

THE STUDY OF THE IMPACT OF ACTIVE MEASURES ON LABOUR MARKET BY FACTOR TECHNIQUES

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Abstract

If before the outbreak of the great recession in the year 2008 the European labour markets were added almost 30 million new jobs, during the crisis the same markets eliminated six million jobs, and unemployment reached a peak of 11% in 2013, the highest rate in more than a decade.

At European level, even though political and economic decision factors took firm measures for alleviating the negative effects of the economic crisis, many economies are still faced with the actual perspective of an extended period of tempered economic growth or even economic decline. The employment of vulnerable labour force and employed population poverty are very important issues needing to be tackled and solved.

The statistical methods and techniques of quantification, the factor analysis for estimating and testing are both represented by a wide and varied multitude of procedures and statistic-mathematical instruments. For deepened analysis of the impact of adopting active measures on the evolution of the main macroeconomic indicators which highlight the employment of labour force, the paper used the method of principal components.

Keywords: *active measures, employment, unemployment, principal components method*

JEL Classification: *C15, C49, J21, J64*

1. Introduction

Globalisation and technological progress had a deep impact on the labour force markets all over the world. In most developed and developing countries the unemployment rate is regarded as an important indicator of labour market performance.

The labour force market from Romania changed dramatically during the economic transition. One of its main characteristics is the diminishment in employed population. This was due to the restructuring of enterprises (which led to job losses that were not compensated by the creation of new jobs), and also because of the process of marked demographic ageing of the population. In the context of the free movement of labour force, Romania recorded significant emigration (including temporary emigration), which led to a labour force deficit. In the context of emigration two extremely important phenomena are highlighted for the sustainability of the labour market in Romania: the emigration of relatively young and high-skilled workforce (the “brain drain” phenomenon increased significantly during the crisis and post-crisis period for professions such as physicians and computer scientists) and, at the same time, low-skilled workers who prefer to earn more abroad.

Another feature of the Romanian labour market is also the shift of part of the labour force that remained jobless towards informal labour forms. Informal work exists mainly in agriculture (under the form of subsistence agriculture), but also in sectors such as constructions, trade, home services, transportation, health and education.

The method of factor analysis is a method having as objective to represent the factor that act on an economic phenomenon (variable) or on several phenomena (variables), the grouping and measurement of their influences. In the analysis model, the factors can be classified as: common, that is acting on several variables and specific that act on a single variable.

2. Theoretical Formulation of the Factor Analysis Method

On the mass phenomena analysed by statistics act a series of main and secondary factors essential and non-essential, systematic or random, objective and subjective, that are either found or not in mutual relationships.

The factor analysis can be a solution in some instances for the multi-co-linearity problems of the predictors in the regression analysis (an increased degree of co-linearity of the predictors in the regression analysis creates a series of problems related to the partitioning of the common variance between predictors, instable solutions of the equation, standard errors and increased confidence intervals). If the variables with a high degree of co-linearity measure the same theoretic dimension/ construct, then the solution is either the construction of a scale or the use of a latent factor.

In the models of structural equations the use of latent factors in such instances provides for advantages against the use of scales because in such measurement models the differentiation can be made between the variance that captures the theoretic dimension of interest and the unique variance (variance catching other concepts + variance determined by measurement errors).

Considering that statistics analysis the mass phenomena from the perspective of statistical laws that govern them, and which are characterised by the trend form, known and verified only at the level of the whole, naturally, it is necessary to analyse the links between the mass phenomena studied by the statistics also under the form of a trend of the causality relationships.

The factor analysis appeared in order to solve a series of issues, among which can be mentioned: reducing data complexity; highlighting and determining the pattern of associations (correlations) between variables; determining latent (fewer) variables that are behind the measured (more) variables.

The hidden, latent variables are called **factors** and therein resides the name of the factor analysis methods.

The use of operationalised latent variables with the help of several indicators/observed variables provides the opportunity for more detailed modelling of theoretic concepts as compared with the use of a single indicator for each theoretic dimension.

