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LABOUR MARKET CHARACTERISTICS AGAINST THE BACKDROP OF SOCIO-ECONOMIC PHENOMENA IN POLAND IN 2008-2023

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Purpose: The aim of this study is to identify and assess the diversity, strength and direction of relationships between key labour market characteristics and selected socio-economic areas.
Design/methodology/approach: The study was conducted on statistical data for 16 voivodeships of Poland from 2008 to 2023. Multi-criteria assessments for selected socio-economic areas were obtained using the TOPSIS method, followed by correlation analysis to determine the interdependence with the considered labour market characteristics.
Findings: The results indicate the existence of relationships between the dynamics of labour market characteristics and multi-criteria assessments for the analysed areas, as well as their regional diversity.
Research limitations/implications: The limitation of the study is the dependence of the results on the quality and availability of statistical data. The results obtained may serve as a starting point for further comparative studies and long-term analyses.
Practical implications: The study is the basis for designing activities to support the sustainable economic and social development of voivodeships.
Originality/value: The originality of the research lies in the combination of the TOPSIS method with correlation analysis in relation to Polish voivodeships, which allows for a comprehensive assessment of the relationships between key socio-economic phenomena and labour market characteristics.
Keywords: labour market, TOPSIS, multi-criteria analysis, socio-economic phenomena.
Category of the paper: Research paper.

1. Introduction

The labour market is a fundamental element of the economy, determining its efficient functioning and supporting stable and sustainable development. The literature on the subject contains numerous theories and approaches explaining the mechanisms and processes occurring in this market, pointing to its complex and multidimensional nature (Zieliński, 2023).

Demographic factors, including low birth rates, ageing populations and integration processes between countries, have a significant impact on the labour market. Social and economic migration and the impact of the COVID-19 pandemic are also important factors (Gajdos, Lewandowska-Gwarda, 2022; Mrugała, Kowalska, Kilichowski, 2024). The rapidly advancing processes of digitalisation and the popularisation of artificial intelligence applications in various spheres of social and economic life are also playing an increasingly important role (Górniak, Jelonek, 2023; Hollanders, 2023; Huseynov, 2023; World Economic Forum, 2023). These factors can both stimulate the development of the labour market and pose threats to its proper functioning. Mainly they are the result of civilisational and economic changes. This makes it necessary to conduct an in-depth analysis of the relationships between the labour market and important socio-economic areas.

The aim of this study is to identify and assess the diversity, strength and direction of correlations between labour market characteristics (average employment, unemployment rate, long-term unemployment, net number of workplaces) and selected socio-economic areas (Demographics, Economy, Innovations and R&D). The analysed areas are represented by multi-criteria assessments, determined using the TOPSIS method, considering the division into Polish voivodeships for data covering the years 2008-2023. The results of the research may serve as a basis for further comparative analyses and for formulating recommendations for labour market policy in the context of socio-economic phenomena, as well as for designing activities to support the sustainable development of voivodeships.

2. Research methodology

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is one of the multi-criteria decision support methods developed by Hwang and Yoon (Hwang, Yoon, 1981). It is used for the alternatives' evaluation when the simultaneous consideration of multiple criteria is required, often of a conflicting nature (Pośpiech, 2021; Roszkowska, Wachowicz, 2024). Its essence lies in the assumption that the best alternative should be both as close as possible to the positive ideal solution PIS (a hypothetical alternative with the best values for all criteria) and as far as possible from the negative ideal solution NIS (the alternative with the worst values). The procedure for determining multi-criteria rankings using the TOPSIS method has been extensively discussed in the literature (Hwang, Yoon, 1981; Lai, Liu, Hwang, 1994; Roszkowska, Wachowicz, 2013; Trzaskalik, 2014).

The TOPSIS procedure involves the following steps:

Step 1. Construct a decision matrix containing the values of criteria $C_1, C_2, \ldots, C_n$ for the evaluated alternatives $A_1, A_2, \ldots, A_m$:

$$\boldsymbol{X} = [x_{ik}] \tag{1}$$

where x_{ik} is the value of the k-th criterion for the i-th alternative for $i = 1, 2, \ldots, m$ and $k = 1, 2, \ldots, n$.

Step 2. Normalise data to enable comparison when criteria have different scales:

- for stimulants

$$z_{ik} = \frac{x_{ik} - \min\limits_{1 \le i \le m} \{x_{ik}\}}{\max\limits_{1 \le i \le m} \{x_{ik}\} - \min\limits_{1 \le i \le m} \{x_{ik}\}} \tag{2}$$

- for destimulants

$$z_{ik} = \frac{\max\limits_{1 \le i \le m} \{x_{ik}\} - x_{ik}}{\max\limits_{1 \le i \le m} \{x_{ik}\} - \min\limits_{1 \le i \le m} \{x_{ik}\}} \tag{3}$$

for $i = 1, 2, \ldots, m$ and $k = 1, 2, \ldots, n$.

Step 3. Determine the weights of criteria reflecting their importance:

$$w = [w_1, w_2, \ldots, w_n] \tag{4}$$

where:

w_k denotes the weight of the k-th criterion for $k = 1, 2, \ldots, n$ and $\sum_{k=1}^{n} w_k = 1$.

Step 4. Calculate the weighted normalised matrix:

$$\boldsymbol{V} = [v_{ik}] \tag{5}$$

where $v_{ik} = w_k \cdot z_{ik}$ for $i = 1, 2, \ldots, m$ and $k = 1, 2, \ldots, n$.

Step 5. Construct the weighted reference points PIS (positive ideal solution) $\boldsymbol{v}^+ = [v_1^+, v_2^+, \ldots, v_m^+]$ and NIS (negative ideal solution) $\boldsymbol{v}^- = [v_1^-, v_2^-, \ldots, v_m^-]$ based on the formulas:

$$v_k^+ = \max_{1 \le i \le m} \{v_{ik}\} \tag{6}$$

and

$$v_k^- = \min_{1 \le i \le m} \{v_{ik}\} \tag{7}$$

for $k = 1, 2, \ldots, n$.

Step 6. Calculate the distance of each alternative form the weighted reference points PIS and NIS (usually using the Euclidean matric):

$$d_i^+ = \sqrt{\sum_{k=1}^{n} (v_{ik} - v_k^+)^2} \tag{8}$$

and

$$d_i^- = \sqrt{\sum_{k=1}^{n} (v_{ik} - v_k^-)^2} \tag{9}$$

for $i = 1, 2, \ldots, m$.

Step 7. Determine the value of multi-criteria measure:

$$R_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{10}$$

for $i = 1, 2, \ldots, m$.

The values R_i obtained based on the procedure are the starting point for determining the final ranking of alternatives. This measure takes values from the range [0, 1], with a higher value indicating a higher position in the ranking.

3. Results and Discussion

3.1. Selection of diagnostic variable

In this research the alternatives assessed are the voivodeships of Poland. Due to the purpose of the research, diagnostic variables that characterise the labour market and variables that represent various socio-economic categories were selected (Grajewska, 2013; Malina, 2020; Roszkowska, Karwowska, 2014; Sokołowska, Filipowicz-Chomko, 2015). The set of diagnostic variables are divided into the following four areas: Area I – Labour Market, Area II – Demographics, Area III – Economy, Area IV – Innovations and R&D.

