind the development of contemporary economies. Over time, production factors and their relationships undergo significant changes, causing alterations in the specific nature of development processes in global economies. The varying pace of technological progress is becoming one of the primary causes of the creation and deepening of differences in the level and dynamics of economic development worldwide (Çalışkan, 2015; Parente & Prescott, 1999; Romer, 1990).

Nowadays, one can observe a process of economic convergence among highly developed countries. This process is particularly prominent in economies belonging to various types of integration groups. Several factors contribute to shaping these trends. The synergistic effect of their action is the convergence of per capita incomes between countries. Technological changes are an important factor driving the convergence of economies. As a result, technological convergence is one of the main forces driving economic convergence (Žižmond & Novak, 2007, p. 633).

Copyright © 2026 The Author(s). Published by Vilnius Gediminas Technical University

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

The purpose of the article is to measure the technological level of the EU-27 economies and to assess the degree and direction of technological convergence among these countries. The article applies the dynamic TOPSIS method (using Weber median in the process of normalization) and the σ- and β-convergence methods. The study covers the years 2007 to 2023. The study formulates a hypothesis that global supply shocks (the pandemic and the war in Ukraine, which deepened the geopolitical crisis in the world) occurring from 2020 slowed down the pace of technological convergence of the EU-27 economies.

The authors would like to express their sincere gratitude to the Reviewers for their valuable comments and suggestions, which significantly contributed to improving the quality of this paper.

2. Theoretical background

The conceptualization of the concept of technology is not a straightforward task, as it is a heterogeneous and multidimensional category. In economics, technology is most often identified with material resources and the relationships between them (Bijker et al., 1993, p. 4). It is viewed as a physical manifestation of the practical application of human knowledge (Mesthene, 1970), which becomes an essential resource for companies in their production processes (Steele, 1989, p. 6; Trott, 2012, p. 19), thereby shaping their competitive advantages (Torkkeli & Tuominen, 2002, p. 272). Nowadays, a broader approach to this category is increasingly encountered. Technology is identified with a combination of three elements, linked by static and dynamic relationships (*network*), namely: human capital, i.e., *brainware*, material capital, i.e., *hardware*, and broadly understood intangible (disembodied) resources, i.e., *software* (Georgantzas, 2015, p. 96; Karagözoğlu, 2017, p. 106; Zeleny, 1986, p. 110). That definition is applied in the article.

Over the years, the interpretation and nature of technological change in macroeconomic research have evolved. Solow (1957, p. 312) used the term "technological change" to refer to any shift in the macroeconomic production function, whether a slowdown or acceleration in qualitative changes in labor and capital inputs. Based on the neoclassical production function (Cobb & Douglas, 1928), he extracted it from the growth rate in the form of a location parameter, referred to as the Solow residual (equated with the total factor productivity, i.e., TFP). In this manner, qualitative changes in production factors were separated from them and attributed to exogenous technological change (Mata & Louçã, 2009, p. 336). In Solow's approach, technological change is "*just a black box*, *outside the model and outside the influence of economic incentives*" (Acemoğlu, 2009, p. 69), which may, in a sense, exempt us from searching for the factors that determine it. Romer (1986, 1990) attributed the feature of endogeneity to technological changes. Including them in the group of internal factors, expanded the possibilities for research into their determinants. However, above all, it made it possible to link them to other determinants of growth.

In this article, technological change is understood as any change in the technological level of the economy (macroeconomic approach). Suppose these changes are positive (improvement in the technological level), they can be described as technological progress. And if they are negative (deterioration in the technological level), they can be described as technological regression.

The economic convergence is one of the most important issues considered in macroeconomic research. In fact, since the 1990s, a debate in the literature has emerged, leading to a new perspective on the long-term development patterns of modern economies (Islam, 2003). Since then, several studies have been published to determine the scale and sources of differences in the development of economies and regions around the world. In research on economic convergence, the discourse on how to understand and measure it is still relevant (Galor, 1996, pp. 1056–1057). In the vast majority of cases, the analysis focuses mainly on changes in the level and dynamics of per capita income (Barro & Sala-i-Martin, 1991; Chatterji, 1992; Harb et al., 2024). However, this approach appears to be overly reductionist (Grafström & Alm, 2025, pp. 730–731) and is no longer sufficient today (Strielkowski & Höschle, 2016, p. 628). It is also worthwhile to consider technological changes (de la Fuente, 1997, p. 69), which enable a deeper examination of economic convergence, particularly that occurring between highly developed economies (Rodrik, 2022, pp. 78–80).

Convergence in technological advancement drives convergence in per capita income in the long term. To a certain extent, income convergence can be achieved without technological convergence. Archibugi and Pianta (1994) revealed that in the 1980s, EU countries experienced income convergence accompanied by technological divergence. There are also opinions that technological progress can lead to an acceleration in economic growth only in countries with low or medium levels of development, as "*the contribution of technological diffusion to income convergence is probably almost exhausted by now*, *as most countries should be quite close to their stationary level of relative technical efficiency*" (de la Fuente, 1997, p. 66).

Technological changes are crucial in escaping the middle-income trap. Technological progress, supported by investments in human capital, accelerates economic growth and helps close the technological gap (Andreoni & Tregenna, 2020). The authors use the term "the middle-income technology trap" to highlight the strong connection between the middle-income trap and technological development. Their research reveals that countries that invest in technology, industrial policy, entrepreneurship support, and property rights protection have been successful.

The implementation of public policies ensuring access to technological infrastructure, together with appropriate labor market policies and intellectual property rights protection, are essential in the context of technological progress in economies (Agénor et al., 2012). In less developed countries, policies promoting structural transformation, i.e., the transfer of labor from agriculture to industry and services, and the adaptation of foreign technologies are necessary. In the later stages of income and productivity growth, investments in new technologies become crucial, generating significant marginal benefits from the diffusion of knowledge. The causes of the low convergence rate of countries caught in the middle-income trap include among others high prices of investment goods and low levels of exports of industrial goods and advanced technologies (Lee, 2020).

The article assumes that technological convergence is a form of absolute economic convergence in terms of the technological level of the economy. On the one hand, it is a process of catching up by economies with a low technological level with those with a high technological level (β-technological convergence), and also a process of reducing differences between economies in this respect (σ-technological convergence). The approach to technological

convergence used in this article is an alternative to the commonly used assessment through changes in TFP (Cameron et al., 2005, pp. 779–781; Kusideł, 2013, p. 30).

Countries that invest in new technologies can achieve a range of economic, social, and environmental benefits. This requires adequate investment in research and development, as well as improvements in human capital, particularly in terms of learning-by-doing processes (Arrow, 1962), improving the quality of education, and knowledge accumulation (Acemoğlu, 2009). It is also necessary to create a favorable environment for institutions (securing property rights and conducting business activities) and organizations (Coe et al., 2009). Globalization (Archibugi & Pietrobelli, 2003) and economic integration are also important factors in technological convergence. They enhance the transfer of knowledge between economies, which can lead to beneficial technological advancements in less developed economies (Filippetti & Peyrache, 2017, p. 284). The diffusion and absorption of technology can accelerate the process of technological convergence, but may not be "*powerful enough to overcome the erosion of absorptive capacity causing divergence*" (Howitt & Mayer-Foulkes, 2005, p. 173) between economies. Countries that do not invest in technological progress or invest on a small scale usually face difficulties in reaping the benefits from the implementation of imported new solutions (Castellacci, 2011, p. 180).

The article formulates a research proposition according to which **supply shocks occurring from 2020 have significantly slowed down the pace of technological convergence of the EU-27 economies**. These economies are linked not only by geographical proximity, but also by membership in the European Union's integration structures. Therefore, it can be expected that they will gradually become more similar in terms of technological level, thanks to the numerous benefits of EU membership. Economic integration promotes technological convergence. In particular, countries with a relatively lower technological level are observed to be raising their technological level. Thanks to their participation in the single market, they can achieve several benefits (Szczepańska-Woszczyna et al., 2022, pp. 1584–1586) from easier access to physical capital and financing for technological activities (Petrova & Sznajder Lee, 2024), improved transfer of knowledge and technology (Hafner, 2014), and the flow of skilled labor (Golynker, 2020; Șerban et al., 2020).

3. Research methods

3.1. The TOPSIS algorithm with the Weber median normalization

The technological level of the economy is a highly complex and directly unobservable category. A single indicator cannot determine it. Consequently, empirical analysis needs to rely on a synthetic (composite) indicator of technology level to achieve a linear ordering of objects and to capture the multidimensional nature of such a phenomenon.

The literature offers a broad range of statistical approaches for constructing composite indicators, reflecting different conceptual and methodological perspectives on aggregation and measurement (Młodak, 2006; Nardo et al., 2005).

In the study, a synthetic measure is constructed to identify the differentiation of EU-27 economies in terms of their technological level over the period 2007–2023 and to assess the extent of technological convergence or divergence within this group of countries. The

paper applies an extended TOPSIS algorithm (Hwang & Yoon, 1981), based on the use of the Weber median (L1 median), to construct the composite measure of the technological level of the EU-27 economies. The procedure proceeds in the following stages (Kozera et al., 2017, pp. 274–276; Kozera & Głowicka-Wołoszyn, 2016, pp. 526–527):

Stage 1. The selection of diagnostic variables (indicators) based on substantive and statistical premises.

$$\mathbb{X}_{n\times k} = \left[x_{ij}\right], \tag{1}$$

where: x is a diagnostic variable (indicator); i is an object number (1, 2, ..., n); j is a diagnostic variable (indicator) number (1, 2, ..., k).