The factor model (of the linear type) can be represented as follows:

$$\begin{cases} Z_1 = a_{11}F_1 + a_{21}F_2 + \dots + a_{1n}F_m + a_1V_1 \\ Z_2 = a_{21}F_1 + a_{22}F_2 + \dots + a_{2n}F_m + a_2V_2 \\ : \\ Z_n = a_{n1}F_1 + a_{n2}F_2 + \dots + a_{mn}F_m + a_nV_n \end{cases} \quad (1)$$

where: $F_1; F_2; \dots, F_m$ represent the common factors;

$V_1; V_2; \dots, V_n$ specific factors;

$Z_1; Z_2; \dots, Z_n$ analysed variables; coefficients.

The method of the factor analysis implies two stages:

- the development of the model, when the common and specific factors are determined and the hypotheses with respect to the validity of the model are checked;
- evaluation of the factors' influences on variables.

In the simplest form, the direct conditioning ling of the factors takes the expression of a function: $Y = f(x)$. The fundamental relationships

between the variables of a model are of a determinist or stochastic type. The methods used for separating the influences of the factors are dependent on the mathematical form taken by the relationships between them. In the case of deterministic-type relationships are used: the balance method; the method of chain-substitution; the method of indices, etc.

In the case of stochastic-type relationships, the correlation method, the regression analysis method, the Markov chains, the Poisson processes, the expectations theory, the PERT method and other methods of the probabilistic type are employed.

One of the most used methods for realising the factor analysis is also the **principal components method**. By means of this method, an entire set of data can be reduced to a compact form but that still can highlight certain fundamental structures of the data. The method allows for highlighting some significant relationships of interdependency, which could not be known by simple data examination. The purpose of this analysis is to diminish complexity, by identifying a small number of factors whose characteristics can be the backbone for some evaluations or decisions.

The core idea of the principal components method consists in determining the share (percentage) in total variance (sum of variances for the initial p variables) of each new variable.

By the principal components method the set of correlated variables (x_1, x_2, \dots, x_p) is changed into a set of uncorrelated variables (y_1, y_2, \dots, y_p) called *principal components*, by the relationship:

$$\begin{cases} y_1 = a_{11}x_1 + a_{21}x_2 + \dots + a_{p1}x_p \\ y_2 = a_{12}x_1 + a_{22}x_2 + \dots + a_{p2}x_p \\ : \\ y_p = a_{1p}x_1 + a_{2p}x_2 + \dots + a_{pp}x_p \end{cases} \quad (2)$$

Each component is a weighted sum of the variable x , and a_{ij} are weights or coefficients to which certain restrictions are imposed. The analysis on principal components being a reduction method of the number of characteristics allows also for geometrical representations of the individuals and characteristics. Therefore, also the algebraic formulation equivalent to the orthogonal rotation is necessary, as well. As result, the a_{ij} coefficients must satisfy also the conditions:

$$\sum_{i=1}^p a_{ij}^2 = 1, j = 1, \dots, p \quad \text{and}$$

$$\sum_{i=1}^p a_{ij}a_{ik} = 0, j \neq k; j = 1, \dots, p; k = 1, \dots, p \quad (3)$$

An important consequence of orthogonality is that the total variation of components y is equal to the one of variables x , that is:

$$\sum_{j=1}^p \text{var}(y_j) = \sum_{i=1}^p \text{var}(x_i) \quad (4)$$

❖ Selection of the number of principal components

In selecting the number of components it should be taken into account that for the proposed analysis it is good to retain a set as small of components as possible, but at the same time, to have enough numbers that would deliver a good representation of the initial data. The variance of the component j is its own value λ_j . The components are selected in the decreasing order of their own values: $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p$. If the x variables are standardised (normalised), than the sum of x variances shall be equal to p . Under these conditions, the sum of the own values of the total variance y shall also be p . The share (percentage) in the total variance explained by the component j is:

$$\frac{\lambda_j}{\lambda_1 + \lambda_2 + \dots + \lambda_p} \quad (5)$$

And the cumulated share (percentage) of the first k components is:

$$\frac{\lambda_1 + \lambda_2 + \dots + \lambda_k}{\lambda_1 + \lambda_2 + \dots + \lambda_p} \quad (6)$$

Amongst the most used criteria in taking a decision about selecting the principal component that can be retained for analysis are counted:

- The first k components are retained when these represent a higher percentage of the variance (70-80%);
- If the correlation matrix is analysed only those components are retained that have own values higher than 1;
- Graphics examination: if the dependencies between own values and the number of principal components are represented, then those components are selected for which own values decrease very quickly;
- The graphic method, suggested by Kaiser and Cattell.