Considering the availability of data, 40 diagnostic variables were considered, of which, for substantive, formal and statistical reasons – universality, comparability, appropriate variation[1] (Młodak, 2006; Gdakowicz, Hozer-Koćmiel, Markowicz, 2023), a set of 23 characteristics was ultimately selected (Table 1).

Table 1.
Set of diagnostic variables

Areas	Diagnostic variables	
Area I – Labour Market	1.1	Average employment per 1000 inhabitants
	1.2	Registered unemployment rate
	1.3	Registered unemployed persons out of job for longer than 1 year per 1000 inhabitants
	1.4	Net number of workplaces per 10,000 inhabitants
Area II – Demographics	2.1	Natural increase per 1000 inhabitants
	2.2	Working-age registrations for permanent residence per 1000 inhabitants
	2.3	Working-age registrations of departure per 1000 inhabitants
Area III – Economy	3.1	Average monthly gross wages
	3.2	Sold production of industry per capita (entities with >9 employees)
	3.3	Investment outlays in enterprises per capita
	3.4	Investment outlays per capita
	3.5	GDP per capita
	3.6	State budget revenue from personal income tax (PIT) per capita
	3.7	State budget revenue from corporate income tax (CIT) per capita
	3.8	Entities entered in the REGON register per 10,000 inhabitants
	3.9	New-registered entities in the REGON register per 10,000 inhabitants
	3.10	Entities unregistered from the REGON register per 10,000 inhabitants
Area IV – Innovations and R&D	4.1	Intramural expenditure on R&D per capita
	4.2	Intramural expenditure on R&D as a percentage of GPD (current prices)
	4.3	Average employment in section J of the NACE rev2 classification per 1000 inhabitants
	4.4	Share of net income from the sale of products in entities classified to high and medium-high technology in net income from the sale of products in entities classified in the Manufacturing section
	4.5	Entities engaged in R&D per 100,000 inhabitants
	4.6	Entities engaged in R&D per 100,000 entities of the national economy

Source: Own research.

[1] Variables for which the coefficient of variation did not exceed 10% were eliminated (for variable 3.1, in 2019-2023, this coefficient ranged between 9-10%, but for substantive reasons, this variable was included in the study).

The variables included in the first area (Labour Market) were treated as separate characteristics against which the multi-criteria assessments obtained for the other three areas were compared. The multi-criteria TOPSIS method was used, so an important element of the research was to identify stimulants and destimulants among the diagnostic variables (selection criteria). Considering substantive requirements, it was determined that variables 2.3 and 3.10 are destimulants, while the remaining variables from areas II-IV are stimulants. Each of the criteria was considered equally important, so they were given the same weight. Furthermore, to enable comparison of values, the same (global) positive and negative ideal solutions were adopted for all years. The research period covered the years 2008-2023.

3.2. Presentation of selected Labour Market characteristics

Four characteristics were selected for the analysis of the Labour Market (Table 1). In addition to one of the most frequently studied variables, namely the unemployment rate (1.2), a variable describing average employment (1.1) and a variable representing long-term unemployment (1.3) were also included. In addition, a less typical characteristic was added to the group of variables, showing the dynamics of net number of workplaces (1.4).

The values of the first variable – average employment (1.1) – is shown in Figure 1.

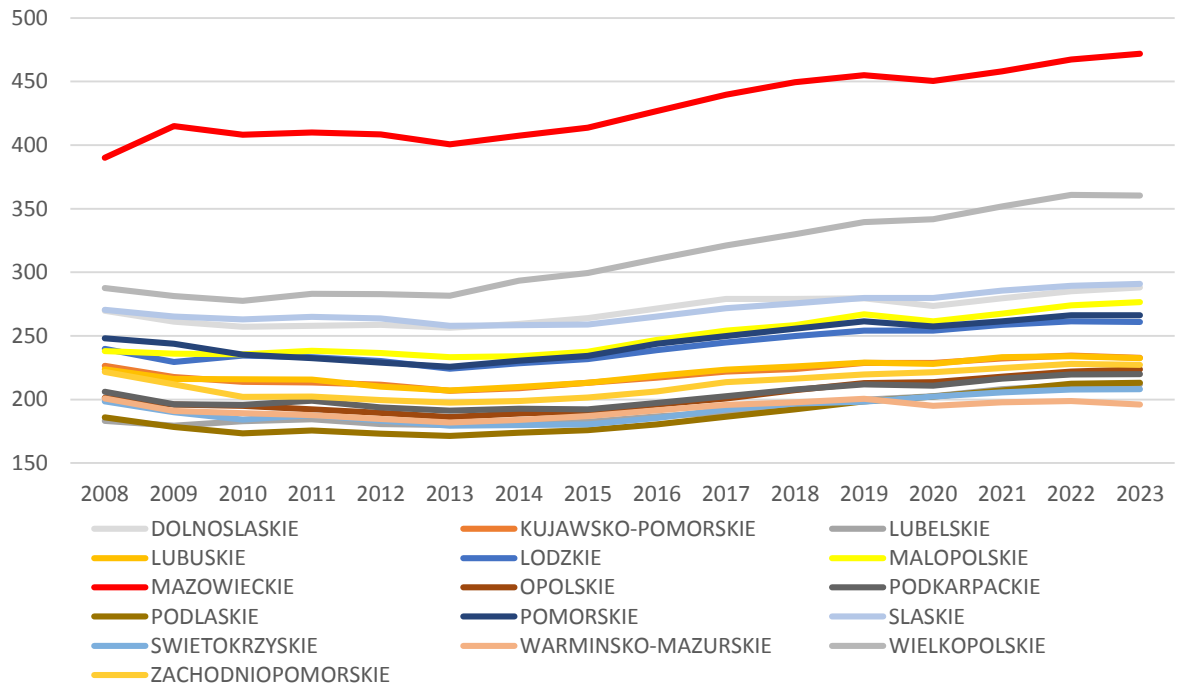

Figure 1. Values of variable 1.1 – Average employment per 1,000 inhabitants.

Source: Own research.

The highest average employment per 1000 inhabitants, significantly higher than in other voivodeships, was recorded in Mazowieckie[2]. Throughout almost the entire period, the figures did not fall below 400 people per 1000 inhabitants. Since 2013, there has been a noticeable upward trend, with a slight slowdown in 2020 (the beginning of the coronavirus pandemic). Next in the ranking was the Wielkopolskie Voivodeship – a similar trend to that in the Capital Voivodeship (Mazowieckie), but with values ranging between 277 and 368 persons per 1000 inhabitants. The next two voivodeships, with similar average employment levels, were Dolnoslaskie and Slaskie. Here, the values ranged between 256 and 290 employees per 1000 inhabitants. The next voivodeships in the ranking are Lodzkie, Malopolskie and Pomorskie – the values ranged between 224 and 276. The voivodeships with the lowest number of people employed per 1000 inhabitants, between 171 and 213, are Podlaskie, Swietokrzyskie and Warminsko-Mazurskie. The above-mentioned trend – growing since 2013 with a slowdown in 2020 – continued in almost every voivodeship.

The second of the Labour Market variables, the registered unemployment rate, took on the values shown in Figure 2.

