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THE APPLICATION OF MARKOV CHAIN MODEL TO THE DESCRIPTION OF HUNGARIAN LABOR MARKET PROCESSES

Summary

Different methods can be selected from the statistical mathematical toolbar to describe labor market processes. The paper applies Markov model, a method rarely used in regard to labor market. This method is popular in several disciplines including regional economics to manage income inequalities, sociology, microeconomics and public health. The advantage of the model is that it illustrates well the mobility in each status making it easier to generate predictions. The paper examines NUTS3 level unemployment data in Hungary over the period 1992–2009 using Markov chain model.

Keywords: discrete-time Markov chain, transition probability, labor market processes

Introduction

> 2010 must mark a new beginning. I want Europe to emerge stronger from the economic and financial crisis. Economic realities are moving faster than political realities, as we have seen with the global impact of the financial crisis. We need to accept that the increased economic interdependence demands also a more determined and coherent response at the political level. The last two years have left millions unemployed. It has brought a burden of debt that will last for many years. It has brought new pressures on our social cohesion. It has also exposed some fundamental truths about the challenges that the European economy faces. And in the meantime, the global economy is moving forward [Europe 2020 Strategy, 2009: 3].

The paper addresses the following research questions:

– What are the characteristics of the Hungarian labor market taking into account the past years and what is the current situation?
– Can Hungary break out of the unemployment situation? Can the relative position of the areas change?

– What kind of unemployment groups can be created using Markov chain model and how these groups change over time?

Evaluation of labor market position in the European Union and Hungary

What are the characteristics of the Hungarian labor market taking into account the past years and what is the current situation?

In order to clear up the first mentioned questions, the paper presents a general situation report first, places the Hungarian counties in the wider geographical area. Then, the specific analysis is carried out using Markov model. Each country tries to solve the problem of unemployment as it means global burden, but the existence of unemployment is still not the same.

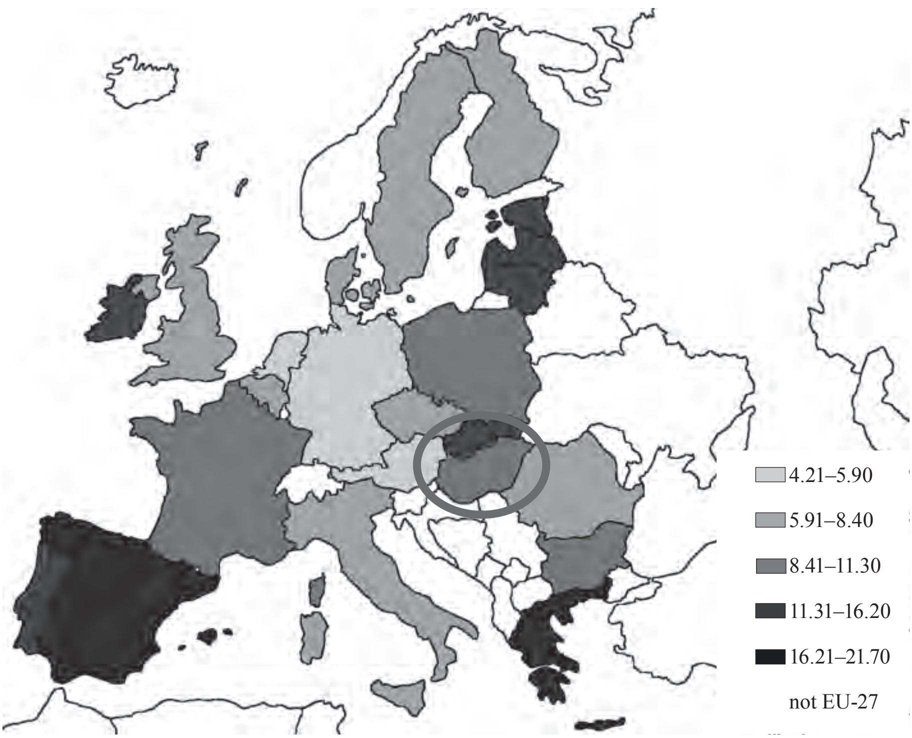

Figure 1. Unemployment rate (%) in the European Union, 2011

Source: own compilation based on Eurostat database.

The map (figure 1) shows the unemployment rates in 2011 within the European Union. The situation was the worst in Spain (21.7%), Greece (17.7%), Latvia (16.2%) and Lithuania (15.4%). In Hungary the unemployment rate was 10.9%. The lowest values belonged to the Netherlands (4.4%) and Austria (4.2%).

Labor market conditions are positioned with the data of employment and unemployment rate in the 27 member states of the European Union, in Japan and in the United States of America (figure 2).