The weight given by the variable i in the j component is a_{ij} . The size of a_{ij} reflects the relative contribution given by each variable in component. Very often the coefficients are recalculated as coefficients for the most important components. These new coefficients called also *loaded components* are the coefficients used for reconstructing the variables x from y and are calculated after the relationship:

$$a_{ij}^* = \sqrt{\lambda_j} a_{ij} \quad i = 1, \dots, p; \quad j = 1, \dots, p \quad (7)$$

When analysing the correlation matrix for the variables x the coefficients a_{ij}^* must be interpreted as correlation coefficients between the variable i and the component j .

3. Applying the principal components analysis to the study of the impact of active measures employed on the labour market from Romania

Law 76/2002 regarding the unemployment benefits' system and stimulating labour force with the subsequent amendments and changes, regulates the measures for realising the strategies and policies developed in view of protecting individuals against unemployment risks, assuring a high level of employment and labour force adjustment to the requirements of the labour market, the purpose of these measures being to achieve some actual objectives of the labour market, respectively:

- preventing unemployment and combating social effects thereof;
- employment or reemployment of job seeking individuals;
- supporting employment for individuals from disadvantaged categories of the population;
- ensuring equality of chances on labour market;
- incentives for unemployed in view of gainful employment;
- stimulating employers for hiring individuals searching for a job;
- improvement of the occupation structure on economic activities and geographic areas;
- increasing labour force mobility under the conditions of the structural changes occurring within the national economy;
- individuals' protection in the framework of the unemployment benefits' system.

The measures for stimulating labour force employment aim at:

- a) increasing the employment chances of individuals searching for a job;
- b) stimulating employers to hire unemployed and create new jobs.

Increasing the employment chances of individuals searching for a job:

- a) professional information and counselling;
- b) labour mediation;
- c) vocational training;
- d) consulting and assistance for starting-up an independent activity or for initiating a business;
- e) supplementing wage incomes for employees;
- f) stimulating labour force mobility;
- g) services preceding lay-offs.

The volume and structure of employment are indirectly influenced and very often also decisively by the macroeconomic policies (by economic growth) and by the fiscal policies (the level of tax and duties), as well, along with the monetary (level of interest rates), and wage policies or by the level of public investments in infrastructure.

Another series of public policy measures, of lesser amplitude have as a rule a direct and short-term impact on the employment level of individuals in the labour market; these can be grouped into two large categories depending on the nature and intensity of their influence on the labour supply and demand structure.

The so-called “passive” employment measures are material support measures (unemployment indemnity, support allocation) that have the role of compensating to a certain degree the lack of incomes because of the unemployment or inactivity situation and, accordingly, to maintain the labour capacity in the period between losing the job and finding a new workplace.

In turn, “active” *employment measures* constitute a set of interventions that influence directly and on short-term the volume and structure of employment and, accordingly the unemployment one, in view of finding a balance between the demand and supply of jobs either for increasing labour force demand or diminishing an oversized supply thereof.

The increase of labour force demand can be stimulated by granting subventions to employers and by measures aiming to develop the entrepreneurial capacity of a community or region, while for instance granting mobility bonuses are interventions aimed to diminish a relatively oversized labour force supply.

The active measures of the labour force employment policy are directed both to the employers and to individuals in search of a job; last but not least *vocational training and employment services (for stimulating employment)* represent the most important active measures with direct addressability to the individuals in search of a job.

