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CLASSIFICATION OF DISTRICT EMPLOYMENT AGENCIES IN TERMS OF EMPLOYMENT AND COST-EFFECTIVENESS USING REGRESSION TREES*

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Abstract

Research background: The efficiency of the functioning of District Employment Agencies is often assessed on the basis of the level of employment and cost-effectiveness indices. The values of these indices are influenced by various socio-economic factors, which were grouped into five areas in the paper: unemployment, demography, environment, entities and the human potential of District Employment Agencies (PUPs). The research was conducted in 340 District Employment Agencies in 2017.

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Purpose: The purpose of the study is to separate groups of District Employment Agencies with similar values of employment and cost-effectiveness indices, with the simultaneous identification of the level of factors that characterize the socio-economic situation and staff potential in each of the separated groups.
Research methodology: One of the methods of a multidimensional statistical analysis – the regression trees method was used in the work.
Results: The use of regression trees allowed the separation of groups of District Employment Agencies, which differed in terms of the level of employment and cost-effectiveness indices, and characterized these groups due to socio-economic factors and staffing potential.
Novelty: The survey covers all District Employment Agencies in Poland and the obtained research results can be useful for labor market institutions to assess the efficiency of PUPs.

Keywords: employment efficiency, cost-effectiveness, regression trees, District Employment Agencies

JEL classification: C38, J64, J68

Introduction

District Employment Agencies (PUPs), by using appropriate forms of professional activation; try to bring unemployed people back to the open labor market. Pursuant to the Act on the promotion of employment and labor market institutions (Dz.U. 1065, 2017) the basic forms of employment activity include: internships, training, intervention works, public works, co-financing of undertaking business activity, reimbursement of costs of furnishing and equipping the workplace. These forms are the basis for calculating general indices of employment and cost-effectiveness, which are used by superior institutions to assess the efficiency of the functioning of individual District Employment Agencies. This assessment is of significant importance and therefore one can find many studies, in which organizational and legal aspects, as well as methodological aspects related to measuring the effectiveness of services and labor market instruments in Poland, are presented: Błędowski (2008), Wiśniewski, Zawadzki (2011), Maksim, Wiśniewski (2012), *Analiza rozwiązań*…, (2017).

Also in other European countries, the problem of measuring and assessing the effectiveness of forms of active labor market policy (ALMP) occupies an important place in combating unemployment. For example, in the paper of A. Bánociová and S. Martinková (2017), the expenditure on active labor market policies (ALMP) in percent of GDP was analyzed against the background of the unemployment rate in 2007–2015. The research shows that the most effective means were used in the Nordic countries and Luxembourg. In turn, an insufficient level was found for Slovakia, Lithuania, and Spain. G. Guzman (2014) in the paper related to activation activities and employment policy in the European Union states that:

- instruments such as tax reliefs or direct job creation are not sufficient to reduce unemployment and at the same time introduce imbalances in the labor market, by increasing salary rates,
- the activities of state employment agencies (job centers) are sufficient to reduce unemployment,
- unemployment benefits have a major impact on the size of the unemployment rate, and their amount and period of receiving them affects the time of finding a job by an unemployed person,
- training activities have a significant impact on reducing unemployment, as they increase the productivity of the workforce,
- the effects of applying active policies on the labor market (ALMP) are different for different European Union countries and depend on the legal order related to counteracting unemployment.

Similar conclusions can be found, among others, in the works of Calmfors, Forslund, Hemström (2001), Kluve (2006), Escudero (2015) and in a study by the European Commission (EU, 2016). Also noteworthy are the results of the research project "*Study on the effectiveness of ALMP*" (Kluve et al., 2005) conducted in countries such as the Netherlands, Sweden, Austria, Germany, Italy, Denmark, Estonia, Poland, Spain, France, and the United Kingdom. This research has shown that there is large diversity across countries in terms of spending on ALMPs, the types of programs and their evaluation practices. Some countries spend a substantial share of GDP on active measures (e.g. The Netherlands, Denmark, Sweden) and offer a comprehensive set of various types of ALMP (e.g. Germany), while other countries spend much less (e.g. the UK, Italy) and offer a relatively narrow set of programs (e.g. Estonia, Spain). In the case of ALMP evaluation practices, Sweden was the best and Spain and Italy the worst. Moreover, it was observed that most of the evaluation studies were concentrated on the effectiveness of ALMPs at the microeconomic level. According to the authors, a more complete assessment of the costs and benefits of their implementation would be advisable, as this would make it possible to assess whether the program should be continued, extended, modified or abandoned. The studies also show that traditional training programs have little impact on the increase in the employment rate at the end of the program. However, the private sector incentive schemes (e.g. wage subsidies, start-up grants) and services aimed at increasing the efficiency of job searching (e.g. counseling) have a much greater positive impact on employment rates. It has also been observed that the target group is important for professional activation - programs aimed specifically at young people activate the unemployed less than programs targeted at adults.