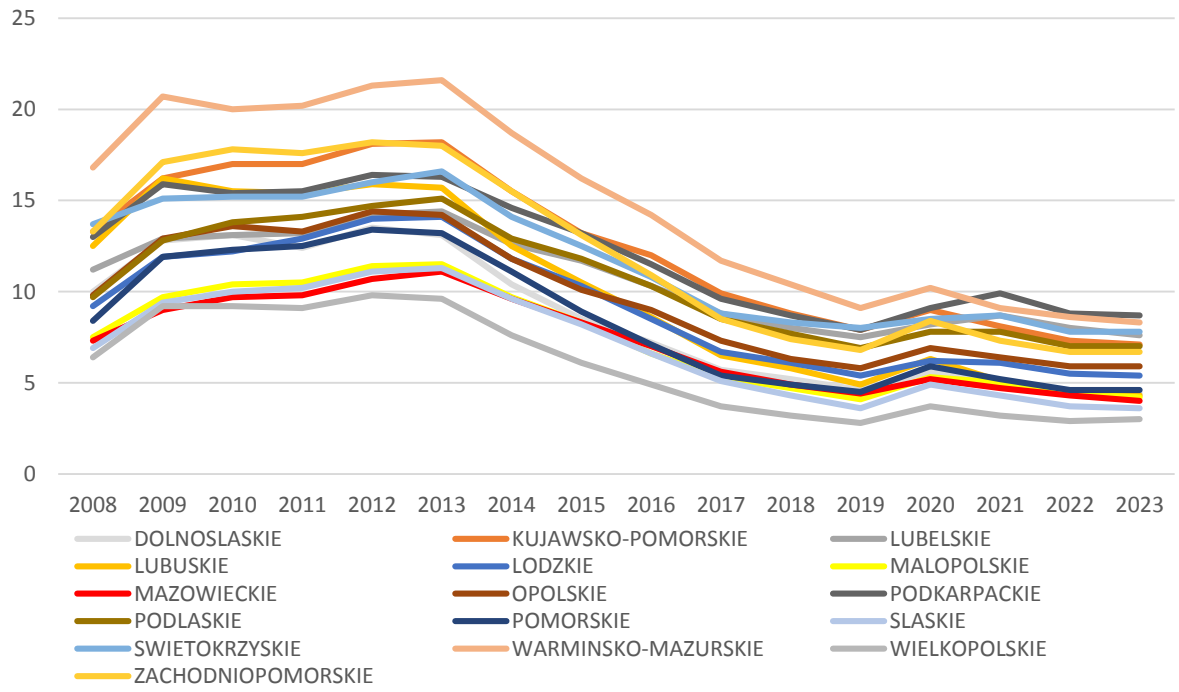

Figure 2. Values of variable 1.2 – Registered unemployment rate.

Source: Own research.

Figure 2 shows a certain pattern – an increase in registered unemployment in 2008-2013, followed by a decline until 2019, a renewed increase in 2020 or 2021 caused by the outbreak of the pandemic, and a slow decline until the end of the period under review. The highest values

[2] This is justified given that it is the capital voivodeship. It would be reasonable to exclude the capital city of Warsaw from the Mazowieckie voivodeship and conduct an analysis taking these two areas separately, but due to the unavailability of some data, no such division was made in the study.

throughout almost the entire period were recorded in the Warminsko-Mazurskie Voivodeship – in 2009-2013 they exceeded 20%. During the same period, in five voivodeships: Kujawsko-Pomorskie, Lubuskie, Podkarpackie, Swietokrzyskie and Zachodniopomorskie, the registered unemployment rate was over 15%. In turn, the lowest unemployment rate was recorded in the Wielkopolskie Voivodeship – it did not exceed 10% throughout the entire period, and since 2016 it has been below 5%. Other voivodeships with the lowest unemployment rates were: Malopolskie, Mazowieckie and Slaskie. In 2023, unemployment rates fluctuated between 3% and 9%.

The levels of the variable describing long-term unemployment (1.3) are shown in Figure 3.

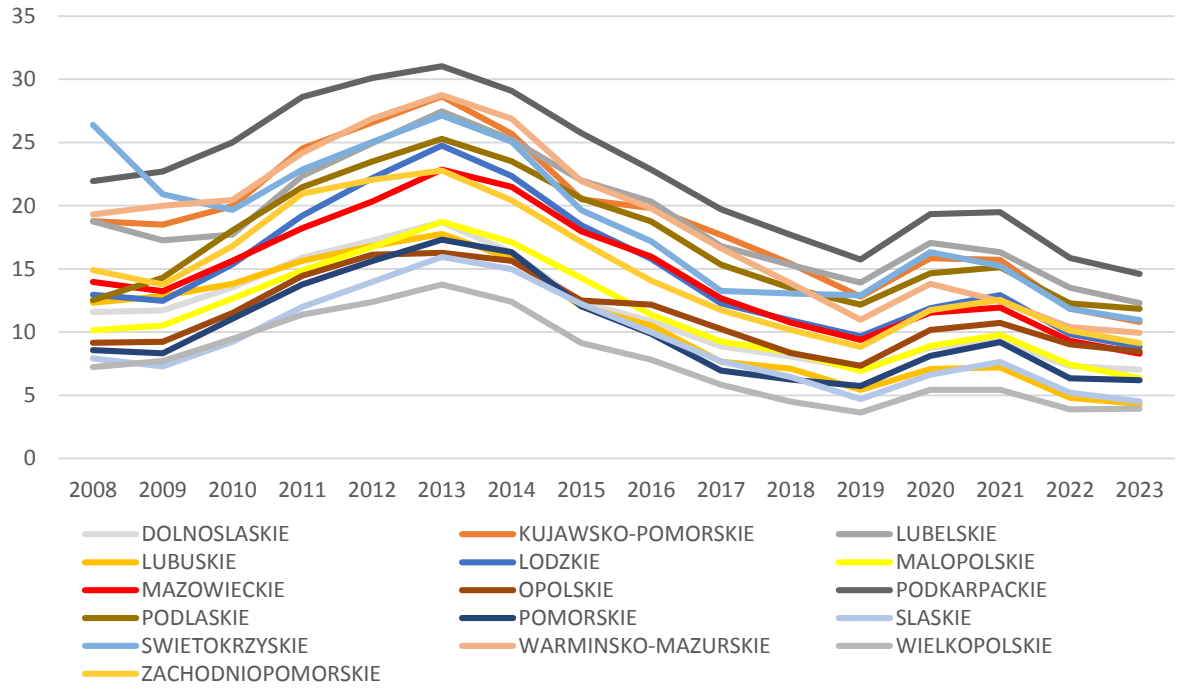

Figure 3. Values of variable 1.3 – Registered unemployed persons out of job for longer than 1 year per 1000 inhabitants.

Source: Own research.

The behaviour of this variable is analogous to that of the variable representing the registered unemployment rate. In almost every voivodeship, the number of long-term unemployed per 1000 inhabitants increased until 2013, then decreased until 2019, followed by another increase (2020-2021) and another decrease. The voivodeships with the highest levels of this variable are Podkarpackie (in 2008-2016 it did not fall below 20 people per 1,000 inhabitants), followed by Kujawsko-Pomorskie, Lubelskie, Swietokrzyskie and Warminsko-Mazurskie. The voivodeships with the lowest values for this variable are: Wielkopolskie, Slaskie, Pomorskie, Opolskie, Malopolskie, Lubuskie and Dolnoslaskie. In the last year considered (2023), the number of people unemployed for more than a year fluctuated between 4 and 15 persons per 1000 inhabitants.