Selected diagnostic variables should be commonly known, applied in contemporary empirical studies, and possess appropriate statistical properties. The final set of diagnostic variables should consist only of such variables that (Nowak, 1990, pp. 24–28):

- are in the form of intensity indicators, thus enabling comparative analysis of objects;
- are characterized by a sufficiently high ability to discriminate objects, namely adequate cross-sectional differentiation; this criterion is considered to be fulfilled if diagnostic variables record a value of the classical coefficient of variation (2) of 10% or higher;

$$V\left(x_j\right) = \frac{s\left(x_j\right)}{m\left(x_j\right)}; \tag{2}$$

$$m\left(x_j\right) = \frac{\sum_{i=1}^{n} x_{ij}}{n},\ s\left(x_j\right) = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{ij} - m\left(x_j\right)\right)^2}{n}}. \tag{3}$$

- are correlated with each other properly, that is: 1) the direction of correlation between diagnostic variables is consistent as to the sign, and 2) they are not strongly correlated with each other (they do not duplicate the information loading)[1].

Stage 2. The standardization of the values of diagnostic variables using the Weber median vector[2].

$$z_{ij} = \frac{x_{ij} - m\tilde{e}d\left(x_j\right)}{1.4826 \cdot m\tilde{a}d\left(x_j\right)}; \tag{4}$$

$$\sum_{i=1}^{n}\left(\sqrt{\sum_{j=1}^{k}\left(x_{ij} - m\tilde{e}d\left(x_j\right)\right)^2}\right) \to \min,\ m\tilde{a}d\left(x_j\right) = med\left|x_{ij} - m\tilde{e}d\left(x_j\right)\right|, \tag{5}$$

where: $m\tilde{e}d$ is a Weber median vector element (the Weber median); $m\tilde{a}d$ is a median absolute deviation; 1.4826 is a fixed correction factor for the value of the median absolute deviation from the sample.

[1] In order to eliminate diagnostic variables that are too highly correlated with the others, the technique of diagonal element inverse correlation matrix was applied (Malina & Zeliaś, 1997). Variables are gradually excluded from the set until the correct numerical properties of the correlation matrix are obtained, that is, the absolute values of the diagonal elements of the inverse correlation matrix are lower than 15.

[2] The Weber median vector can be calculated using an Excel spreadsheet (Solver add-in, evolutionary programming) or the pcaPP package (l1median function) from the R computing environment.

"*The Weber median is presented in the literature as a multi-dimensional generalization of the classical notion of the median*" (Cheba et al., 2023, p. 452). The use of the Weber median vector in the standardization of variables (4) has two main advantages. First, it allows for the obtaining of results that are resistant to outliers, limiting their negative impact on the reliability of the results obtained, and also reduces the problem of asymmetric distribution of variables (Łuczak & Just, 2020). Secondly, it "*treats the set of diagnostic variables as a whole, maximizing the exploitation of all their mutual relationships*" (Młodak, 2006, p. 138)[3]. These are two properties that contribute to improving the credibility of the constructed synthetic measure (Nardo et al., 2005, pp. 20–21).

Stage 3. The determination of the common pattern (ideal solution) and the anti-pattern (non-ideal solution).

$$z_{0j}^{+} = \max_{i}\left(z_{ijt}\right),\ z_{0j}^{-} = \min_{i}\left(z_{ijt}\right), \tag{6}$$

where: t – year of the study (t = 2007, 2008, ..., T; T = 2023).

The adoption of a common pattern and anti-pattern (6) when calculating the synthetic variable for all analyzed years allows for the assessment and comparison of changes in its values over time. The use of a dynamic measurement approach is crucial in the analysis of convergence, both β and σ types.

Stage 4. The calculation of median distances from the pattern and anti-pattern.

$$d_i^{+} = med\left|z_{ij} - z_{0j}^{+}\right|,\ d_i^{-} = med\left|z_{ij} - z_{0j}^{-}\right|. \tag{7}$$

Stage 5. The construction of a synthetic measure.

$$q_i = \frac{d_i^{-}}{d_i^{-} + d_i^{+}}. \tag{8}$$

The synthetic measure (8) takes values from 0.000 to 1.000, with higher values indicating a higher level of the phenomenon under study that is not directly observable.

Stage 6. The classification of objects according to the synthetic measure values using the mean and standard deviation.

- Class I, i.e., countries with a relatively very high level of synthetic measure values:

$$\overline{q}_j + s_j \le q_{ij}. \tag{9}$$

- Class II, i.e., countries with a relatively high level of synthetic measure values:

$$\overline{q}_j \le q_{ij} < \overline{q}_j + s_j. \tag{10}$$

- Class III, i.e., countries with a relatively moderate level of synthetic measure values:

$$\overline{q}_j - s_j \le q_{ij} < \overline{q}_j. \tag{11}$$

[3] It should be noted that multivariate dimension-reduction techniques, such as Principal Component Analysis (PCA) or Factor Analysis (FA), also treat the set of variables jointly by explicitly exploiting their correlation structure. However, unlike the Weber median–based approach, they rely on second-moment-based statistics and are therefore sensitive to outliers and distributional asymmetries (Hubert et al., 2012, p. 64).

- Class IV, i.e., countries with a relatively low level of synthetic measure values:

$$q_{ij} < \overline{q}_j - s_j. \tag{12}$$

Stage 7. The assessment of the discriminatory capabilities of a synthetic measure using the Sokołowski coefficient (1985).

$$G = 1 - \sum_{i=1}^{n-1} \min_i \left\{ \frac{q_i - q_{i+1}}{\max_i \left(q_i\right) - \min_i \left(q_i\right)}, \frac{1}{n-1} \right\}. \tag{13}$$

The Sokolowski coefficient (13) ranges from 0.000 to 0.962 (for 27 objects, i.e., EU-27), with higher values indicating a better ability of the synthetic variable to group objects.

Stage 8. Robustness analysis using alternative aggregation methods.

To assess the robustness of the results with respect to the choice of aggregation method, alternative synthetic measures were constructed using:

- an extended TOPSIS algorithm, applied in the article, but employing the Chebyshev, instead of the median, distance metric, which reduces compensability (Munda, 2005, pp. 121–124) by focusing on the largest deviation from the ideal solution (Zeng et al., 2013, pp. 851–852), and
- a Principal Component Analysis (Hotelling, 1933) based ranking (employing panel standardization, using a common mean and standard deviation over the entire period), which serves as a statistical benchmark by identifying the dominant latent dimension of variability in the set of technological indicators, independent of any normative aggregation rule (Filmer & Pritchett, 2001, pp. 116–117; Lialikava et al., 2020, pp. 157–158).

The robustness of the rankings with respect to the choice of the aggregation method is assessed using the following measures (Lorenz & Löffler, 2015, pp. 199–200): Spearman's ρ-correlation coefficient and the median of absolute rank differences across countries (14).

$$MRD\left(A,B\right) = med\left| r_i^{(A)} - r_i^{(B)} \right|. \tag{14}$$

3.2. Measures of σ- and β-convergence in measuring technological convergence

The analysis of technological convergence is based on a dynamic analysis of the values of a constructed measure of the technological level of the economy and the values of the indicators used to create it. It proceeds in the following steps:

Stage 1. The calculation of synthetic variables for selected years.

$$\mathbb{Q}_{n\times T} = \left[q_{it}\right]. \tag{15}$$

Stage 2. The determination of coefficients of variation for a synthetic variable in selected years.

$$V\left(q_t\right) = \frac{s\left(q_t\right)}{m\left(q_t\right)}; \tag{16}$$

$$m\left(q_t\right) = \frac{\sum_{i=1}^{n} q_{it}}{n},\ s\left(q_t\right) = \sqrt{\frac{\sum_{i=1}^{n} \left(q_{it} - m\left(q_t\right)\right)^2}{n}}. \tag{17}$$

Stage 3. The assessment of σ-technological convergence based on a synthetic measure.

$$V\left(q_t\right) = \alpha_1 t + \alpha_0 + \varepsilon_t. \tag{18}$$

The σ-convergence occurs in a group of economies when "*the dispersion of*" their technological levels "*tends to decrease over time*" (Sala-i-Martin, 1996, p. 1020). Any measure of variability can measure dispersion. The study uses the classic coefficient of variation (16), which is time-dependent. A negative, statistically significant parameter α_1 in the Equation (18) indicates the occurrence of σ-convergence in terms of technological level among EU countries (Kusideł, 2013, p. 63).

In the context of σ-convergence, a change in the slope of the dispersion trend corresponds to a change in the pace of convergence rather than its reversal, which can be formally modelled using a trend-dummy interaction (Perron, 1989). In Equation (19), the coefficient α_2 captures a change in the slope of the dispersion trend between subperiods. In this specification, the interaction term captures a shift in the slope of the dispersion trend during the crisis period; hence, the post-crisis slope equals $\alpha_1 + \alpha_2$.

$$V\left(q_t\right) = \alpha_1 \tau_t + \alpha_2\left(\tau_t \times Dummy_t\right) + \alpha_0 + \varepsilon_t; \tag{19}$$

$$\tau_t = t_t - t_1 + 1; \tag{20}$$

$$Dummy_t = \begin{cases} 1 & \text{for crisis period} \\ 0 & \text{for otherwise} \end{cases}. \tag{21}$$

Stage 4. The assessment of σ-technological convergence through the perspective of technological level indicators.

While σ-convergence captures the evolution of cross-country dispersion in technological levels over time, β-convergence is examined as a complementary perspective, assessing whether countries with lower initial technological levels tend to grow faster and thereby contribute to the observed changes in dispersion (Young et al., 2008, p. 1086).

Stage 5. The assessment of β-technological convergence based on a synthetic measure.