In the Polish legislation - in the Act on employment promotion and labor market institutions art. 109 section 7j (Dz.U. 1065, 2017) – four indicators have been given and defined to assess the efficiency of District Employment Agencies. Two of them relate to human potential and the degree of its use in District Employment Agencies. On the other hand, the other two are the employment efficiency index and the cost-effectiveness index of basic forms of professional activation. According to the Act, the employment efficiency index (EZ) should be understood as a percentage of the number of persons who during or after participation in the basic forms of reactivation have been shown as employed, in relation to the number of people who have completed their participation in the basic forms of reactivation by100%. On the other hand, the cost-effectiveness index (EK) is the ratio of the amount of Labor Fund expenditure incurred by poviat self-governments to finance basic forms of professional activation to the number of persons who were shown as employed during or after their participation in the basic forms of professional activation. These two performance indices are most often used in practice.

The purpose of the study is to separate groups of District Employment Agencies with similar values of employment and cost-effectiveness indices, with the simultaneous identification of the level of factors that characterize the socio-economic situation and staff potential in each of the separated groups.

As a tool for classifying District Employment Agencies regression trees were selected, in which the employment efficiency index and the cost-effectiveness index were adopted as dependent variables. The same set of independent variables was proposed for both dependent variables, which consists of quantitative predictors characterizing the socio-economic situation in the area of the functioning of District Employment Agencies and their human resources potential. 48 predictors were considered, divided into five groups: unemployment (11 predictors), demography (6 predictors), environment (13 predictors), entities (11 predictors), human resources potential (7 predictors).

Regression trees for employment (EZ) and cost (EK) indices were built using three variants of a set of independent variables (quantitative predictors):

– all factors proposed in the study,
– selected factors that were significantly correlated with the dependent variable,
– factors selected using the Hellwig information capacity indicator method, i.e. significantly correlated with a dependent variable and irrelevantly with one another.

The purpose of suggesting three sets of independent variables in the study was to check to what extent the initial selection of variables affects the size of the tree, and thus its logical interpretation.

1. Material characteristics and research method

The classification was conducted for 340 District Employment Agencies in Poland in 2017. The data on dependent variables (the employment and cost-effectiveness index) and staff potential come from the Ministry of Family, Labor and Social Policy, while independent variables – from the CSO Local Data Bank.[1] The independent variables were grouped into five areas: unemployment, demography, environment, entities and staff potential of PUPs, and their names and symbols – used in the presentation of results – are given in Table 1. It is worth mentioning that the selection of independent variables in individual areas was preceded by a study conducted using the CATI method (computer-assisted telephone interview), which covered the entire population, i.e. 340 PUPs. By design, the interviews were conducted with directors of offices or persons designated by them. A total of 260 effective interviews were received, which represents 76% of the total number of District Employment Agencies in Poland (*Badanie ilościowe*…, 2018).

Table 1. Names and symbols of variables

Symbols	Names of variables
1	2
Unemployment	
B_1	The number of unemployed persons with tertiary education in the total number of unemployed in percent
B_2	The number of unemployed persons with tertiary education in the working-age population in percent
B_3	The number of young unemployed people (24 years and younger) in the total number of unemployed persons in percent
B_4	The number of young unemployed (24 years and less) people in the working age population in percent
B_5	The number of unemployed persons for over 12 months in the total number of unemployed persons in percent
B_6	The number of unemployed persons from 12 to 24 months in the total number of unemployed people in percent
B_7	The number of unemployed persons for over 24 months in the total number of unemployed people in percent
B_8	The registered unemployment rate in percent
B_9	The number of job vacancies per 100 unemployed

[1] In the case of 39 District Employment Agencies operating in townships and country poviats, the values of independent variables were obtained by aggregating relevant data from these poviats.