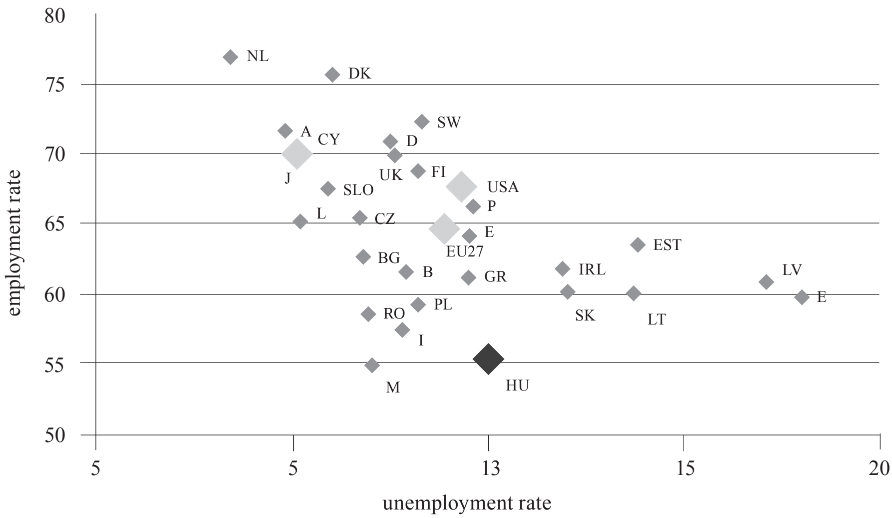

Figure 2. Labor market status in the case of EU-27, Japan and the USA, 2009

Source: own compilation based on Eurostat data.

The illustration of them in one co-ordinate system highlights that EU-27 is in a more unfavorable position on the whole than the USA and Japan. Out of the three action centers of the world economy, Japan has the most favorable position as for labor market data. As far as the Union member states are concerned, the Netherlands, Denmark and Austria are in favorable positions, while Hungary and Malta have the worst positions. Relatively high unemployment rate is associated with low employment rate.

"The classical approach states that the position of a region is mostly determined by its natural, climatic potentials, its territorial extension, fieldland value, etc. Historical experiences show that the rate of economic growth was highly associated with the amount and structure of the available resources in the region" [Kocziszky, 1997: 57]. The analysis includes the unemployment rates of the Hungarian counties, so only a part of labor market analysis is highlighted. Unemployment was selected because objectives in both economic and employment policies try to decrease long term unemployment. At the same time, this is the status from which returning to employment status is not easy.

Figure 3 shows the frequency distributions of the unemployment rate at the beginning and at the end of the examined period. At the beginning period, unemployment follows a more equal distribution. By 2009, however, the situation had changed. The unemployment rate of 11% had become more frequent than any other values. The frequency distribution is not suitable to draw more considerable consequences.

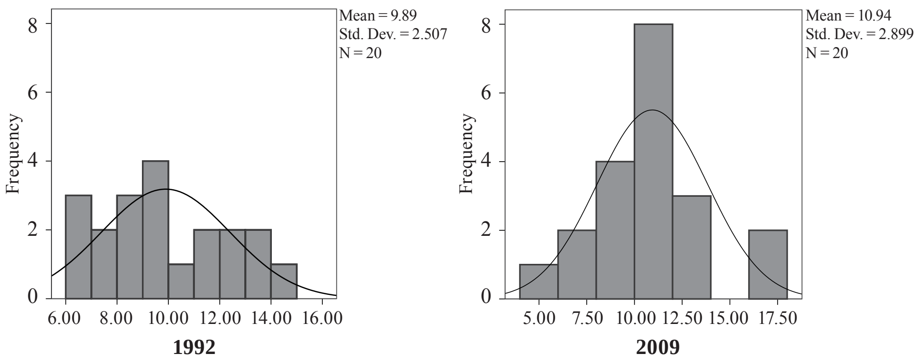

Figure 3. Frequency distribution of unemployment rate in Hungary in 1992 and 2009

Source: own compilation.

The box plot figure of county level unemployment rate data (figure 4) highlights fluctuations and the changing position from one year to the other. By examining the unemployment rate in the long run, periodicity is distinctly visible. The high unemployment in the beginning decreases in the next period until 2001, then an increase can be seen. Starting from 2007, the distance between the minimum and maximum values is getting bigger and bigger. The two counties in the worst position, namely Borsod-Abaúj-Zemplén and Szabolcs-Szatmár-Bereg counties appear as outliers.