The β-technological convergence occurs when countries with a relatively lower technological level exhibit a faster average annual rate of improvement compared to countries with a relatively higher level of technological development. To verify this, a simple regression Equation (22) is applied, in which the negative and statistically significant parameter α_1 indicates the occurrence of β-technological convergence between the countries studied (Matkowski et al., 2016, p. 869).

$$\frac{1}{T}\ln\frac{q_{iT}}{q_{i0}} = \alpha_1 \ln q_{i0} + \alpha_0 + \varepsilon. \tag{22}$$

The rate of β-convergence can be determined using Equation (23), applying the transformation proposed by Barro and Sala-i-Martin (1992, p. 230), bearing in mind that in Equation (24) the explanatory variable is of an annual average nature. The number of years necessary to reduce the differences in the studied variable by half can be determined using the half-life coefficient (Barro & Sala-i-Martin, 2004, p. 58), i.e., HL (17).

$$\beta = -\ln\left(1 + \alpha_1\right); \tag{23}$$

$$HL = \frac{\ln 2}{\beta}. \tag{24}$$

In theory, the results obtained using both methods of measuring convergence should be consistent. However, there may be situations in which less technologically developed economies demonstrate a higher rate of technology level growth, while the technological gap between economies may widen (Próchniak, 2006, p. 75). In these cases, "*the process of 'catching up' turns into a process of 'overtaking' richer areas by initially poorer ones*" (Kusideł, 2014, p. 109).

Stage 6. The assessment of β-technological convergence through the perspective of technological level indicators.

3.3. The selection of diagnostic variables determining the technological level of EU-27 economies

The technological level of the EU-27 economies will be determined through the perspective of its heterogeneous elements, which are both embodied and disembodied. "*Technological capabilities are embodied in capital goods, equipment, infrastructures, and in disembodied forms such as human skills and scientific and technical expertise*" (Archibugi & Coco, 2005, p. 177). In addition, the assessment of the technological level will take into account the combination of tangible, intangible, and human capital in the form of measures reflecting the degree of global production efficiency (Archibugi et al., 2009, p. 930), i.e., productivity (Porter et al., 2001, p. 487). Measures related to the intensity of intellectual property patenting are often used to assess the technological capabilities of an economy (Ivanova et al., 2017; Khayyat & Lee, 2015; Park, 2017). In this study, this dimension is excluded for two main reasons:

- patents do not fit into the adopted definition of technological level; they are the result of the technological capacity of the economy, not its determinant;
- not every patent is associated with a new, revolutionary technological solution; it may, but does not necessarily, serve to improve the technological level of the economy (Reeb & Zhao, 2020).

Table 1 contains diagnostic variables that are selected to measure the technological level of the EU-27 economies. Firstly, the technological level of an economy is determined by investment flows aimed at replacing and improving both physical and intangible capital stock. Gross fixed capital formation per employee ($TECH_1$) is a classical measure of physical capital intensity, commonly used as a proxy for the degree of capital deepening in an economy.

Table 1. Selected indicators of the technological level of the economy (TECH) (source: authors' own work)

Symbol	Diagnostic variable	Source of data
$TECH_1$	Gross fixed capital formation (EUR per employee, constant prices 2020)	Eurostat, ILOSTAT
$TECH_2$	Gross domestic expenditure on R&D (EUR per inhabitant, constant prices 2020)	Eurostat
$TECH_3$	R&D personnel (% of population in the labor force)	Eurostat
$TECH_4$	ICT specialists employed (% of total employment)	Eurostat
$TECH_5$	Labor productivity (USD per hour worked, constant prices 2021)	ILOSTAT
$TECH_6$	Resource productivity (EUR per kilogram, constant prices 2020)	Eurostat

It reflects the extent to which labor is equipped with modern capital goods and the adoption and use of more advanced production technologies (Navarro Zapata et al., 2024; Sheng, 2025). Gross domestic expenditure on R&D per capita ($TECH_2$) captures investment in intangible capital, which constitutes a core component of the technological capabilities of an economy (Blanco et al., 2020; Grafström & Alm, 2025; Raghupathi & Raghupathi, 2017).

Secondly, the technological level of an economy depends on the availability of a skilled, knowledge-intensive labor force that enables the effective use, operation, and upgrading of existing technologies. In this context, the share of R&D personnel in the labor force ($TECH_3$) captures the human component of technological capabilities, reflecting the availability of specialized labor that underpins the technological change in the economy (Tutak & Brodny, 2024; Halaskova et al., 2020). ICT specialists employed as a share of total employment ($TECH_4$) reflect the availability of ICT-related skills in the workforce, indicating the extent to which digital technologies can be effectively utilized within the economy (Horváthová & Mokrišová, 2024; Hernández de Rojas et al., 2024).

Finally, the technological level is reflected in the efficiency with which economies transform inputs into outputs. Labor productivity ($TECH_5$) measures the amount of output generated per unit of labor input, whereas resource productivity ($TECH_6$) captures the amount of economic output produced per unit of material input. Such productivity measures are commonly employed in macroeconomic studies to assess the technological advancement of an economy (Eder et al., 2024; Mushafiq & Prusak, 2023; Tsiapa, 2023).

The selected diagnostic variables fulfill the necessary criteria, both substantive and statistical. All of them are stimulants, so an increase in the value of each of them contributes to an improvement in the technological level of the economy.

For the research, the proposition has been transformed into an empirical hypothesis, which is as follows: **the pace of σ- and β-convergence in the EU-27 economies slowed down due to crises caused by supply-side shocks that began in 2020**. According to the hypothesis, it is expected that allowing for a change in the slope of the dispersion trend will reveal a slowdown in the pace of σ-convergence during the crisis period, reflected in a weaker reduction of technological disparities among EU-27 economies compared to the pre-crisis years. From a complementary perspective, β-convergence is examined to assess whether countries with lower initial technological levels continued to grow faster than more advanced economies. In this case, the hypothesis implies that the estimated β-parameters will indicate a slowdown in the pace of technological catching-up during the crisis period relative to the period excluding the years 2021–2023.

4. Research results

4.1. Technology level differences among EU-27 economies from 2007 to 2023

The rankings of the EU-27 economies by technological level (TECH) in 2007, 2019, and 2023 are presented in Figure 1. Substantive considerations dictated the choice of these years – the presentation covered two non-crisis years (2007 and 2019) as well as the year in which the most recent statistical data was available (2023). In 2007, the highest technological level

(TECH) was reported in Luxembourg, while the lowest was in Bulgaria. In 2019, Luxembourg remained the leader in the ranking, and Bulgaria was at the bottom. In 2023, Ireland achieved the highest value of the synthetic variable of technological level (TECH), while Bulgaria again achieved the lowest.

Based on the range of the synthetic measure of the technological level, conclusions can be drawn regarding the technological gap between the economies studied. The difference between the leaders and the economies at the bottom of the rankings has been decreasing year by year. This indicates a gradual reduction in the differences between the EU-27 economies in terms of technological level. However, it should be noted that this is due to the increasingly lower maximum values achieved by the leaders in the rankings. The consistency between the technological level rankings in 2007–2023 was relatively high, i.e., the Spearman's ρ between pairs of rankings was on average higher than 0.85. Although changes in the values of synthetic variables for individual countries have been observed over the years, on average, the ranking has not changed significantly.

Figure 2 presents a typological division of EU-27 economies in terms of technological level in 2007, 2019, and 2023. In 2007, the group of economies with a relatively low technological level comprised Poland, Romania, and Bulgaria. Economies with a relatively moderate technological level in that year consisted of Spain, Slovenia, Czechia, Malta, Greece, Portugal, Estonia, Hungary, Slovakia, Croatia, Latvia, Cyprus, and Lithuania. Seven EU-27 economies exhibited a relatively high technological level: Germany, Belgium, Austria, France, the Netherlands, Ireland, and Italy. Luxembourg, Sweden, Finland, and Denmark were classified as economies with a relatively very high technological level in 2007.

In 2019, three EU-27 economies – Cyprus, Romania, and Bulgaria – were classified as having a relatively low level of technological development. The most numerous groups consisted of countries with a relatively moderate technological level, including: Slovenia, Spain, Czechia,

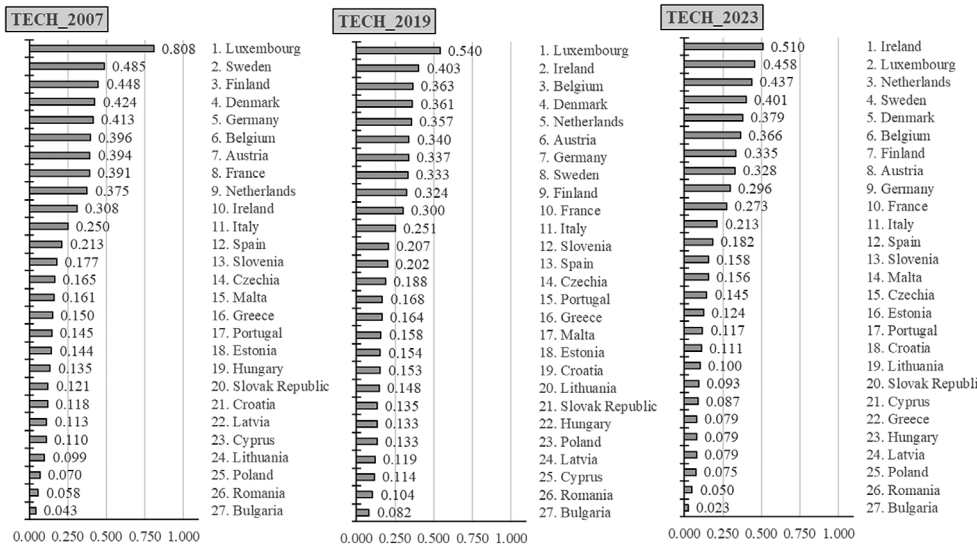


Figure 1. Rankings of EU-27 economies in terms of technological level (TECH) in 2007, 2029, and 2023

Portugal, Greece, Malta, Estonia, Croatia, Lithuania, Slovakia, Hungary, Poland, and Latvia. In 2019, the group with a relatively high technological level consisted of Austria, Germany, Sweden, Finland, France, and Italy. Economies with a relatively very high technological level included: Luxembourg, Ireland, Belgium, Denmark, and the Netherlands.