For determining the impact of active measures applied in the field of labour force employment was taken into account the data set regarding the number of individuals employed in each year for the period 2006-2013 by means of the measures adopted at the level of the National Employment Agency (Table no. 1);

Table no.1 *Active measures of employment adopted in view of implementing the Labour Force Employment Programme*

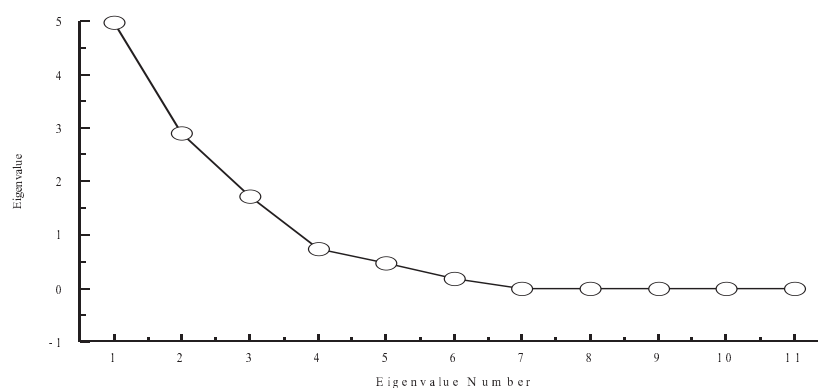
X1	Professional information and counselling
X2	Vocational training
X3	Stimulating employment of graduates of higher education
X4	Unemployed hiring before the expiry of the indemnity period
X5	Employment of individuals over 45 years of age or unemployed who are the head of Monoparental families
X6	Employment by stimulating labour force mobility
X7	Employment of handicapped persons
X8	Providing assistance and consulting services for starting-up an independent activity
X9	Labour mediation
X10	Personalised social guidance provided to youth exposed to the marginalisation risks
X11	Unemployment prevention measures

Applying the principal components method for the first set of data taken into account led to obtaining the correlation matrix presented in Table no. 1 (Annex 1), which allowed for establishing the positive or negative correlations between the considered variables.

Based on the analysis of the correlation matrix of the own values is highlighted that the percentage cumulated in total variance of the first four components is of 94%. The analysis of the own vectors variation graphic allows, as suggested by Kaiser in 1960 and Cattell in 1966, for determining the number of principal factors (components). It is highlighted that the first 4 factors are dominant (Figure 1), having a strong development towards the axis ox , followed by an evolution with a lower angular coefficient that, as of factor 7 has a substantial reduced slope. This development suggests the fact

that for this set of measures the first 4 components can be regarded as dominant.

Figure 1 *Evolution of own values for the component elements of the set of active employment measures*



Source: own processing of the author with the aid of the KyPlot programme

Own values and vectors (eigenvalues and eigenvectors) are associated with the initial variables correlation matrix. An own value higher than 1 for a component indicates that, the respective component has a higher contribution than the one of an initial variable hence it would be indicated to be extracted. The own vectors, associated to own values shall constitute the weights in the calculation of the respective linear combinations.

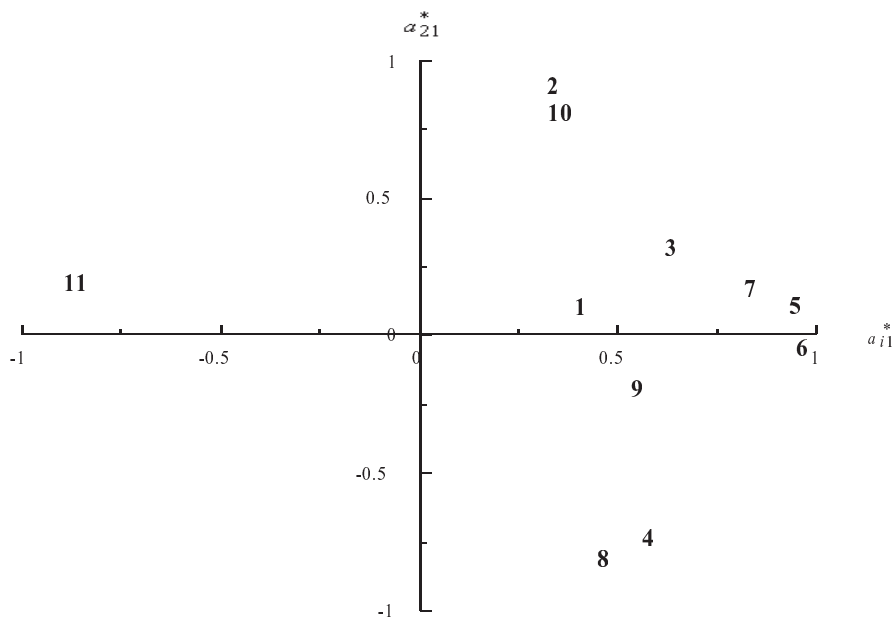
For determining the correlations between the principal components and the initial characteristics was used the correlation matrix of the "loaded" components for each group of active measures taken into account. The outcomes are presented in Table no. 2 from Annex 1.