The fourth variable considered – the net number of workplaces per 10,000 inhabitants – is presented in Figure 4.

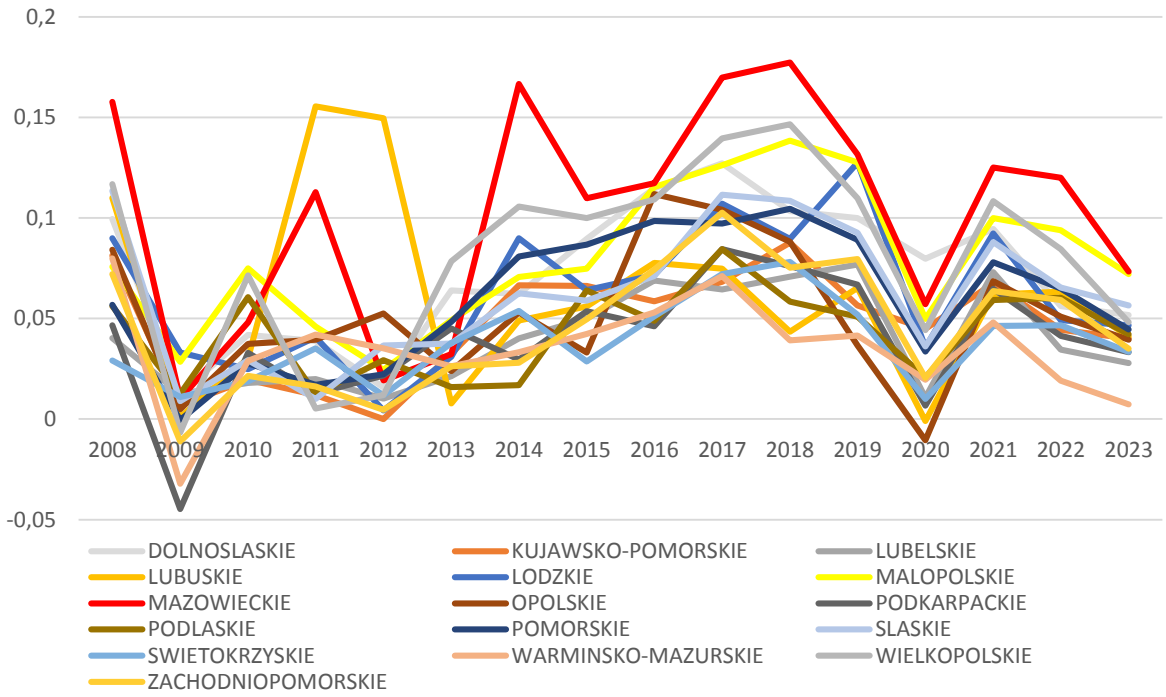

Figure 4. Values of variable 1.4 – Net number of workplaces per 10,000 inhabitants.
Source: Own research.

The net number of workplaces per 10,000 inhabitants over the period under review shows the dynamics of changes in the difference between newly created and liquidated workplaces. This variable is important because it represents the potential for hiring employees. It is characterised by high volatility in the period under review. However, it can be seen that, except for 2009 and 2020 which were strongly affected first by the global economic crisis and then by the onset of the coronavirus pandemic, the balance is positive. The highest values of this variable, especially after 2013, were recorded in the voivodeships of Mazowieckie, Wielkopolskie, Malopolskie and Dolnoslaskie, while the lowest values were observed in the voivodeships of Warminsko-Mazurskie, Podlaskie and Swietokrzyskie, among others. There is also a visible decline in the value of the variable after 2021, which may have been caused by the situation of employers or enterprises during and after the pandemic.

3.3. Assessment of voivodeships for the studied areas and their connections with the characteristics of the Labour Market

The voivodeships were assessed based on multi-criteria TOPSIS indicators obtained for each of the areas under consideration: Area II (Demographics), Area III (Economy), and Area IV (Innovations and R&D). The set of criteria in each area corresponds to the set of variables listed in Table 1. The values of the TOPSIS assessment for Area II – Demographics are shown in Figure 5.

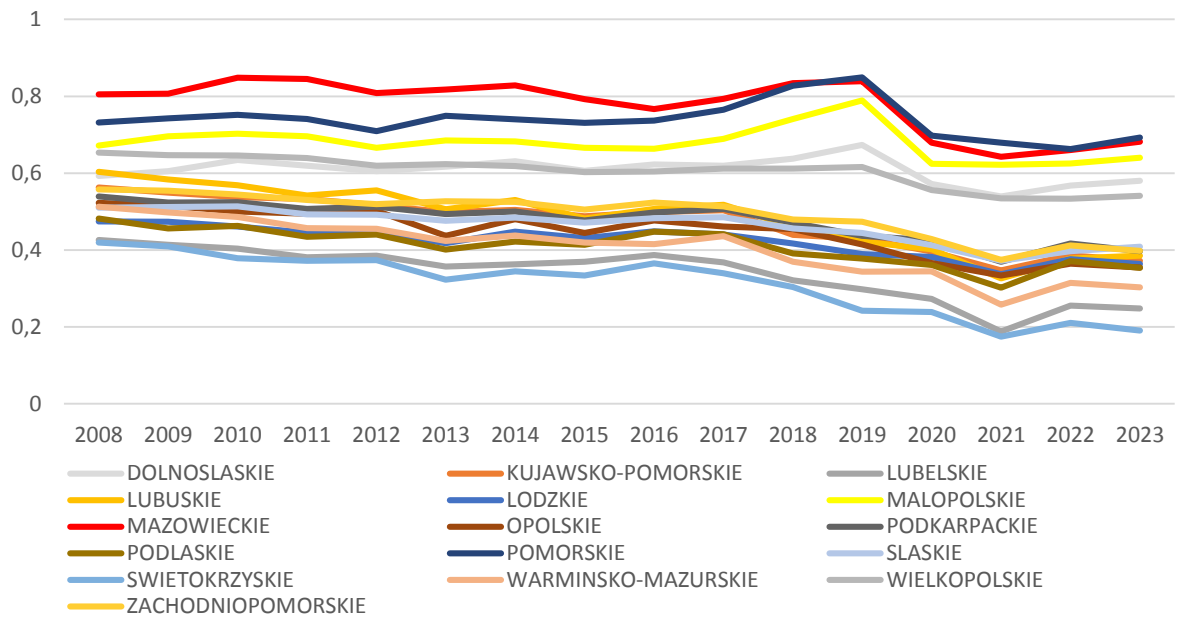

Figure 5. TOPSIS values for Area II (Demographics).

Source: Own research.

Throughout the period, the highest-ranked voivodeships maintained similar scores for this area, while for the remaining voivodeships a slight decrease was observed. The Mazowieckie Voivodeship was closest to the PIS and furthest from the NIS, followed by the Pomorskie, Malopolskie, Dolnoslaskie, and Wielkopolskie voivodeships. These voivodeships, therefore, performed best in the Demographics category. The Swietokrzyskie and Lubelskie voivodeships, on the other hand, were rated least favourably in this area. In each voivodeship, a significant decline in the values was noticeable after 2019, reflecting the "collapse" in the area caused by the COVID-19. This indicator's value did not increase until 2022.