In 2023, the group of EU-27 economies with a relatively low technological level consists of Romania and Bulgaria. Fourteen economies were characterized by a relatively moderate technological level: Spain, Slovenia, Malta, Czechia, Estonia, Portugal, Croatia, Lithuania, Slovakia, Cyprus, Greece and Hungary. The third group included: Finland, Austria, Germany, France, and Italy. Economies with a relatively very high technological level included: Ireland, Luxembourg, the Netherlands, Sweden, Denmark, and Belgium.

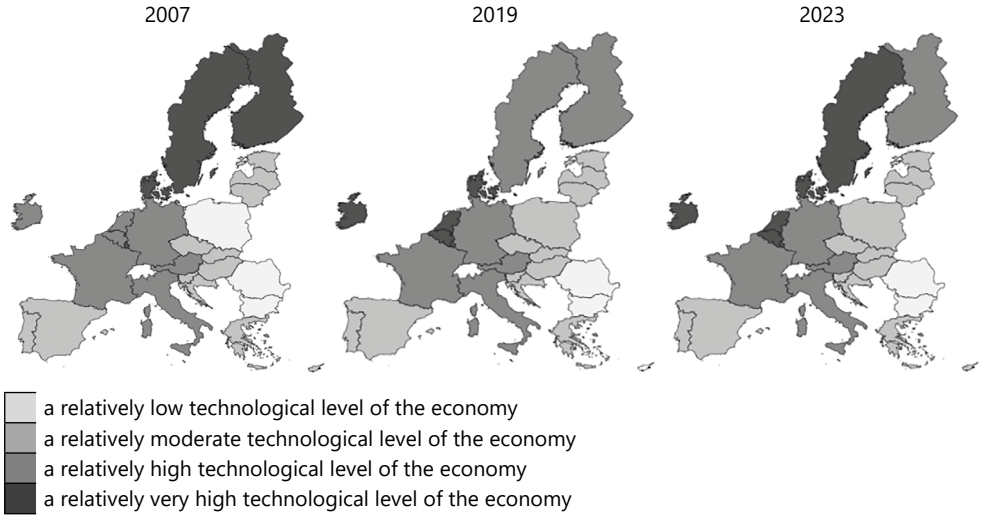


Figure 2. Classes of EU-27 economies by technological level (TECH) in 2007, 2019, and 2023

In summary, during the analyzed period, the relatively highest technological level among the EU-27 was observed in the Scandinavian economies (especially Sweden), the Benelux region (in particular Luxembourg), and Ireland. On the other hand, the economies of Central and Eastern Europe, as well as Greece, and Cyprus, achieved lower technological levels compared to the other EU-27 economies.

Table 2 contains selected descriptive statistics for the synthetic variable of the technological level of the EU-27 economies in 2007–2023. Particularly noteworthy is the decreasing range of values of the technological level measure among the EU-27 economies over the years. The downward trend in the difference between the maximum and minimum values of the TECH measure is due to the gradual deterioration in the technological level of the leaders in the rankings in individual years. On average, year on year, the leader in the rankings was the economy that achieved a lower TECH value compared to the leaders from the previous year. Based on the value of the Sokołowski coefficient, it can be assumed that the synthetic variable has a reasonably good ability to discriminate between the economies of the EU-27 into typological groups.

Table 2. Selected indicators of the technological level of the economy (TECH) (source: authors' own work)

	min	max	R	med	m	s	V_s [%]	G
2007	0.043 (BG)	0.808 (LU)	0.765	0.165	0.249	0.174	69.997	0.460
2008	0.040 (BG)	0.604 (LU)	0.564	0.144	0.191	0.125	65.247	0.444
2009	0.049 (BG)	0.634 (LU)	0.585	0.152	0.220	0.141	63.965	0.481
2010	0.045 (BG)	0.557 (LU)	0.512	0.179	0.208	0.126	60.709	0.389
2011	0.053 (BG)	0.644 (LU)	0.592	0.188	0.240	0.143	59.393	0.373
2012	0.037 (BG)	0.576 (LU)	0.540	0.167	0.210	0.131	62.480	0.400
2013	0.049 (BG)	0.597 (LU)	0.549	0.154	0.212	0.131	61.885	0.441
2014	0.056 (BG)	0.595 (LU)	0.539	0.156	0.209	0.128	61.102	0.462
2015	0.048 (BG)	0.525 (LU)	0.477	0.176	0.207	0.124	59.894	0.388
2016	0.054 (BG)	0.545 (LU)	0.490	0.175	0.215	0.127	58.858	0.429
2017	0.054 (BG)	0.596 (LU)	0.542	0.213	0.246	0.141	57.197	0.392
2018	0.087 (BG)	0.588 (LU)	0.501	0.194	0.240	0.121	50.451	0.459
2019	0.082 (BG)	0.540 (LU)	0.459	0.188	0.232	0.114	49.132	0.428
2020	0.076 (BG)	0.581 (LU)	0.504	0.224	0.265	0.135	50.791	0.351
2021	0.017 (BG)	0.505 (LU)	0.488	0.154	0.204	0.139	67.983	0.415
2022	0.020 (BG)	0.566 (LU)	0.546	0.177	0.221	0.148	67.167	0.352
2023	0.023 (BG)	0.510 (IE)	0.487	0.156	0.209	0.142	67.581	0.294

Due to the use of a panel, common pattern, and anti-pattern, it is also possible to compare changes in the values of synthetic variables over time (Figure 3). In the first subperiod (2007–2019), several Western and Northern European economies experienced declines in the value of the synthetic technological indicator compared to their 2007 levels, while positive changes were more frequently observed among Central, Eastern, and Southern European countries. In contrast, during the second subperiod (2019–2023), negative changes in the technological level measure became more widespread, and the dispersion of outcomes across countries increased. This suggests a less uniform evolution of technological levels during the crisis period, with stronger declines observed in a number of economies. The comparison of changes over the entire period (2007–2023) illustrates the cumulative effect of these dynamics, reflecting both the pre-crisis convergence tendencies and the heterogeneous, often adverse developments observed after 2019.

The robustness analysis in Table 3 reveals a high degree of consistency between the baseline TOPSIS (L1) ranking and alternative aggregation methods. The comparison between the baseline TOPSIS (L1) measure and the Chebyshev-distance variant reveals a high degree of rank concordance across all analyzed years, with Spearman's ρ ranging from 0.811 to 0.918 and a median value of 0.900 over the 2007–2023 period. At the same time, the median absolute rank differences remain small (between one and three positions), indicating that while the overall ranking structure is preserved, the reduced compensability embedded in the Chebyshev metric leads to limited local reordering of countries. In contrast, the PCA-based ranking exhibits almost perfect alignment with the baseline TOPSIS results across all examined years. Spearman's rank correlation coefficients remain very high, and median absolute rank

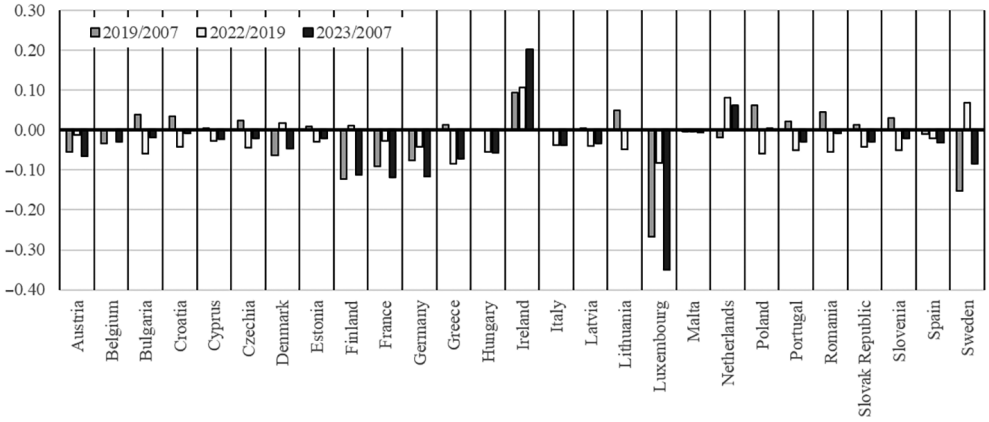


Figure 3. Changes in the values of the TECH variable between 2007 and 2023 in the EU-27 countries

Table 3. Robustness of the TECH measure: comparison across aggregation methods (source: authors' own work)

Comparison	Measure	2007	2019	2023	2007–2023		
					min	max	med
TOPSIS (L1) vs. TOPSIS (Chebyshev)	Spearman's ρ	0.887	0.918	0.811	0.811	0.953	0.900
	MRD	3	1	2	1	3	2
TOPSIS (L1) vs. PCA[a]	Spearman's ρ	0.979	0.987	0.984	0.974	0.995	0.987
	MRD	1	1	1	0	1	1

Note: [a] two main components that explain 86.49% of the variability of the phenomenon under study.

differences do not exceed one position. This outcome points to a strongly unidimensional structure of the technological indicators, with the first two principal components capturing a dominant common factor underlying technological development. Consequently, the main patterns of technological differentiation across EU-27 economies are invariant to the choice between distance-based and statistical aggregation methods.