The correlations presented in Table no.2 from Annex 1 allow for a first analysis of the impact of each active measure adopted in increasing the employment degree, and depending on the sign of the values from the tables the positive or negative correlations can be determined between the variables subjected to the study and, thus, of the way in which these can influence the development of employment on the labour force market.

The loading coefficients (PC loadings) are precisely the correlation coefficients between the original variables and the scores. They express the importance of each initial variable in explaining each new component.

The use of the relationships (7) and of the “loading” diagrams for two principal components, Figure 2, allows for highlighting the contribution of each measure to the evolution of the employment degree:

Figure 2 Contribution of each active measure to achieving the employment objectives on labour force market



Source : own processing of the author with the aid of the KyPlot programme

where each number from the figure represents the ordinal number of the active measure taken into account. Thus, the components that are in the first frame are those with positive correlation and hence, those to influence most strongly the employment on labour market.

The first factor axis is, usually, the *size factor* as it separates alongside the small outcomes from the high ones. The second factor axis is the *shape factor* that nuances the differences realised by the first factor. The measures adopted for vocational training, professional information and counselling, stimulating employment of graduates of higher-education, employment of individuals over 45 years of age or unemployed that are

single heads of Monoparental families, and the one of personalised social guidance granted to youths exposed to marginalisation are, based on this method, the ones delivering good results in increasing employment on labour market.

Labour mediation, providing assistance and consulting services for starting-up and independent activity, employment by stimulating labour force mobility and the measure of employing the unemployed before the expiry of the indemnity period are less efficient in increasing employment on the labour market in Romania.

With respect to the measure of preventing unemployment, the data from diagram 2 show that the adoption of this measure is not efficient in increasing the employment degree of the Romanian labour force.

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Acknowledgement

The article has enjoyed the support of the Project “Pluri and interdisciplinarity in doctoral and postdoctoral program” co-financed by the Ministry of National Education – OIR POSDRU, Contract no. POSDRU/159/1.5/S/141086.

Annex 1

Table no. 1 *The correlation matrix of active employment measures*

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
X1	1										
X2	0.11	1									
X3	0.28	0.58	1								
X4	0.39	-0.48	0.19	1							
X5	0.37	0.39	0.57	0.40	1						
X6	0.26	0.35	0.63	0.57	0.88	1					
X7	0.27	0.38	0.44	0.22	0.96	0.76	1				
X8	0.15	-0.51	0.13	0.89	0.29	0.55	0.15	1			
X9	-0.51	0.11	0.25	0.22	0.58	0.65	0.59	0.35	1		
X10	0.42	0.87	0.38	-0.27	0.36	0.34	0.30	-0.43	-0.13	1	
X11	-0.49	-0.06	-0.30	-0.73	-0.73	-0.78	-0.62	-0.48	-0.36	-0.31	1

Source: own processing of the author with the aid of the KyPlot programme

Table no. 2 *The correlation matrix of components "loaded"*

Principal Component Loadings from Correlation Matrix				
	Comp. 1	Comp. 2	Comp. 3	Comp. 4
X1	0.411	0.106	0.876	-0.074
X2	0.343	0.909	-0.111	0.155
X3	0.640	0.323	-0.003	0.646
X4	0.581	-0.732	0.307	0.111
X5	0.954	0.112	-0.096	-0.185
X6	0.969	-0.041	-0.122	0.112
X7	0.840	0.173	-0.210	-0.327
X8	0.471	-0.806	0.064	0.235
X9	0.556	-0.190	-0.802	-0.050
X10	0.371	0.810	0.274	-0.060
X11	-0.850	0.193	-0.238	0.258

Source: own processing of the author with the aid of the KyPlot programme