Figure 6 shows the intensity of the indicator values describing the Demographics area in selected years: 2008 – the beginning of the period under study and the peak year of the global crisis; 2013 – the year in which turning points for many diagnostic variables were observed; 2020 – the beginning of the COVID-19 pandemic; and 2023 – the final year of the period under study. The darker the colour, the higher the value of the multi-criteria indicator and the higher the rating of the given voivodeship within the area under consideration. Because the ratings for the entire period under study were standardized, it is reasonable to compare the results of the analyses over time.

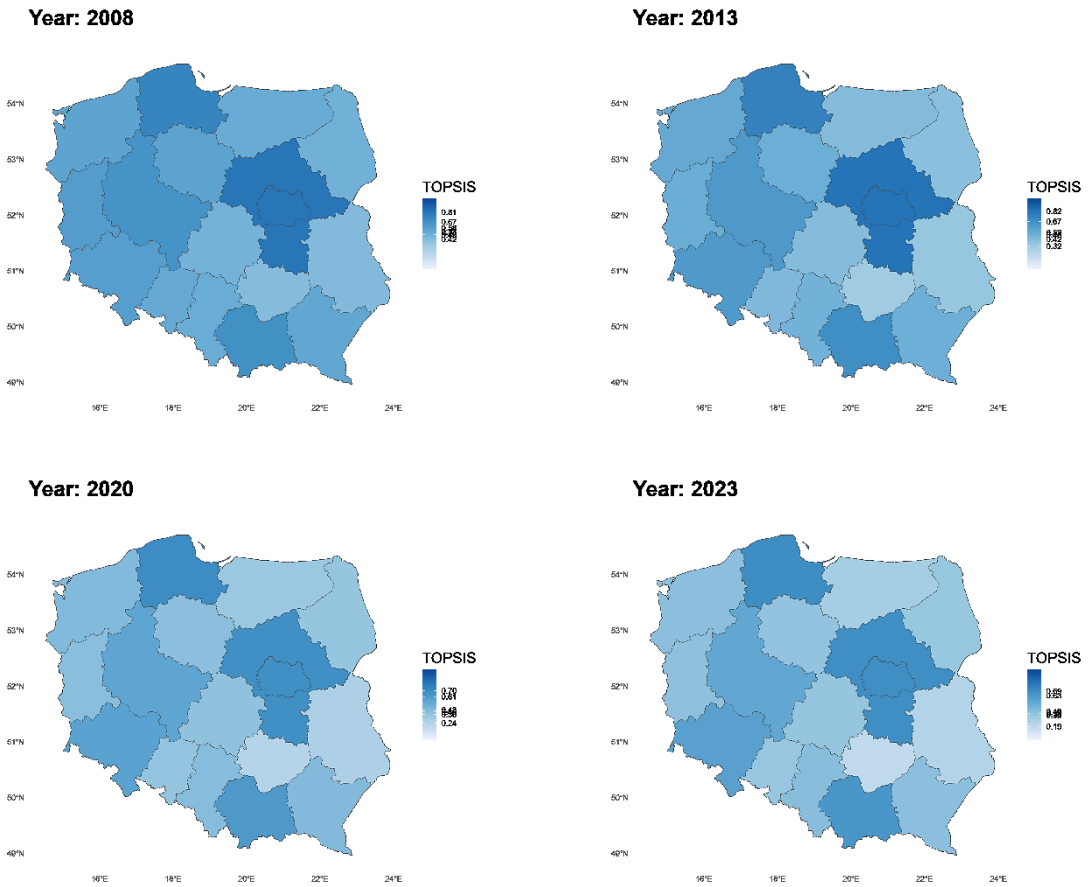

Figure 6. Intensity of the multi-criteria indicator value for Area II (Demographics).
Source: Own research.

At the beginning of the period, differences were noticeable between the Mazowieckie Voivodeship and most of the other voivodeships (the Pomorskie and Malopolskie voivodeships recorded the most similar multi-criteria values to the Mazowieckie Voivodeship). Over the years, the values have continued to diversify in favour of the Mazowieckie Voivodeship, but these differences are greater in the voivodeships located primarily in the eastern and northeastern regions, but also in comparison to some voivodeships in central and western Poland. In the final year of the period under review, the Malopolskie, Pomorskie, and Dolnoslaskie voivodeships achieved increasingly similar multi-criteria values to those for the Mazowieckie Voivodeship, demonstrating positive demographic changes in these regions. The differences in index values for the remaining voivodeships compared to the leaders are greater. Therefore, in the Demographics area, unfavourable changes are observed in the above-mentioned voivodeships of eastern, western, and central Poland.

Pearson's linear correlation coefficient[3] was used to compare the obtained multi-criteria scores with the values of labour market variables. The following table was obtained (Table 2).

Table 2.
Correlation of multi-criteria assessments of Area II (Demographics) with variables from the Labour Market area

Year	Pearson correlation coefficients for Area II with the given variable			
	1.1	1.2	1.3	1.4
2008	0,770	-0,486	-0,485	0,610
2009	0,776	-0,453	-0,482	0,047
2010	0,786	-0,484	-0,420	0,488
2011	0,785	-0,515	-0,469	0,311
2012	0,782	-0,515	-0,498	0,047
2013	0,767	-0,536	-0,464	0,475
2014	0,784	-0,543	-0,473	0,712
2015	0,782	-0,616	-0,453	0,855
2016	0,761	-0,648	-0,510	0,763
2017	0,751	-0,624	-0,471	0,733
2018	0,737	-0,672	-0,525	0,764
2019	0,723	-0,674	-0,519	0,672
2020	0,711	-0,647	-0,553	0,657
2021	0,701	-0,694	-0,503	0,751
2022	0,707	-0,667	-0,484	0,753
2023	0,717	-0,703	-0,523	0,724

Source: Own research.

The correlation between average employment per 1000 inhabitants (variable 1.1) and the multi-criteria assessment of the Demographics area is strong, which is justified. This indicates that demographic conditions have a strong relationship with average employment. Variable 1.2 – the unemployment rate – is negatively correlated with the variable representing the Demographics area, weaker at the beginning of the period, but increasingly stronger over the years. This relationship seems justified – the higher the level of the indicator in the Demographics area, the lower the unemployment rate. Like the registered unemployment rate, long-term unemployment (variable 1.3) is negatively correlated with the multi-criteria assessment of the Demographics area. However, a slightly weaker correlation (at a moderate level) is visible compared to the registered unemployment rate, indicating that demographic factors are less strongly correlated with being unemployed for more than a year, and this area has a smaller impact on long-term unemployment. Assessing the correlation between the variable representing the net number of workplaces per 10,000 inhabitants (variable 1.4) and the study area, it can be observed that the correlation is rather low (positive) or moderate in the years 2008-2013. A stronger correlation for variable 1.4 (ranging between 0.657 and 0.855) is observed in the period 2014-2023. Reasons for this may include the fact that employees are currently more inclined to move between voivodeships for work.