4.2. The technological convergence of the EU-27 countries between 2007 and 2023

The analysis of technological convergence begins with an examination of σ-convergence, defined as a systematic decline in cross-country dispersion of technological levels over time. To this end, a trend model of the classical coefficient of variation of the technological level (TECH) synthetic variable was estimated for the period 2007–2023. The results are presented in Figure 4. The estimation of the baseline trend specification over the entire period does not indicate a statistically significant downward trend in the dispersion of technological levels across EU-27 economies. This suggests that assuming a constant pace of σ-convergence over the whole period may be overly restrictive. However, when the analysis is restricted to the pre-crisis subperiod (2007–2020), a clear and statistically significant (p < 1%) downward trend in the coefficient of variation is observed, indicating the presence of σ-convergence prior

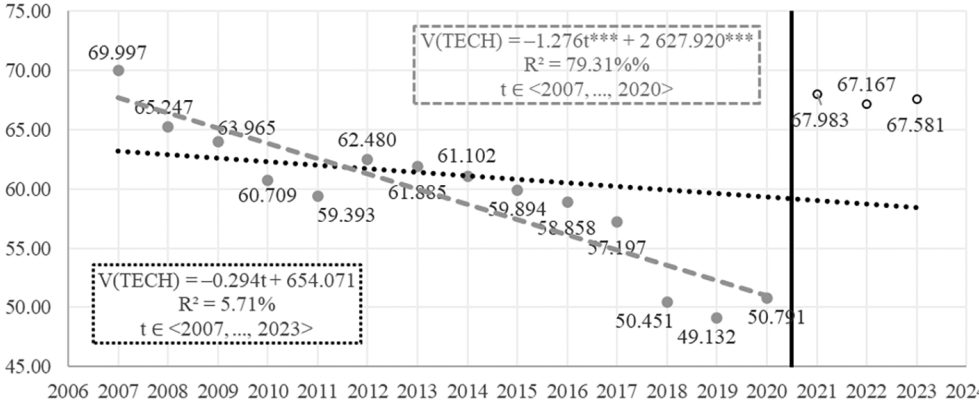


Figure 4. The σ-convergence of EU-27 economies in 2007–2023 in terms of the synthetic variable TECH – values of the TECH's coefficient of variation

to the onset of major global disruptions. The contrast between these two trends estimates points to a change in dispersion dynamics in the post-2020 period, motivating a more flexible specification that allows for a shift in the pace of σ-convergence.

Consistent with those results, visual inspection of the dispersion dynamics suggests a potential change in the pace of σ-convergence around the end of the 2010s, marked by a noticeable flattening of the downward trend after 2020. This observation motivates the use of an extended specification allowing for a change in the slope of the dispersion trend.

$$V\left(TECH\right) = \underset{\left(0.156\right)}{-1.285^{***}}\ \tau + \underset{\left(0.125\right)}{1.195^{***}}\left(\tau \times POST2020\right) + \underset{\left(1.328\right)}{69.001^{***}}, \quad (25)$$

$$R^2 = 87.47\%, \tau \epsilon \langle 1, 2, \ldots 17 \rangle.$$

The results of the extended trend specification confirm the presence of σ-convergence in the pre-crisis period. Between 2007 and 2020, on average, the value of the classic coefficient of variation decreased by approximately 1.285 percentage points annually (p < 1%), *ceteris paribus*, indicating a systematic reduction in dispersion of technological level among EU-27 economies. The interaction term between the time trend and the post-2020 dummy variable is positive and statistically significant (p < 1%), pointing to a change in the pace of σ-convergence after 2020. Considering that the post-crisis slope equals the sum of the estimated coefficients, the average annual rate of change in the coefficient of variation in the post-2020 period amounts to approximately 0.09 percentage points, implying that the process of σ-convergence slowed down after 2020.

The results presented in Table 4 reveal a heterogeneous pattern of σ-convergence across individual technological level indicators. Prior to 2020, most indicators exhibited negative and statistically significant trends, confirming the presence of σ-convergence, although the strength of this process varied considerably across dimensions. Following 2020, the interaction terms are predominantly positive, indicating a slowdown in the pace of convergence. For several indicators, the implied post-2020 slopes are close to zero, suggesting that the reduction in dispersion of technology level effectively stalled. At the same time, a limited number of indicators display either no convergence throughout the period or a distinct adjustment pattern after 2020, highlighting the asymmetric impact of recent shocks across technological dimensions.

Table 4. The σ-convergence of EU-27 economies in 2007–2023 in terms of the TECH indicators – values of the TECH's indicators coefficients of variation (source: authors' own work)

Dependent variable	τ[a]		$\tau \times POST2020$[a]		$\tau + (\tau \times POST2020)$	R^2
V_s of $TECH_1$	1.707	***	–1.502	***	0.204	69.15%
V_s of $TECH_2$	–1.271	***	0.029	*	–1.242	93.18%
V_s of $TECH_3$	–1.131	***	0.152	***	–0.979	96.42%
V_s of $TECH_4$	0.001		–0.151		0.000	26.36%
V_s of $TECH_5$	–0.916	***	0.283	**	–0.633	82.44%
V_s of $TECH_6$	–0.243	**	0.189	**	–0.054	29.45%

Note: [a] *** is the significance at the $p < 1\%$; ** is the significance at the $p < 5\%$; * is the significance at the $p < 10\%$.

The results of the β-convergence analysis for the synthetic variable TECH (Table 5) are consistent with the σ-convergence findings. In the pre-crisis period (2007–2020), a statistically significant ($p < 1\%$) negative relationship between the initial technological level and subsequent growth is observed, indicating the presence of β-convergence with an estimated speed of adjustment of approximately 2.16% per year. This implies that the time required to halve the technological gap between EU-27 economies exceeded 30 years (HL = 32.105). When the crisis years are included (2007–2023), the convergence relationship disappears, suggesting that the catching-up process was disrupted. Focusing exclusively on the crisis period (2020–2023), the estimated slope becomes positive and statistically significant ($p < 1\%$), pointing to β-divergence, whereby technologically more advanced economies experienced faster improvements than less advanced ones. In general, the results suggest that recent supply shocks significantly weakened the technological catching-up process within the EU-27.

Table 5. β-convergence of EU-27 economies in 2007–2023 in terms of the TECH variable (source: authors' own work)

Period of time	Slope[a]		β	HL	R^2
2007–2020	–0.021	***	2.16%	32.105	65.17%
2007–2023	0.001		–	–	0.44%
2020–2023	0.034	***	–	–	76.41%

Note: [a] *** is the significance at the $p < 1\%$.

The results of the β-convergence analysis for individual technological level indicators, reported in Table 6, reveal a heterogeneous pattern across dimensions and periods. In the pre-crisis years (2007–2020), β-convergence is observed for most indicators, indicating that countries with lower initial levels in specific technological dimensions tended to grow faster. When the crisis years are included (2007–2023), the convergence relationship weakens and becomes less uniform. Focusing on the crisis period alone (2020–2023), the β-convergence mechanism largely disappears, with only isolated indicators displaying statistically significant catching-up. This evidence suggests that recent shocks disrupted the standard technological diffusion process, with convergence becoming highly dimension-specific and, in some cases, temporarily stalled.

Table 6. β-convergence of EU-27 economies in 2007–2023 in terms of the TECH indicators (source: authors' own work)

Indicator	Period of time	Slope[a]		β	HL	R^2
$TECH_1$	2007–2020	0.003		–	–	0.79%
	2007–2023	–0.006		–	–	6.81%
	2020–2023	–0.014	***	1.38%	50.343	46.72%
$TECH_2$	2007–2020	–0.016	***	1.58%	43.751	55.63%
	2007–2023	–0.015	***	1.46%	47.445	56.97%
	2020–2023	–0.003		–	–	7.47%
$TECH_3$	2007–2020	–0.017	***	1.73%	40.020	28.88%
	2007–2023	–0.012	**	1.22%	56.672	19.20%
	2020–2023	0.004		–	–	7.70%
$TECH_4$	2007–2020	–0.022	*	2.24%	30.922	15.43%
	2007–2023	–0.031	***	3.13%	22.121	28.66%
	2020–2023	–0.011		–	–	10.36%
$TECH_5$	2007–2020	–0.013	***	1.34%	51.725	30.03%
	2007–2023	–0.014	***	1.44%	48.224	39.19%
	2020–2023	–0.005	**	0.47%	147.74	22.11%
$TECH_6$	2007–2020	–0.002		–	–	0.56%
	2007–2023	–0.001		–	–	0.10%
	2020–2023	0.001		–	–	0.62%

Note: [a] *** is the significance at the $p < 1\%$; ** is the significance at the $p < 5\%$; * is the significance at the $p < 10\%$.

5. Discussion

The empirical analysis indicates that the processes of both σ- and β-technological convergence occur among EU-27 economies, but their pace weakened after 2020. Similar results are achieved by Grafström and Alm (2025), whose research reveals that the process of technological convergence in the EU-27 countries is underway, albeit at a slow pace. Therefore, the time required to close the gap in this area is considerable. The occurrence of technological convergence in EU economies is also confirmed by the research of other authors, including Borović et al. (2024), Kijek and Matras-Bolibok (2020), and Žižmond and Novak (2007).

During the period 2007–2020, the σ-technological convergence was observed, with the coefficient of variation of the technological level decreasing at an average rate of approximately 1.29 percentage points per year, *ceteris paribus*. After 2020, the reduction in cross-country dispersion weakened, indicating a slowdown in the process of σ-convergence. These findings are further supported by the β-convergence analysis. Between 2007 and 2020, the rate of β-technological convergence was approximately 2.16% per year, which is consistent with typical results reported in studies on economic convergence (Abreu et al., 2005; Witkowski & Próchniak, 2014). An analysis restricted to the 2020–2023 period reveals β-divergence, with faster technological advancement observed among leading economies. Overall, the results

suggest that recent supply shocks have undermined the technological convergence process within the EU-27.