Table 1 shows the unemployment data of the examined period. The minimal value is nearly the same at the beginning and at the end of the time period, approximately 6%. In the whole sample, however, the lowest unemployment rate value is 3.25%, belonging to Győr-Moson-Sopron county in 2003. In the case of maximum values, the difference is bigger. It was 14.48% in 1992 (Borsod-Abaúj-Zemplén county) that had increased to 17.68% (Szabolcs-Szatmár-Bereg county) by 2009. In the whole sample, the highest value, 17.72% was reached by Borsod-Abaúj-Zemplén in 1993.

Hungary split into two or rather three parts during the 20 years after the change of regime. The regional development level of the regions left of the Danube lag far behind the central and Trans-Danubian regions. It is demonstrated by the economic performance and unemployment trends. The regional differences greatly increased among counties, regions and the various types of settlements in the years following the change of regime in Hungary.

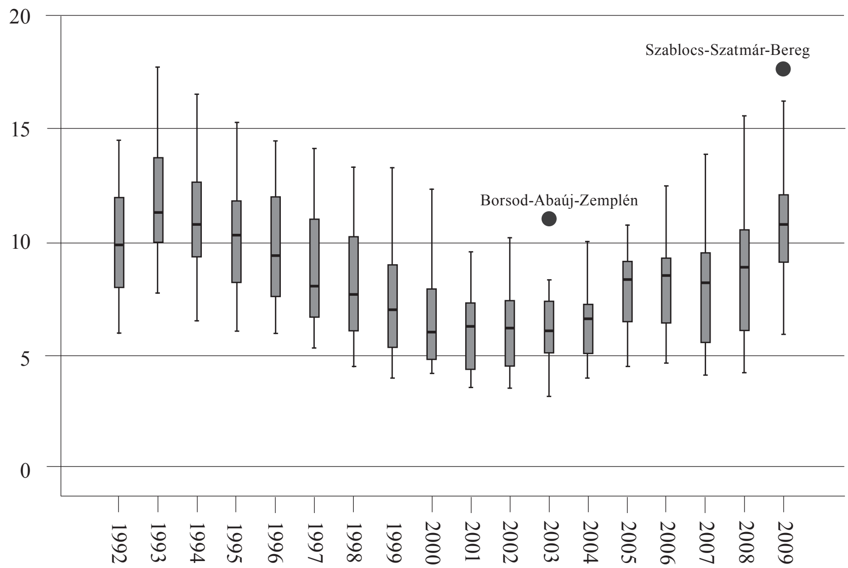

Figure 4. Box-plot figure of Hungarian county level unemployment rate

Source: own compilation.

Table 1. The main statistical values of unemployment rate

	1992	**2009**	**1992–2009**
minimum	6.01	5.98	3.25
maximum	14.48	17.68	17.72
mean	9.86	10.89	8.44
standard deviation	2.39	2.76	2.89
variation	5.70	7.64	8.33

Source: own compilation.

Can Hungary break out of the unemployment situation? Can the relative position of the areas change?

County level unemployment rate data for 2009 are illustrated on a map as well (figure 5) with the name of the counties. Equal class intervals are created using the values of the rate. As for unemployment, counties in Northern Hungary and Northern Great Plain are in the worst position. Transdanubian counties have much lower unemployment rate values. "Regional backwardness is a complex feature that can be well studied in the Northern Hungarian region and extends to about one third of the region's settlements. Its treatment is possible only with multidimensional, integrated development that affects the components of backwardness jointly" [Fekete, 2006: 57].

Figure 5. Unemployment rate of Hungarian NUTS 3 counties (%), 2009

Source: own compilation.

Counties can be classified based on the relative position of employment and unemployment rate data (figure 6). The labor market position is the worst in Borsod-Abaúj-Zemplén and Szabolcs-Szatmár-Bereg counties, while it is the most favorable in the capital, in Pest and Győr-Moson-Sopron counties.

The long term increase of unemployment in the past several years has three main causes in Hungary, just like in Europe:

– low rate of economic growth,
– rationalization decimates the workforce of large companies,
– relatively fast increase of labor supply.

While there is a strong relationship between growth and employment, the relationship between economic growth and unemployment rate is weak. In the case of new workplaces, they are often not unemployed who are employed, but the appropriate people from other countries.