[3] For the absolute values of the Pearson correlation coefficient, the following interpretations were adopted: [0; 0.2) – very weak linear relationship, [0.2; 0.4) – weak linear relationship, [0.4; 0.7) – moderate linear relationship, [0.7; 1] – strong linear relationship (Ostasiewicz, Rusnak, Siedlecka, 1998).

The next area under consideration is Area III – Economy. The multi-criteria assessment levels obtained after applying the TOPSIS method are presented in Figure 7.

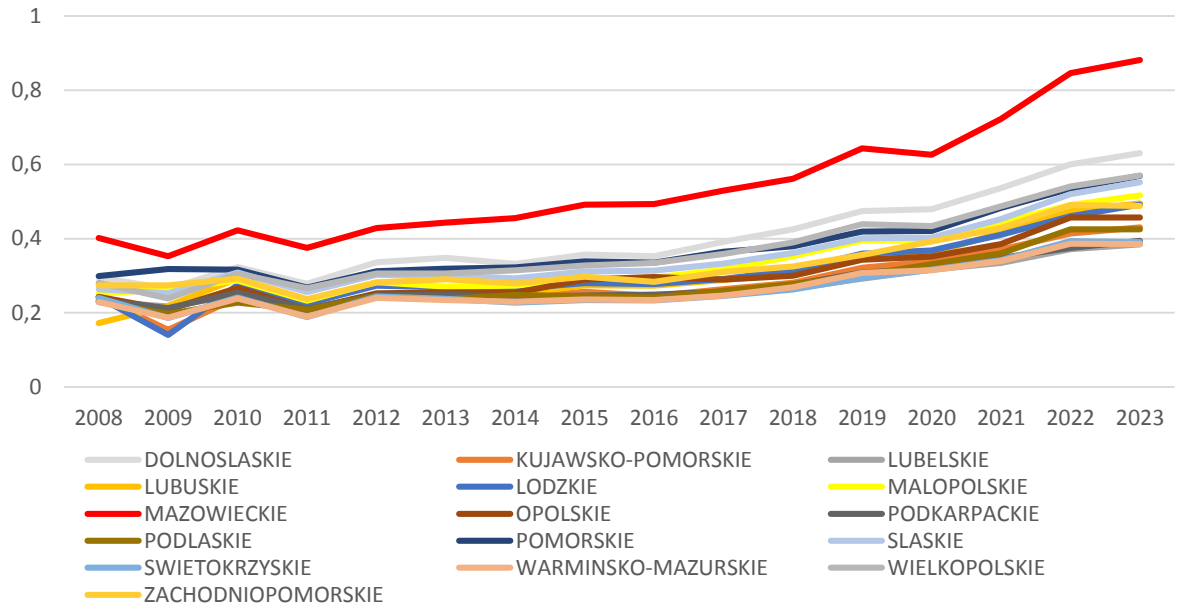

Figure 7. TOPSIS values for Area III (Economy).

Source: Own research.

The trend for all voivodeships is upward, so the multi-criteria assessment characterizing the Economy area is achieving increasingly higher values year by year. This is a positive sign, demonstrating the study area as a developing one. The highest scores, significantly outperforming the others, were achieved by the Mazowieckie Voivodeship. The next highest-scoring voivodeships were Dolnoslaskie, Wielkopolskie, Pomorskie, and Slaskie. Among the voivodeships with the lowest multi-criteria assessments were the Warminsko-Mazurskie, Podkarpackie, Swietokrzyskie, and Kujawsko-Pomorskie voivodeships.

Additionally, the evolution of the multi-criteria indicator value for Area III is presented on maps (Figure 8). Due to the upward trend in the multi-criteria assessment describing the Economy area in each voivodeship, especially in the two years specified at the end of the period (2020 and 2023), darker colours are visible, suggesting that the level of assessments within this area has significantly increased. The greatest differences are visible in 2023, when the Mazowieckie Voivodeship achieved very high values of the multi-criteria measure, while the remaining voivodeships, also despite noticeable increases, significantly differ from the level of the Mazowieckie Voivodeship.

The correlation of multi-criteria assessments of Area III with the Labour Market variables is presented in Table 3.

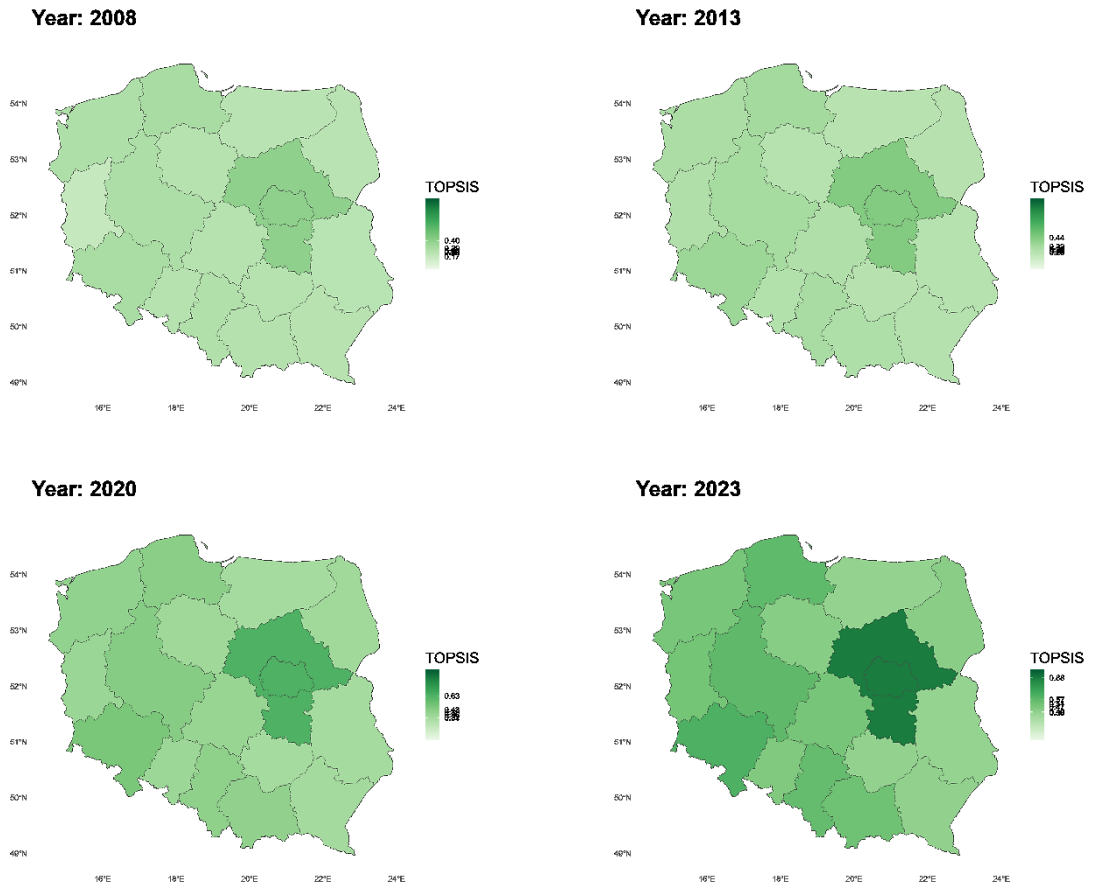

Figure 8. Intensity of the multi-criteria indicator value for Area III (Economy).

Source: Own research.