1	2
B_{10}	The number of unemployed per 100 working-age people
B_{11}	The number of unemployed women in the total number of unemployed persons in percent
B_{12}	The number of unemployed persons without professional qualifications per 100 working-age people
B_{13}	The share of the unemployed people without professional qualifications in the total number of unemployed persons in percent
B_{14}	The share of unemployed persons aged 55–64 remaining without work for a period longer than 1 year in the total number of unemployed people in percent
B_{15}	The share of unemployed with vocational education in the total number of unemployed people in percent
Demography	
D_1	The number of post-working age people per 100 persons at working age
D_2	The number of pre-working age people per 100 persons at working age
D_3	The number of post-working age people to the number of pre-working age people
D_4	Pre-working people age in the total population in percent
D_5	Working-age people in the total population in percent
D_6	Pensioners in the total population in percent
Environment	
O_1	The number of police-recorded offences in general per 1,000 inhabitants
O_2	(The number of employees in entities employing over 9 persons to the total population) · 100%
O_3	(The number of employees in entities employing over 9 persons to the number of working-age people) · 100%
O_4	(The estimated number of employees[a] to the total population) · 100%
O_5	(The estimated number of employees to the population of working age people) · 100%
O_6	Local and district roads with hard surfaces per 100 km^2
O_7	Taxes on natural persons per capita in PLN
O_8	Corporate taxes per capita in PLN
O_9	The number of low-qualified schools[b] per 10,000 inhabitants
O_{10}	The number of graduates of low-qualified schools per 10,000 inhabitants
O_{11}	The number of highly-qualified schools per 100,000 inhabitants
O_{12}	The number of highly-qualified school graduates per 10,000 inhabitants
O_{13}	The number of training institutions per 10,000[c] inhabitants
Entities	
P_1	The number of economic entities in the REGON register per 10,000 people
P_2	The number of national economy entities per 10,000 working-age people
P_3	The number of economic entities employing 0-9 persons per 10,000 working-age people
P_4	The number of economic entities employing 10-49 persons per 10,000 working age people
P_5	The number of economic entities employing 50-249 persons per 10,000 working age people
P_6	The number of economic entities employing 250 persons and more per 10,000 working-age people
P_7	The number of public sector entities per 10,000 working-age people
P_8	The number of private sector entities per 10,000 working-age people
P_9	The number of agriculture sector entities per 10,000 working-age people

1	2
P_{10}	The number of economic entities in the industry and construction sector per 10,000 working-age people
P_{11}	The number of economic entities in the sector of activities n.e.c. per 10,000 working-age people
Staff potential of PUPs	
W_1	The number of client advisors in the total employment in PUPs in percent
W_2	The number of vocational counsellors in the total employment in PUPs in percent
W_3	The number of unemployed persons per 1 employee of PUP
W_4	The number of unemployed persons per one key worker of PUP
W_5	The number of unemployed persons per 1 employment agent in PUP
W_6	The number of unemployed persons per 1 vocational counsellor in PUP
W_7	The number of unemployed persons per one client advisor in PUP

[a] The estimated number of employees was calculated as follows: the number of economically active people – the number of registered unemployed persons, where the number of economically active people was calculated as the ratio of the number of unemployed persons and the registered unemployment rate multiplied by 100%.

[b] Schools that educate students to obtain the Matura exam (secondary school final exam), i.e. schools: primary schools, lower secondary school, basic vocational school, general secondary schools, secondary vocational schools.

[c] The data come from the Register of Training Institutions (www.stor.praca.gov.pl, accessed: 20.09.2018).

Source: own elaboration.

Due to the fact that dependent variables are quantitative, regression trees have been chosen as a tool for classifying District Employment Agencies, which are included in the methods of a multivariate statistical analysis. They are used to classify objects when (Gatnar, Walesiak, 2004):

– in the set of examined variables one can distinguish a dependent variable, which is measured on strong scales (interval, quotient),
– independent variables can be measured on both weak (nominal, ordinal) and strong scales.