The reasons for the slowdown in technological convergence may be found in global macroeconomic supply shocks, which affected the EU-27 economies to a greater or lesser extent. Research by Izsak and Radošević (2017) revealed that the 2008 financial crisis contributed to a noticeable slowdown in the convergence process in terms of technological advancement, especially in the area of R&D, in EU countries. Archibugi and Filippetti (2011) come to a similar conclusion, and their research covered not only the analysis of technological convergence but also the results of innovation activities.

According to the research, the global financial crisis did not cause as severe a slowdown in the process of technological convergence as the supply shocks that began in 2020. The reason for this probably lies in the different nature of both crises. Unlike the 2008 financial crisis, which was primarily related to the financial sector (Bengtsson, 2013; Cetorelli & Goldberg, 2011), the pandemic and geopolitical crisis (exacerbated by the war in Ukraine) are characterized by a much broader scope and multi-channel impact on the real, monetary, and regulatory spheres of economies around the world (Chen & Yeh, 2021).

The scale of disruption caused by the pandemic and the geopolitical crisis forced governments to implement numerous institutional anti-crisis solutions, many of which had not previously been used on such a large scale. The consequences of these actions included restrictions on (Abrhám & Vošta, 2022; Belitski et al., 2022; Gonçalves & Moro, 2023; Rose et al., 2023; Sunge et al., 2024; Tong, 2024):

- economic activity, the sphere of entrepreneurship, which is mainly responsible for inducing technological progress;
- migration;
- the intensity of trade, which has resulted in the breakdown of supply and value chains, as well as problems with the availability and prices of goods and services, especially energy.

In addition, both the public and private sectors have changed the structure and scale of their expenditure (costs). A large part of spending has been redirected or generated to address the direct and indirect negative effects of the pandemic (Mitsi, 2023). What is more, in times of political instability, countries spend more on security-related issues. This situation has contributed to a vast reduction in funding for other areas, including capital formation and R&D activities (Protasiewicz, 2021, p. 487), but also to the creation of long-term debts. Studies can be found in the literature indicating that the current crises have also been a stimulus for positive technological changes, especially in terms of ICT development (Dosi et al., 2021, pp. 2978–2979). However, it seems that their net impact on the process of technological convergence is still negative.

The study was limited by the low availability of data reflecting the technological level of the economy. In particular, this limitation concerns indicators capturing digital infrastructure and digital capital, such as ICT capital stock, broadband penetration, and advanced digital connectivity, as well as emerging measures related to the adoption of artificial intelligence technologies in production processes. Many recently proposed indicators related to digital technologies and artificial intelligence are still affected by substantial data gaps, limited

cross-country comparability, and evolving methodological standards, which currently restrict their consistent use in long-term, cross-country empirical analyses (Organisation for Economic Co-operation and Development, 2019, pp. 20, 29). Although the period covered, 2007–2023, can be considered methodologically sufficient in the context of the analysis, its use may have affected the comprehensiveness and accuracy of the empirical results obtained.

Furthermore, the study is macroeconomic, so when comparing economies, "*the fact that large parts of countries could be lagging behind, while most of the economic prosperity is concentrated and developed in specific economic areas geographically*" (Grafström & Alm, 2025, p. 748) is being omitted. By relying on national-level generalizations, the analysis may conceal substantial regional heterogeneity within countries, particularly in terms of technological levels. Consequently, convergence observed at the country level should be interpreted as convergence between national technological systems and does not preclude the coexistence of persistent or even widening technological disparities at the sub-national level. A regional-level analysis based on NUTS2 data could therefore provide a more detailed picture of technological dynamics within countries; however, such an extension lies beyond the scope of the present study and rather represents a matter for future research.

6. Conclusions

Based on the empirical analysis, it can be concluded that there was a coexistence of σ- and β-technological convergence among the EU-27 economies in the years 2007–2023. Although these economies are becoming similar in terms of technological advancement, the pace of convergence in this area is slow and has been slowing down over the years analyzed (especially over the last few years, from 2020).

It should be emphasized, however, that the observed σ-convergence over the period 2007–2020 does not necessarily reflect a uniform and strong catching-up process among technologically lagging economies. The reduction in dispersion appears to have been driven by a combination of moderate improvements among less advanced countries, as indicated by the β-convergence results, and a gradual relative slowdown in technological performance among leading economies, as suggested by the dynamic analysis of the TECH indicator over time. After 2020, the relative importance of the latter mechanism appears to increase, while the catching-up process weakens or even temporarily reverses. This shift sets the context for the recent developments in technological convergence within the EU-27.

The article provides a method for measuring the technological level of the EU-27 economies and proposes a modified approach to assessing technological convergence between these countries. Based on empirical research and literature review, the assumption and research hypothesis can be considered positively verified. Between 2007 and 2023, the EU-27 countries underwent a process of technological convergence. However, its pace weakened significantly after 2020, coinciding with major supply shocks, including the COVID-19 pandemic and the escalation of geopolitical tensions related to the war in Ukraine. These findings suggest that recent crises have disrupted the technological catching-up process and highlight the importance of policies aimed at strengthening technological capabilities, particularly in economies with relatively lower technological levels.

The robustness of the obtained results has been additionally verified by applying alternative approaches to the construction of the synthetic technological indicator. In particular, the ranking of EU-27 economies based on the baseline TOPSIS method was compared with results derived from a Principal Component Analysis (PCA) and an alternative distance-based specification. The high consistency of rankings and convergence patterns across these approaches indicates that the main findings, particularly the slowdown of technological convergence after 2020, are not driven by a specific methodological choice. This strengthens the reliability of the empirical results and supports the validity of the conclusions drawn from the analysis.

Technological convergence within the EU is slowing, especially in countries with lower economic development. The deceleration of technical progress in these nations poses a challenge for their economic policies. Adapting to changes in expenditure structure, driven by evolving social needs, is becoming increasingly difficult. Supporting innovative activities and maintaining the pre-pandemic pace of technical progress are now more challenging. This situation requires a search for alternative approaches to innovation policy at both national and EU levels.

This article serves as a point of departure for an in-depth consideration of the process of economic convergence among the EU-27 countries. Subsequent studies will focus on the analysis of other dimensions of convergence that extend beyond the technological aspect, also from a regional perspective (an analysis that considers heterogeneity within economies). In particular, a diagnosis of institutional convergence, which is one of the key dimensions of economic convergence, is planned.

Funding

This work was supported by the Ministry of Science and Higher Education (Poland) under the "*Regionalna Inicjatywa Doskonałości dla nauk społecznych Uniwersytetu w Białymstoku*" program, administered by the University of Bialystok, Poland [number E/1/2/RID/2025].

Author contributions

EG and MB have made an equal contribution to the creation of this research paper.

Disclosure statement

The authors declare no potential conflict of interest.

References

Abreu, M., de Groot, H. L. F., & Florax, R. J. G. M. (2005). A meta-analysis of β-convergence: The legendary 2%. *Journal of Economic Surveys*, *19*(3), 389–420. https://doi.org/10.1111/j.0950-0804.2005.00253.x

Abrhám, J., & Vošta, M. (2022). Impact of the COVID-19 pandemic on EU convergence. *Journal of Risk and Financial Management*, *15*(9), Article 384. https://doi.org/10.3390/jrfm15090384

Acemoğlu, D. (2009). *Introduction to modern economic growth*. Princeton University Press.

Agénor, P.-R., Canuto, O., & Jelenic, M. (2012). *Avoiding middle-income growth traps*. World Bank. https://doi.org/10.1596/16954

Andreoni, A., & Tregenna, F. (2020). Escaping the middle-income technology trap: A comparative analysis of industrial policies in China, Brazil and South Africa. *Structural Change and Economic Dynamics*, *54*, 324–340. https://doi.org/10.1016/j.strueco.2020.05.008

Archibugi, D., & Coco, A. (2005). Measuring technological capabilities at the country level: A survey and a menu for choice. *Research Policy*, *34*(2), 175–194. https://doi.org/10.1016/j.respol.2004.12.002

Archibugi, D., & Filippetti, A. (2011). Is the economic crisis impairing convergence in innovation performance across Europe? *Journal of Common Market Studies*, *49*(6), 1153–1182. https://doi.org/10.1111/j.1468-5965.2011.02191.x

Archibugi, D., & Pianta, M. (1994). Aggregate convergence and sectoral specialization in innovation. *Journal of Evolutionary Economics*, *4*(1), 17–33. https://doi.org/10.1007/BF01200835

Archibugi, D., & Pietrobelli, C. (2003). The globalisation of technology and its implications for developing countries: Windows of opportunity or further burden? *Technological Forecasting and Social Change*, *70*(9), 861–883. https://doi.org/10.1016/S0040-1625(02)00409-2

Archibugi, D., Denni, M., & Filippetti, A. (2009). The technological capabilities of nations: The state of the art of synthetic indicators. *Technological Forecasting and Social Change*, *76*(7), 917–931. https://doi.org/10.1016/j.techfore.2009.01.002

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, *29*(3), 155–173. https://doi.org/10.2307/2295952

Barro, R. J., & Sala-i-Martin, X. (1991). Convergence across states and regions. *Brookings Papers on Economic Activity*, *22*(1), 107–182. https://doi.org/10.2307/2534639

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, *100*(2), 223–251. https://doi.org/10.1086/261816

Barro, R. J., & Sala-i-Martin, X. (2004). *Economic growth*. The MIT Press.