Table 3.

Correlation of multi-criteria assessments of Area III (Economy) with variables from the Labour Market area

Year	Pearson correlation coefficients for Area III with the given variable			
	1.1	**1.2**	**1.3**	**1.4**
2008	0,849	-0,498	-0,236	0,517
2009	0,692	-0,462	-0,457	-0,015
2010	0,937	-0,579	-0,482	0,255
2011	0,951	-0,624	-0,460	0,343
2012	0,947	-0,605	-0,475	-0,043
2013	0,932	-0,575	-0,405	0,346
2014	0,943	-0,598	-0,390	0,831
2015	0,938	-0,637	-0,430	0,784
2016	0,945	-0,660	-0,457	0,755
2017	0,946	-0,663	-0,465	0,886
2018	0,953	-0,687	-0,497	0,831
2019	0,957	-0,676	-0,484	0,705
2020	0,934	-0,659	-0,481	0,674
2021	0,933	-0,704	-0,469	0,829
2022	0,923	-0,670	-0,459	0,830
2023	0,938	-0,723	-0,500	0,754

Source: Own research.

Average employment per 1000 inhabitants (variable 1.1) is very strongly correlated with the multi-criteria assessment of the Economy area. This relationship is justified – increased employment stimulates the economy and its determinants. The correlation between the assessments for the considered area and the registered unemployment rate (variable 1.2) is negative – at the beginning of the period, this relationship is weaker (moderate), and it becomes increasingly stronger over the years. Again, this relationship is justified – lower unemployment and economic growth are interrelated. The correlation between the economic area assessment and the variable representing long-term unemployment (variable 1.3) is also negative, but weaker than that of the registered unemployment rate – it is stronger in the second part of the period under review than at the beginning. This observation again indicates that being unemployed for more than a year has a negative impact on the economy but is less strongly correlated with the area under review than the unemployment rate. The last of the considered variables from the Labour market area (variable 1.4) in the second part of the analysed period is strongly, positively correlated with the Economy area – this strong relationship has been observed since 2014. A larger number of newly created workplaces stimulates the development of the economy, and at the same time, a developing economy generates new workplaces.

The last area considered is Area IV – Innovations and R&D. The multi-criteria assessment values obtained using the TOPSIS method for this area are presented in Figure 9.

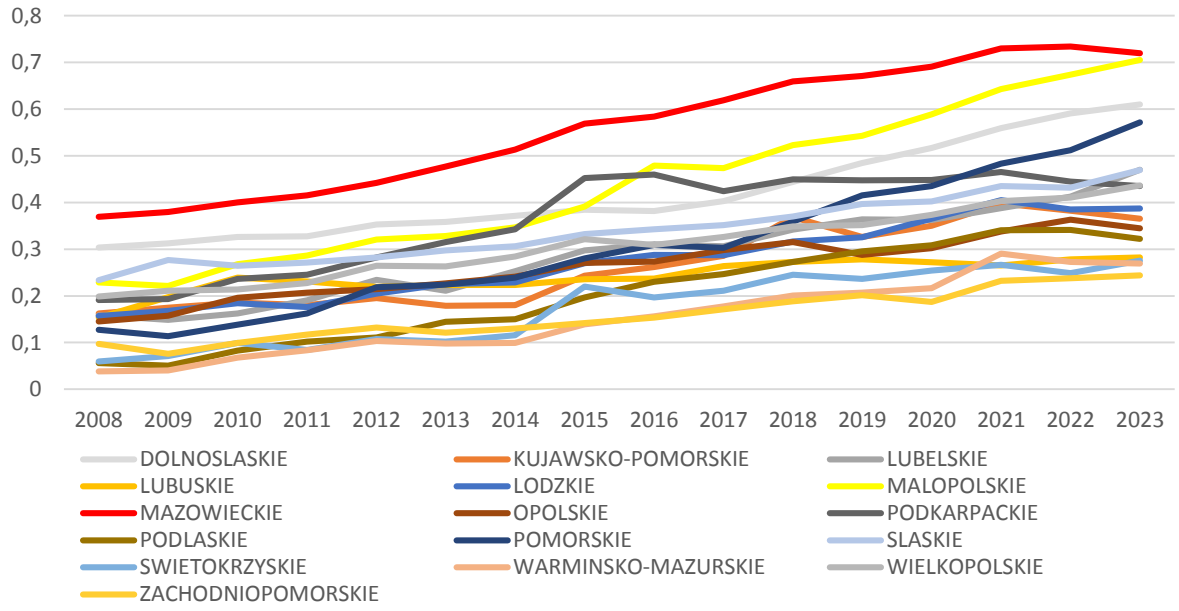

Figure 9. TOPSIS values for Area IV (Innovations and R&D).

Source: Own research.

In the case of the variable describing the area of Innovations and R&D, an upward trend is visible (although with varying intensity). Over the years, this area has played an increasingly important role in shaping many socio-economic phenomena. The highest values were again recorded for the Mazowieckie Voivodeship, with the multi-criteria assessments significantly exceeding those for the other voivodeships. The next voivodeships to rank high were the

Malopolskie Voivodeship, which almost equalled the Mazowieckie Voivodeship in 2023, and then the Dolnoslaskie Voivodeship. Interestingly, the Podkarpackie Voivodeship also achieved higher values for the multi-criteria measure describing this area between 2015 and 2018. This was the result of several factors, including the fact that real spending from the new EU perspective (2014-2020) began, companies and universities significantly increased their R&D expenditures, and the region benefited from a low base effect, making growth more visible than in wealthier voivodeships (Lichota, 2018). The least favourable results within the studied area were observed in the Swietokrzyskie, Warminsko-Mazurskie, and Zachodniopomorskie voivodeships.

Figure 10 shows the dynamics of changes in TOPSIS values in selected years of the period under consideration for all voivodeships.