Regression trees are a graphical representation of the following model (Gatnar, 2008):

$$Y = f(\mathbf{x}_i) = \sum_{k=1}^{K} \alpha_k I(\mathbf{x}_i \in R_k) \tag{1}$$

where: Y – dependent variable, R_k ($k = 1, ..., K$, K – number of segments) are subspaces (segments) of exogenous variable spaces $\mathbf{X}^L$ (X_1, X_2, ..., X_L, L – number of exogenous variables), $\mathbf{x}_i$= [x_{i1}, x_{i2}, ..., x_{iL}] – observations from a recognizable set, α_k – model parameters, I – indicator function.

If the dependent variable Y in the model (1) is measured on strong scales, then this model is a regression model and its graphical form is the regression tree. The parameters α_k of the regression model are calculated according to the formula:

$$\alpha_k = \frac{1}{N(k)} \sum_{\mathbf{x}_i \in R_k} y_i \tag{2}$$

where: $N(k)$ – the number of observations located in the segment R_k, y_i – values adopted by the dependent variable in the segment R_k.

When the variables $X_1, X_2, ..., X_L$ are metric, each of the segments R_k is defined by its boundaries in space $\mathbf{X}^L$ as follows:

$$I(\mathbf{x}_i \in R_k) = \prod_{l=1}^{L} I(v_{kl}^{(d)} \le x_{il} \le v_{kl}^{(g)}) \tag{3}$$

where the values $v_{kl}^{(d)}$ and $v_{kl}^{(g)}$ mean respectively the upper and lower limit of the segment in l-th dimension of space.

To assess the quality of the space division of the explanatory variables $\mathbf{X}^L$ in the case of regression trees, the variance of the dependent variable[2]is used.

The usefulness of regression trees for the classification of objects for a metric dependent variable is confirmed by numerous studies, the results of which can be found, among others, in the works by: Misztal (2004), Bąk, Wawrzyniak (2010), Batóg, Mojsiewicz, Wawrzyniak (2011), and Kutyłowska (2017).

2. Research results

The dependent variables in the research are the indices of employment efficiency (EZ) and cost-effectiveness (EK). The same set of independent variables was proposed for both dependent variables, which consist of factors characterizing the socio-economic situation in the area of the functioning of District Employment Agencies and their human resources potential (Table 1).

Regression trees for employment (EZ) and cost efficiency (EK) indices were built using three variants of a set of independent variables (quantitative predictors):

– variant 1 (W1) – the set of predictors includes all the factors proposed in the study,
– variant 2 (W2) – a set of predictors contains selected factors significantly correlated with the dependent variable,
– variant 3 (W3) – the set of predictors includes factors selected using the Hellwig information capacity indicator method.[3]

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[2] The methods of determining and the properties of measures used to assess the quality of the division of variable spaces are discussed, among others, in (Gatnar, 2001), (Gatnar, Walesiak, 2004), (Gatnar, 2008).

[3] The description of this method can be found e.g. in the following works: Młodak (2006), Hozer (2007), Panek (2009), Jarocka (2013).

To determine regression trees, both for the employment and cost-effectiveness index, the CART standard model procedure, programmed in the *Statistica 12.0* package, was used. The process of selecting the tree for further analysis consisted of two stages. In the first stage, for each of the three variants of the independent variables, the tree with the smallest difference between the cost of the cross-checking and the cost of resubstitution including its complexity was selected from the sequence of the obtained trees. In this way, for each dependent variable, the three best trees for the criterion were obtained. The tree for further analysis was selected in step two by using a supporting criterion. In this criterion, the selection of the best tree was determined by its size and no repetition of predictors in split nodes. This resulted in a tree whose end nodes could be logically interpreted.

Table 2 presents the structure of selected regression trees for individual variants of the predictor set.