Possible solutions to cut unemployment

Keynesian economic policy is based on three main ideas: social cooperation, fiscal policy against recession and steady currency policy against inflation. Social cooperation could be increased. The novelty of solving the problem could be the joint consideration of inadequate economic performance and high unemployment level. It requires the implementation of interventions in regional and employment policies that can strengthen each other. Keynesianism tries to move the economy from the state of high unemployment and low rate of economic growth. It can,

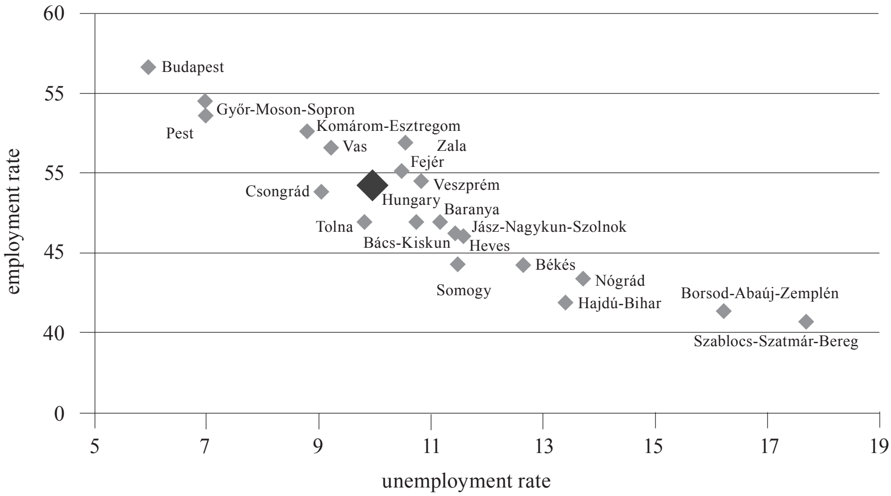

Figure 6. The position of the counties in 2009

Source: own compilation.

however, only be done by accelerating inflation and budget deficit and increasing national debt. Moreover, Keynesianism is suitable only for treating cyclical unemployment, that is unemployment related to economic cycles. The basic idea can be that creating jobs is not possible only for increasing employment. There must be some useful and meaningful economic activity in the background. A spontaneous way to handle the problem can be the recovering non-profit activity and the public work related to local municipalities. They show the ways of exploring the possibilities.

The above presented statistical data supported the fact that Hungary has fallen behind in the world economy and in the context of the European Union. Moreover, the position of Hungarian counties is not homogeneous either. To analyze unemployment in the longer run, Markov model is applied. Its methodology is presented below.

Methodology: The Markov chain model and Markov process model

Markov model is applied in several fields of research, though it cannot be regarded as a frequently used analytical tool. In regional economics, it is used to describe income inequalities [Major, 2007: 55]. In the labor market, it is used to describe the dynamics of the labor market of EU member states [Christodoulakis, Mamatzakis, 2009) and to analyze segmented labor markets [Gaubert, Cottrell, 1999].

Before introducing the model in detail, let me provide you with some information about Andrey Andreyevich Markov (1856–1922), who worked out its theory. The Russian mathematician dealt with the theory of stochastic processes and of convergence of progressions. He lectured as a professor at the Saint Petersburg University for several decades. His most famous achievement is known as Markov chain today.

Markov chains can be used to model stochastic processes where the next phase of the process depends only on the current phase. If time is the parameter, the process can be regarded as a case where the past can affect the future only through present. A discrete time Markov process or a Markov chain means a system where the set of parameters and the phase space are countable. In the computations, transition probability matrices "remember" the events of the previous years, which can help in scrolling the prediction [Ugrósdy, 2002: 97].

In the theory of Markov processes, the distribution of the process' phases is computed. To put it another way, the objects of such stochastic investigations are random variables defined on some probability space. Distributions on the phase space defined by observations are examined in the theory of Markov processes. There is no exclusive definition for Markov chain. Some authors use the term Markov chains only for processes in discrete time. However, the most common meaning is that Markov chains are stationary Markov processes on discrete phase spaces. The theory of stationary Markov processes in discrete time is particularly simple. To find transition probability matrices, it is enough to compute the powers of the one-step transition matrix. The Markov process which has a finite or countable state space is called Markov chain.

The examined object in the Markov chain model, the change of which over time is tried to be explained, is the population distribution observed in different times. This concept describes how the observed population is distributed in a given time based on the observed characteristic. To do so, the observed units have to be classified into different classes (that are mutually exclusive). These classes are generally called *phase* in the literature of Markov model [Major, 2008: 34].

Another important key word is movement. In the analysis, explanation is searched to the regularity of the observed elements' movement from one group to the other.