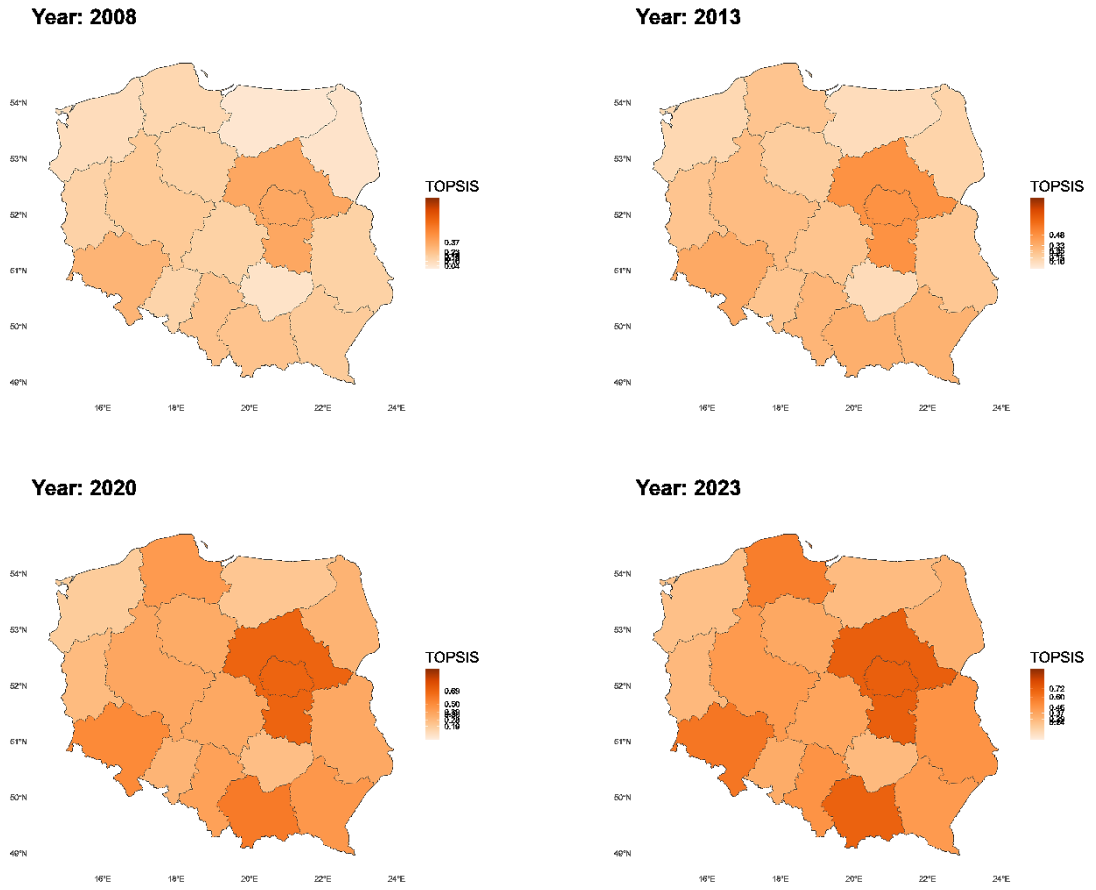

Figure 10. Intensity of the multi-criteria indicator value for Area IV (Innovations and R&D).
Source: Own research.

The intensity of colours on individual maps confirms the increasing importance of this area over the years under consideration. At the beginning of the period, in 2008, the least favourable area was in the northeastern voivodeships and the Swietokrzyskie Voivodeship. In subsequent years, the analysis revealed significantly improving scores for all voivodeships. At the end of the period under review (2023), the most favourable in this category were, as already mentioned, the Mazowiecki, Maloposkie, Dolnoslaskie, and Pomorskie voivodeships. It is confirmed that the voivodeships furthest from the PIS and closest to the NIS were the

Swietokrzyskie, Warminsko-Mazurskie, and Zachodniopomorskie voivodeships, as well as the Lubuskie Voivodeship.

The correlation analysis of Area IV with individual variables from the Labour Market category is presented in Table 4.

Table 4.
Correlation of multi-criteria assessments of Area IV (Innovations and R&D) with variables from the Labour Market area

Year	Pearson correlation coefficients for Area IV with the given variable			
	1.1	**1.2**	**1.3**	**1.4**
2008	0,812	-0,610	-0,361	0,687
2009	0,797	-0,624	-0,378	0,255
2010	0,790	-0,617	-0,327	0,336
2011	0,802	-0,675	-0,394	0,399
2012	0,806	-0,694	-0,385	-0,022
2013	0,809	-0,713	-0,334	0,393
2014	0,794	-0,684	-0,292	0,676
2015	0,726	-0,556	-0,060	0,616
2016	0,693	-0,522	-0,070	0,518
2017	0,759	-0,500	-0,103	0,723
2018	0,742	-0,463	-0,070	0,792
2019	0,748	-0,517	-0,133	0,701
2020	0,727	-0,559	-0,184	0,655
2021	0,718	-0,437	-0,123	0,813
2022	0,708	-0,482	-0,190	0,688
2023	0,687	-0,543	-0,267	0,765

Source: Own research.

The correlation between variable 1.1 – average employment per 1000 inhabitants – and the multi-criteria assessment of area IV is relatively strong, although it weakens slightly over the years – a greater share of innovation results to some extent in an increase in the number of people employed. The relationship between the registered unemployment rate (variable 1.2) and the indicator for the discussed area is at a moderate, negative level, weakening slightly over the years – a higher level of innovation and R&D expenditures favours a reduction in unemployment, as reflected by the negative correlation. Over the years, this relationship weakens slightly, as the impact of innovation on employment becomes indirect – alongside positive effects, there are also phenomena of automation and changes in the structure of labour demand. Negative values of the correlation coefficient between the Area IV measure and the variable representing long-term unemployment (variable 1.3) indicate that higher levels of innovation are accompanied by lower levels of long-term unemployment. However, this correlation is weak, and after 2014, very weak, indicating a weak connection between these characteristics. The last of the considered labour market variables, describing the net number of workplaces (variable 1.4), is weakly correlated with innovation in 2009-2013, after which the correlation becomes moderate to strong. Therefore, the relationship between this variable and innovation and research and development is increasingly strong.

4. Summary

The Polish labour market is characterized by low occupational and spatial mobility of workers, a high share of long-term unemployed individuals, and a mismatch between the skills structure and the needs of the economy (Gajdos, Lewandowska-Gwarda, 2022). Although active labour market policy does not permanently solve employment problems and has numerous limitations, it plays an important role in counteracting professional exclusion, particularly in the case of long-term unemployment.

This study examined the development and relationships between key labour market characteristics and selected socio-economic areas. In the case of the first variable – average employment (variable 1.1), the analyses showed that Area III – Economy – was most closely correlated with this variable. The observed correlations were very high and positive throughout almost the entire period. This indicates that increased employment has a positive impact on the economy, and a growing economy promotes hiring. The remaining two areas: Demographics (over the entire period) and Innovations and R&D (since 2014) are also strongly positively correlated with variable 1.1, confirming their significant relationship.

The second characteristic from the Labour Market area, the registered unemployment rate (variable 1.2), showed mainly moderate negative correlations with the areas under consideration. In the case of the Demographics and Economy areas, these relationships became stronger year by year – unfavourable (low) levels of demographic or economic indicators translate into higher unemployment rates. Area IV (Innovations and R&D) is also moderately and negatively correlated with variable 1.2, although the strength of this correlation has weakened slightly over the years. However, the moderate correlation confirms an important relationship between the studied areas and the registered unemployment rate.

The characteristic representing long-term unemployment (variable 1.3) shows the strongest, moderate, negative correlation with Area II, which, however, is weaker compared to the correlation of this area with the unemployment rate. A similar relationship is visible in the case of variable 1.3 with the Economy area. The weakest correlation, and in the second part of the analysed period, even negligible, was noted between long-term unemployment and the Innovations and R&D area – this weak correlation allows us to conclude that the development of this area has little impact on unemployment lasting longer than a year.

The fourth labour market characteristic (variable 1.4) – the net number of workplaces – in the initial period showed rather little correlation with the areas considered. A quite strong, positive correlation was noted in the second part of the area under consideration (since 2014), which was comparable across all three areas. Therefore, in recent years, the positive influence of demographic and economic factors, as well as research and development activity, has stimulated job creation.

A key focus of socio-economic policy should be investing in human capital and adapting competencies to the dynamically changing demands of the labour market. Better integration of regional policies with innovation and R&D policies by supporting projects that combine economic development with job creation, as well as adapting regional activities to the demographic and economic specificities of individual voivodeships, will enable the country's sustainable development.

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