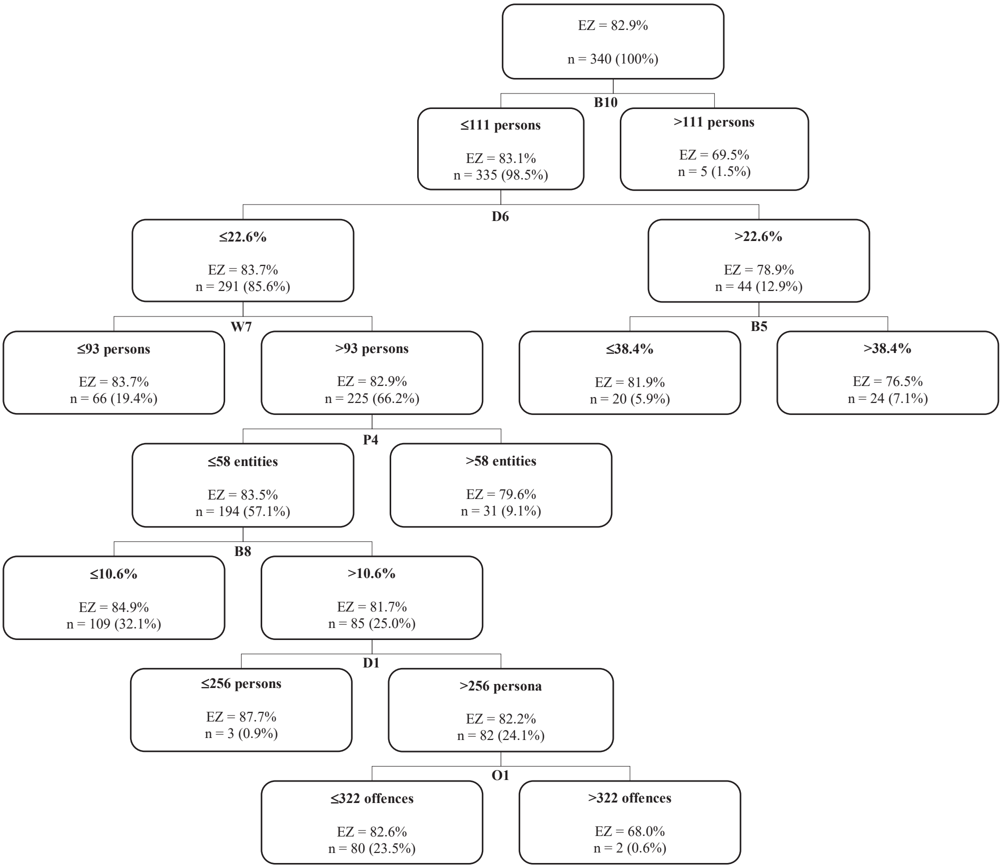
Table 2. The structure of selected regression trees for the employment efficiency index (EZ) and cost efficiency index (EK)

Specification	EZ			EK		
	Variant 1	Variant 2	Variant 3	Variant 1	Variant 2	Variant 3
Number of shared nodes	10	8	10	11	10	7
The number of predictors	10 (2 repeats)	8 none	10 (2 repeats)	10 (2 repeats)	10 (2 repeats)	7 (1 repeat)
Number of end nodes	11	9	11	12	11	8

Source: own elaboration.

For the employment efficiency index, a regression tree was selected, which included the second variant of the predictor set (Figure 1), while for the cost-effectiveness index, a tree with the third variant of the predictor set was selected (Figure 2). It seems that obtaining a tree that meets certain requirements is easier when first the set of independent variables is limited. Thus, having a very large set of quantitative predictors relevant in terms of the substantive criterion – for example, indicated by experts – it is better to opt for the use of a formal and statistical criterion in order to limit their number.

The characteristics of groups of District Employment Agencies due to the average values of the employment and cost-effectiveness index and variants of selected predictors are presented in Tables 3 and 4.



End nodes with more than 5% of the total population are distinguished, and the interest calculated in relation to the total population is given in brackets.