Belitski, M., Guenther, C., Kritikos, A. S., & Thurik, R. (2022). Economic effects of the COVID-19 pandemic on entrepreneurship and small businesses. *Small Business Economics*, *58*(2), 593–609. https://doi.org/10.1007/s11187-021-00544-y

Bengtsson, E. (2013). Shadow banking and financial stability: European money market funds in the global financial crisis. *Journal of International Money and Finance*, *32*, 579–594. https://doi.org/10.1016/j.jimonfin.2012.05.027

Bijker, W. E., Hughes, T. P., & Pinch, T. J. (1993). General Introduction. In W. E. Bijker, T. P. Hughes, & T. J. Pinch (Eds.), *The social construction of technological systems*: *New directions in the sociology and history of technology* (pp. 1–7). The MIT Press.

Blanco, F. A., Delgado, F. J., & Presno, M. J. (2020). R&D expenditure in the EU: Convergence or divergence? *Economic Research-Ekonomska Istraživanja*, *33*(1), 1685–1710. https://doi.org/10.1080/1331677X.2020.1756371

Borović, Z., Radicic, D., Ritan, V., & Tomaš, D. (2024). Convergence and divergence tendencies in the European Union: New evidence on the productivity/institutional puzzle. *Economies*, *12*(12), Article 323. https://doi.org/10.3390/economies12120323

Çalışkan, H. K. (2015). Technological change and economic growth. *Procedia - Social and Behavioral Sciences*, *195*, 649–654. https://doi.org/10.1016/j.sbspro.2015.06.174

Cameron, G., Proudman, J., & Redding, S. (2005). Technological convergence, R&D, trade and productivity growth. *European Economic Review*, *49*(3), 775–807. https://doi.org/10.1016/S0014-2921(03)00070-9

Castellacci, F. (2011). Closing the technology gap? *Review of Development Economics*, *15*(1), 180–197. https://doi.org/10.1111/j.1467-9361.2010.00601.x

Cetorelli, N., & Goldberg, L. S. (2011). Global banks and international shock transmission: Evidence from the crisis. *IMF Economic Review*, *59*(1), 41–76. https://doi.org/10.1057/imfer.2010.9

Chatterji, M. (1992). Convergence clubs and endogenous growth. *Oxford Review of Economic Policy*, *8*(4), 57–69. https://doi.org/10.1093/oxrep/8.4.57

Cheba, K., Bąk, I., & Pietrzak, M. B. (2023). Conditions of the green transformation. The case of the European Union. *Technological and Economic Development of Economy*, *29*(2), 438–467. https://doi.org/10.3846/tede.2022.17993

Chen, H.-C., & Yeh, C.-W. (2021). Global financial crisis and COVID-19: Industrial reactions. *Finance Research Letters*, *42*, Article 101940. https://doi.org/10.1016/j.frl.2021.101940

Cobb, C. W., & Douglas, P. H. (1928). A theory of production. *The American Economic Review*, *18*(1), 139–165.

Coe, D., Helpman, E., & Hoffmaister, A. (2009). International R&D spillovers and institutions. *European Economic Review*, *53*(7), 723–741. https://doi.org/10.1016/j.euroecorev.2009.02.005

de la Fuente, A. (1997). The empirics of growth and convergence: A selective review. *Journal of Economic Dynamics and Control*, *21*(1), 23–73. https://doi.org/10.1016/0165-1889(95)00925-6

Dosi, C., Cocchi, N., & Vignoli, M. (2021). Ten transform energency now! – Facing Covid-19 with open and frugal innovation. *Proceedings of the Design Society*, *1*, 2971–2980. https://doi.org/10.1017/pds.2021.558

Eder, A., Koller, W., & Mahlberg, B. (2024). The contribution of industrial robots to labor productivity growth and economic convergence: A production frontier approach. *Journal of Productivity Analysis*, *61*, 157–181. https://doi.org/10.1007/s11123-023-00707-x

Filippetti, A., & Peyrache, A. (2017). Productivity growth and catching up: A technology gap explanation. *International Review of Applied Economics*, *31*(3), 283–303. https://doi.org/10.1080/02692171.2016.1249831

Filmer, D., & Pritchett, L. H. (2001). Estimating wealth effects without expenditure data-or tears: An application to educational enrollments in states of India. *Demography*, *38*(1), 115–132. https://doi.org/10.1353/dem.2001.0003

Galor, O. (1996). Convergence? Inferences from theoretical models. *The Economic Journal*, *106*(437), 1056–1069. https://doi.org/10.2307/2235378

Georgantzas, N. C. (2015). Politeia: A high-technology human system. *Human Systems Management*, *34*(2), 91–104. https://doi.org/10.3233/HSM-150828

Golynker, O. (2020). EU coordination of social security from the point of view of EU integration theory. *European Journal of Social Security*, *22*(2), 110–137. https://doi.org/10.1177/1388262720938154

Gonçalves, H. S., & Moro, S. (2023). On the economic impacts of COVID-19: A text mining literature analysis. *Review of Development Economics*, *27*(1), 375–394. https://doi.org/10.1111/rode.12931

Grafström, J., & Alm, C. (2025). Diverging or converging technology capabilities in the European Union? *The Journal of Technology Transfer*, *50*(2), 728–751. https://doi.org/10.1007/s10961-024-10070-0

Hafner, K. A. (2014). Technology spillover effects and economic integration: Evidence from integrating EU countries. *Applied Economics*, *46*(25), 3021–3036. https://doi.org/10.1080/00036846.2014.920479

Halaskova, M., Gavurova, B., & Kocisova, K. (2020). Research and development efficiency in public and private sectors: An empirical analysis of EU countries by using DEA methodology. *Sustainability*, *12*(17), Article 7050. https://doi.org/10.3390/su12177050

Harb, G., Bassil, C., & Sahli, Z. E. (2024). Club convergence in productivity among European regions: Recent evidence and policy implications. *The Journal of Economic Integration*, *39*(3), 525–556. https://doi.org/10.11130/jei.2024026

Hernández de Rojas, F., Rodríguez Pita, P., & Pérez Martínez, J. E. (2024). Assessing the European association between digitalization and innovation. *Telecommunications Policy*, *48*(7), Article 102810. https://doi.org/10.1016/j.telpol.2024.102810

Horváthová, J., & Mokrišová, M. (2024). The use of the data envelopment analysis–Malmquist approach to measure the performance of digital transformation in EU countries. *Economies*, *12*(11), Article 291. https://doi.org/10.3390/economies12110291

Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology*, *24*(6), 417–441. https://doi.org/10.1037/h0071325

Howitt, P., & Mayer-Foulkes, D. (2005). R&D, implementation, and stagnation: A Schumpeterian theory of convergence clubs. *Journal of Money, Credit and Banking*, *37*(1), 147–177. https://doi.org/10.1353/mcb.2005.0006

Hubert, M., Rousseeuw, P. J., & Vanden Branden, K. (2005). ROBPCA: A new approach to robust principal component analysis. *Technometrics*, *47*(1), 64–79. https://doi.org/10.1198/004017004000000563

Hwang, C.-L., & Yoon, K. (1981). *Multiple attribute decision making*: *Methods and applications*: *A state-of-the-art survey*. Springer-Verlag. https://doi.org/10.1007/978-3-642-48318-9_3

Islam, N. (2003). What have we learnt from the convergence debate? *Journal of Economic Surveys*, *17*(3), 309–362. https://doi.org/10.1111/1467-6419.00197

Ivanova, I., Strand, Ø., Kushnir, D., & Leydesdorff, L. (2017). Economic and technological complexity: A model study of indicators of knowledge-based innovation systems. *Technological Forecasting and Social Change*, *120*, 77–89. https://doi.org/10.1016/j.techfore.2017.04.007

Izsak, K., & Radošević, S. (2017). EU research and innovation policies as factors of convergence or divergence after the crisis. *Science and Public Policy*, *44*(2), 274–283. https://doi.org/10.1093/scipol/scw063

Karagözoğlu, B. (2017). *Science and technology from global and historical perspectives*. Springer. https://doi.org/10.1007/978-3-319-52890-8

Khayyat, N. T., & Lee, J.-D. (2015). A measure of technological capabilities for developing countries. *Technological Forecasting and Social Change*, *92*, 210–223. https://doi.org/10.1016/j.techfore.2014.09.003

Kijek, A., & Matras-Bolibok, A. (2020). Technological convergence across European regions. *Equilibrium*: *Quarterly Journal of Economics and Economic Policy*, *15*(2), 295–313. https://doi.org/10.24136/eq.2020.014

Kozera, A., & Głowicka-Wołoszyn, R. (2016). Spatial autocorrelation in assessment of financial self-sufficiency of communes of Wielkopolska province. *Statistics in Transition New Series*, *17*(3), 525–540. https://doi.org/10.59170/stattrans-2016-029

Kozera, A., Łuczak, A., & Wysocki, F. (2017). The application of classical and positional TOPSIS methods to assessment financial self-sufficiency levels in local government units. In F. Palumbo, A. Montanari, & M. Vichi (Eds.), *Data science*: *Studies in classification*, *data analysis*, *and knowledge organization* (pp. 273–284). Springer. https://doi.org/10.1007/978-3-319-55723-6_21

Kusideł, E. (2013). *Konwergencja gospodarcza w Polsce i jej znaczenie w osiąganiu celów polityki spójności* [Economic convergence in Poland and its significance for achieving cohesion policy objectives]. Wydawnictwo Uniwersytetu Łódzkiego. https://doi.org/10.18778/7525-877-6

Kusideł, E. (2014). *Zbieżność poziomu rozwoju województw Polski w kontekście kształtowania ładu instytucjonalnego* [Convergence of development levels among Polish provinces in context of institutional order]. *Optimum*. *Studia Ekonomiczne*, *3*(69), 103–117. https://doi.org/10.15290/ose.2014.03.69.07

Lee, J.-W. (2020). Convergence success and the middle-income trap. *The Developing Economies*, *58*(1), 30–62. https://doi.org/10.1111/deve.12214

Lialikava, V., Skrodzka I., & Kalinina, A. (2020). The application of selected methods of multivariate statistical analysis to study objective quality of life in Polish and Belarusian regions. *Przegląd Statystyczny*. *Statistical Review*, *67*(2), 152–173. https://doi.org/10.5604/01.3001.0014.5727

Lorenz, D., & Löffler, A. (2015). Robustness of personal rankings: The Handelsblatt example. *Business Research*, *8*, 189–212. https://doi.org/10.1007/s40685-015-0020-5

Łuczak, A., & Just, M. (2020). A complex MCDM procedure for the assessment of economic development of units at different government levels. *Mathematics*, *8*(7), Article 1067. https://doi.org/10.3390/math8071067

Malina, A., & Zeliaś, A. (1997). Taksonomiczna analiza przestrzennego zróżnicowania jakości życia ludności w Polsce w 1994 r. [A taxonomic analysis of the spatial variation in the quality of life of the population in Poland in 1994]. *Przegląd Statystyczny*, *44*(1), 11–27.