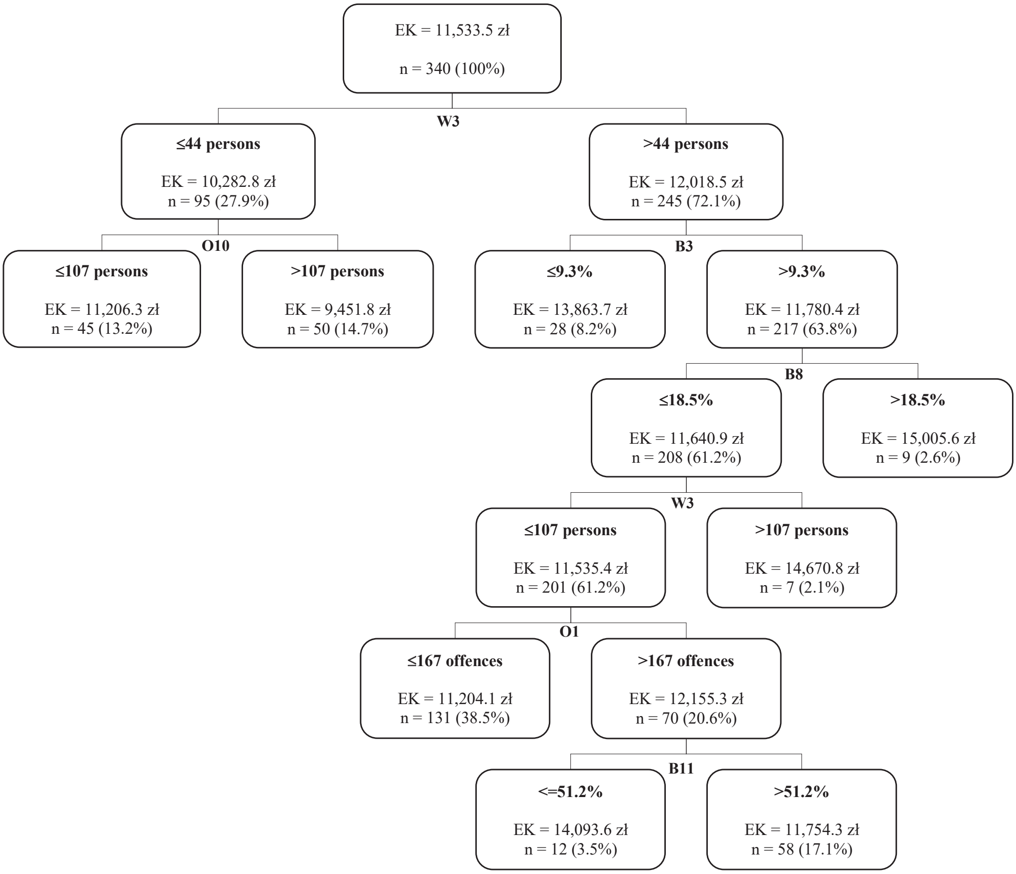
Figure 1. Regression tree for the employment efficiency index (EZ)

Source: own elaboration.

Table 3. Characteristics of groups of District Employment Agencies based on the regression tree for the employment efficiency index (EZ)

No.	Characteristics of the group	EZ average (%)	Standard deviation in percentages	Group size (percent of population surveyed)
1	The number of persons unemployed per 1,000 people of working age does not exceed 111, the share of the population of post-working age does not exceed 22.6%, the number of the unemployed per 1 customer advisor does not exceed 93	86.3	4.7	66 (19.4)
2	The number of persons unemployed per 1,000 people of working age does not exceed 111, the share of the population of post-working age does not exceed 22.6%, the number of the unemployed per 1 customer advisor exceeds 93, the number of entities with a predictable number of 10 to 49 employed persons per 10,000 people at working age is above 58	79.6	5.7	31 (9.1)
3	The number of persons unemployed per 1,000 people of working age does not exceed 111, the share of the population of post-working age does not exceed 22.6%, the number of the unemployed per 1 customer advisor does not exceed 93, the number of entities with a predictable number of 10 to 49 employed persons per 10,000 people in working-age is above 58, the unemployment rate does not exceed 10.6%	84.9	5.1	109 (32.1)
4	The number of persons unemployed per 1,000 people of working age does not exceed 111, the share of the population of post-working age does not exceed 22.6%, the number of the unemployed per 1 customer advisor does not exceed 93, the number of entities with a predictable number of 10 to 49 employed persons per 10,000 people at working age is above 58, the unemployment rate does exceed 10.6%, the number of people at a post-working age per 1,000 working age persons in above 256, the number of police-recorded offences in general per 10,000 inhabitants does not exceed 322	82.6	5.3	80 (23.5)
5	The number of persons unemployed per 1,000 people of working age does not exceed 111, the share of the population of post-working age exceeds 22.6%, the number of people being unemployed longer than 12 months does not exceed 38.4%	81.9	4.0	20 (5.9)
6	The number of persons unemployed per 1,000 people of working age does not exceed 111, the share of the population of post-working age exceeds 22.6%, the number of people being unemployed longer than 12 months exceeds 38.4%	76.5	8.8	24 (5.9)

Source: own elaboration.



End nodes with more than 5% of the total population are distinguished, and the interest calculated in relation to the total population is given in brackets.

Figure 2. Regression tree for the cost-effectiveness index (EK)

Source: own elaboration.

Table 4. Characteristics of groups of District Employment Agencies based on the regression tree for the employment efficiency index (EZ)

No.	Characteristics of the group	Average EK (PLN)	Standard deviation in percentages	Group size (percent of population surveyed)
1	2	3	4	5
1	The number of persons unemployed per employee does not exceed 44, the number of graduates of low-qualified schools per 10,000 residents do not exceed 107 people	11,206.3	1,471.0	45 (13.2)
2	The number of persons unemployed per employee does not exceed 44, the number of graduates of low-qualified schools per 10,000 residents do not exceed 107 people	9,451.6	1,761.1	50 (14.7)

1	2	3	4	5
3	The number of persons unemployed per 1 employee over 44, the share of young unemployed (24 years and less) in the total number of the unemployed does not exceed 9.3%	13,863.7	2,702.4	28 (5.9)
4	The number of persons unemployed per 1 employee over 44, the share of young unemployed (24 years and less) in the total number of the unemployed above 9.3%, the unemployment rate does not exceed 8.5%, The number of the unemployed per 1 employee does not exceed 107 people, the number of police-recorded offences per 10,000 inhabitants does not exceed 167	11,204.1	1,638.9	131 (38.5)
5	The number of persons unemployed per an employee is in the range of 44 to 107 people, the share of young unemployed (24 years and less) in the total number of the unemployed above 9.3%, the unemployment rate does not exceed 8.5%, the total number of police-recorded offences per 10,000 inhabitants exceed 167, the share of unemployed women in the total number of the unemployed exceeds 51.2%	11,754.3	1,889.2	58 (17,1)

Source: own elaboration.

Conclusions

The use of regression trees enabled to group District Employment Agencies, in terms of the level and the degree of employment and cost-effectiveness indices, as well as it characterized these groups due to socio-economic factors and staffing potential.[4]

It appeared that the highest employment efficiency characterizes those District Employment Agencies in which the number of the unemployed per 1,000 people in the working age does not exceed 111 people, the share of the population in the post-working age does not exceed 22.6%, and the number of the unemployed per 1 customer advisor is not greater than 93. The lowest efficiency exists in offices in which the number of unemployed per 1,000 people of working age also does not exceed 111 people, while the share of the population of post-working age is above 22.6%, and the share of the unemployed above 12 months is above 38.4%.

In the case of cost-effectiveness, the lowest average value of the indicator applies to employment offices with no more than 44 unemployed per 1 employee and the number of low-qualified graduates of schools per 10,000 inhabitants is above 107. However, when the number of the unemployed per one employee exceeds 44 and the share of the unemployed aged 24 and

[4] Research on the impact of socio-economic characteristics on the level of employment efficiency index in District Employment Agencies using various methods (correlation and regression analysis, correspondence analysis, regression trees) can be found, among others, in the following papers Bąk, Wawrzyniak, Oesterreich (2019a), Bąk, Wawrzyniak, Sobolewski (2019b), Bąk, Wawrzyniak (2020).However, the study of the impact of socio-economic characteristics on the level of the employment and cost-effectiveness indices using econometric modelling can be found in the article Bąk, Wawrzyniak, Sobolewski (2019c).

under in the total number of the unemployed does not exceed 9.3%, then the offices are in the group with the highest average indicator value.

In addition, based on the conducted research, it was shown that by commencing the construction of regression trees on the basis of a large number of predictors, it is advisable to initially reduce this set preferably using a formal and statistical criterion.

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