Mata, T., & Louçã, F. (2009). The Solow residual as a black box: Attempts at integrating business cycle and growth theories. *History of Political Economy*, *41*(Suppl_1), 334–355. https://doi.org/10.1215/00182702-2009-031

Matkowski, Z., Próchniak, M., & Rapacki, R. (2016). Real income convergence between Central Eastern and Western Europe: Past, present, and prospects. *Ekonomista*, *2016*(6), 853–892.

Mesthene, E. G. (1970). *Technological change*: *Its impact on man and society*. Harvard University Press.

Mitsi, D. (2023). Public debt and economic growth after Covid-19 in Europe: Challenges and policy implications. *Review of European Studies*, *15*(4), 31–43. https://doi.org/10.5539/res.v15n4p31

Młodak, A. (2006). *Analiza taksonomiczna w statystyce przestrzennej* [Taxonomic analysis in spatial statistics]. Difin.

Munda, G. (2005). "Measuring sustainability": A multi-criterion framework. *Environment*, *Development and Sustainability*, *7*, 117–134. https://doi.org/10.1007/s10668-003-4713-0

Mushafiq, M., & Prusak, B. (2023). Resource productivity and environmental degradation in EU-27 countries: Context of material footprint. *Environmental Science and Pollution Research, 30*, 58536–58552. https://doi.org/10.1007/s11356-023-26631-z

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., & Giovannini, E. (2005). *Handbook on constructing composite indicators*: *Methodology and user guide*. OECD.

Navarro Zapata, A., Arrazola, M., & de Hevia, J. (2024). Determinants of high-tech exports: New evidence from OECD countries. *Journal of the Knowledge Economy*, *15*, 1103–1117. https://doi.org/10.1007/s13132-023-01116-z

Nowak, E. (1990). *Metody taksonomiczne w klasyfikacji obiektów społeczno-gospodarczych* [Taxonomic methods in the classification of socio-economic entities]. PWE.

Organisation for Economic Co-operation and Development. (2019). *Measuring the digital transformation*: *A roadmap for the future*. OECD Publishing. https://doi.org/10.1787/9789264311992-en

Parente, S. L., & Prescott, E. C. (1999). *Barriers to riches*. University of Lausanne. https://doi.org/10.7551/mitpress/1519.001.0001

Park, K.-H. (2017). Measuring technological capability and technological catch-up process using patent data at the national level. *Journal of International Trade* & *Commerce*, *13*(1), 85–110. https://doi.org/10.16980/jitc.13.1.201702.85

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica*, *57*(6), 1361–1401. https://doi.org/10.2307/1913712

Petrova, B., & Sznajder Lee, A. (2024). The effect of European integration on economic redistribution in Central and Eastern Europe. *European Union Politics*, *25*(1), 17–41. https://doi.org/10.1177/14651165231210943

Porter, A. L., Roessner, J. D., Jin, X.-Y., & Newman, N. C. (2001). Changes in national technological competitiveness: 1990, 1993, 1996 and 1999. *Technology Analysis* & *Strategic Management*, *13*(4), 477–496. https://doi.org/10.1080/09537320127282

Próchniak, M. (2006). Realna konwergencja typu beta (β) i sigma (σ) w świetle badań empirycznych [Real beta (β) and sigma (σ) convergence. The review of empirical studies]. *International Journal of Management and Economics*, *20*, 74–91.

Protasiewicz, A. (2021). Implications of the COVID-19 crisis on the creation of innovations – assessment attempt. *Studies in Logic, Grammar and Rhetoric*, *66*(4), 483–495. https://doi.org/10.2478/slgr-2021-0027

Raghupathi, V., & Raghupathi, W. (2017). Innovation at country-level: Association between economic development and patents. *Journal of Innovation and Entrepreneurship*, *6*, Article 4. https://doi.org/10.1186/s13731-017-0065-0

Reeb, D. M., & Zhao, W. (2020). Patents do not measure innovation success. *Critical Finance Review*, *9*(1–2), 157–199. https://doi.org/10.1561/104.00000087

Rodrik, D. (2022). Prospects for global economic convergence under new technologies. In Z. Qureshi (Ed.), *An inclusive future? Technology, new dynamics, and policy challenges*. Brookings Institute.

Romer, P. M. (1986). Increasing returns and long-run growth. *The Journal of Political Economy*, *94*(5), 1002–1037. https://doi.org/10.1086/261420

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102. https://doi.org/10.1086/261725

Rose, A., Chen, Z., & Wei, D. (2023). The economic impacts of Russia–Ukraine War export disruptions of grain commodities. *Applied Economic Perspectives and Policy*, *45*(2), 645–665. https://doi.org/10.1002/aepp.13351

Sala-i-Martin, X. X. (1996). The classical approach to convergence analysis. *The Economic Journal*, *106*(437), 1019–1036. https://doi.org/10.2307/2235375

Șerban, A. C., Aceleanu, M. I., Dospinescu, A. S., Țîrcă, D.-M., & Novo-Corti, I. (2020). The impact of EU immigration on economic growth through the skill composition channel. *Technological and Economic Development of Economy*, *26*(2), 479–503. https://doi.org/10.3846/tede.2020.11954

Sheng, Y. (2025). Technological change, capital deepening, and agricultural Total Factor Productivity (TFP) growth: Cross-country comparison of 18 OECD countries. *Applied Economic Perspectives and Policy*, *47*(5), 1848–1868. https://doi.org/10.1002/aepp.13535

Sokołowski, A. (1985). Wybrane zagadnienia pomiaru i ważenia cech w taksonomii [Selected issues relating to the measurement and weighing of traits in taxonomy]. *Zeszyty Naukowe / Akademia Ekonomiczna w Krakowie*, *203*, 41–53.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, *39*(3), 312–320. https://doi.org/10.2307/1926047

Steele, L. W. (1989). *Managing technology*: *The strategic view*. McGraw-Hill Book.

Strielkowski, W., & Höschle, F. (2016). Evidence for economic convergence in the EU: The analysis of past EU enlargements. *Technological and Economic Development of Economy*, *22*(4), 617–630. https://doi.org/10.3846/20294913.2014.890138

Sunge, R., Mudzingiri, C., & Mkhize, N. (2024). The COVID-19 pandemic and economic recovery: The mediating role of governance, a global perspective. *Heliyon*, *10*(22), Article e39869. https://doi.org/10.1016/j.heliyon.2024.e39869

Szczepańska-Woszczyna, K., Gedvilaitė, D., Nazarko, J., Stasiukynas, A., & Rubina, A. (2022). Assessment of economic convergence among countries in the European Union. *Technological and Economic Development of Economy*, *28*(5), 1572–1588. https://doi.org/10.3846/tede.2022.17518

Tong, E. (2024). Repercussions of the Russia–Ukraine war. *International Review of Economics & Finance*, *89*, 366–390. https://doi.org/10.1016/j.iref.2023.07.064

Torkkeli, M., & Tuominen, M. (2002). The contribution of technology selection to core competencies. *International Journal of Production Economics*, *77*(3), 271–284. https://doi.org/10.1016/S0925-5273(01)00227-4

Trott, P. (2012). *Innovation management and new product development*. Pearson. https://doi.org/10.69645/SAEF4278

Tsiapa, M. (2023). A holistic approach of the labour productivity slowdown in the regions of the European Union. *Papers in Regional Science*, *102*(3), 507–532. https://doi.org/10.1111/pirs.12734

Tutak, M., & Brodny, J. (2024). Technological progress in central and eastern Europe: Digitalization and business innovation leaders and outsiders. *Journal of Open Innovation*: *Technology*, *Market*, *and Complexity*, *10*(4), Article 100404. https://doi.org/10.1016/j.joitmc.2024.100404

Witkowski, B., & Próchniak, M. (2014). The legendary 2% convergence parameter: Flexible or fixed? *Collegium of Economic Analysis Annals*, *34*, 227–243.

Young, A. T., Higgins, M. J., & Levy, D. (2008). Sigma Convergence versus Beta Convergence: Evidence from U.S. county-level data. *Journal of Money*, *Credit and Banking*, *40*, 1083–1093. https://doi.org/10.1111/j.1538-4616.2008.00148.x

Zeleny, M. (1986). High technology management. *Human Systems Management*, *6*(2), 109–120. https://doi.org/10.3233/HSM-1986-6203

Zeng, S., Li, W., & Merigo, J. M. (2013). Extended induced ordered weighted averaging distance operators and their application to group decision-making. *International Journal of Information Technology* & *Decision Making*, *12*(4), 789–811. https://doi.org/10.1142/S0219622013500296

Žižmond, E., & Novak, M. (2007). Controversies of technology convergence within the European Union. *Industrial Management* & *Data Systems*, *107*(5), 618–635. https://doi.org/10.1108/02635570710750390