The set of possible phases is called phase space (S). Before the investigation, adequate number of finite categories (classes) has to be created. The population distribution is described with the vector including the probabilities of belonging to the categories. A real number between 0 and 1 belongs to each phase, which shows the probability that an element belongs to the given phase. The probability of belonging to phase i in a given time is signed with p_i. The sum of the classes' probabilities is always one. In formula (1) n is equal to the number of classes [Lu, 2009; Krolzig, Marcellino, Mizon, 2002].

$$\sum_{i=1}^{n} p_i = 1 \tag{1}$$

Transition probabilities can be defined with the maximum likelihood method. The sample size is signed with d, while the one step transitions from phase i to phase j in the sample are signed with d_{ij}. The probabilities to be estimated are signed with p_{ij}. In the case of the maximum likelihood estimator, the parameters that ensure the maximum probability of the sample should be found. The logarithm of the likelihood function is the following:

$$\max_{p_{ij}} \log L = \sum_{D} d_{ij} \log p_{ij} \tag{2}$$

The solution of the equation can be expressed with Lagrange function, where the following formula describes the solution:

$$\hat{p}_{ij} = \frac{d_{ij}}{\sum_j d_{ij}} \tag{3}$$

The estimator of the transition probabilities is the relative frequency of the actual transitions from phase i to phase j, i.e. the observed transitions have to be divided by the sum of the transitions to all other phases.

The movement between classes can be described with stochastic matrix, which is a square and non negative matrix and the sum of elements in any rows is 1. Its further characteristic is that the product of any two stochastic matrices is also a stochastic matrix. This will be important later [Bhatnagar, Kowshik, 2005: 759].

Take a matrix P that is called the transition probability matrix of Markov chain provided that the element p_{ij} is the conditional probability that the element in phase i in the current time will be in phase j in the next time [Toikka, 1976]. The elements in the main diagonal of transition probability matrix are the probabilities that the given element stays in the same class in the next time. Elements outside the main diagonal, however, are the probabilities of movements among the given phases. The elements of matrix P are probabilities that have the sum of one by rows [Guha, Banerji, 1999: 174].

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix} \tag{4}$$

One step and m step transition probabilities have to be introduced , which can help to compute one step and m step transition probability matrices. Let $\{X_m, m \in N\}$ be a Markov chain and the one step transition probability be:

$$p_{ij} = \Pr(X_1 = j | X_o = i) \tag{5}$$

Formula (5) is called homogenous Markov chain if transition probabilities are independent of time. In this case they are independent indeed. In the case of (6), t is the time parameter.

$$p_{ij}(t) = P(X_{t+1} = j|X_t = i) \tag{6}$$

The m step transition probability is:

$$p_{ij}^{(m)} = Pr(X_m = j|X_0 = i) \tag{7}$$

Formula (5) expresses the probability of moving from phase i to phase with by one step, while formula (7) expresses the probability of phase j after the m^{th} step provided that

$$p_0^{(i)} = Pr(X_0 = j) > 0 \text{ (initial distribution)} \tag{8}$$

For the m step transition probabilities, the Chapman-Kolmogorov equation is satisfied, which is the following for each k (if *0<k<m*):

$$p_{ij}^{(m)} = \sum_{r \in S} p_r^{(k)} p_{ij}^{(m-k)} \tag{9}$$

It can also be expressed with another formula:

$$p_{ij}^{(n+m)} = \sum_{r \in S} p_r^{(n)} p_{ij}^{(m)} \tag{10}$$

Transition probability matrix has to be calculated as many times as the number of years taken into consideration. In this way m step transition probability matrix can also be considered, which is signed as P^m.

The extent of mobility for a given time can be calculated from the transition probability matrix using the following formula. In order to calculate the measure of mobility, the main diagonal of the matrix is used, where n is the number of classes.

$$\mu(P) = \frac{n - \sum_i p_{ii}}{n-1} \tag{11}$$

The applied Markov model is stationary and homogenous as the transition probabilities are independent of time. It means that the past does not have greater effect on future events than those appearing in the present. It implies that the past can only affect the future through present and not directly. In the case of unemployment, it should be taken with reservations. Researchers apply Markov model or mover-stayer model to lift stationarity [Major, 2008: 67].

Results of the Markov chain model

What kind of unemployment groups can be created using Markov chain model and how these groups change over time?

Markov model is calculated based on the methodology of Major. It is different from the one applied by Ugrósdy in a way that it creates classes immediately diminishing the assumption system of the method. The unemployment rates of the 19 counties of Hungary and Budapest are analyzed between 1992 and 2009. The aim of the research is to describe and predict the changes in the unemployment. As the unemployment rate is a rate itself, it is not necessary to modify it. It is weighted in relation to the population. The assumption of the Markov chain is that the examined elements belong to any of the phases (that have finite number) in each moment. In order to carry out the analysis, it is necessary to discretize, i.e. categorize the values. A frequently used way to discretize the phase space is the categorization based on equal number of observations, i.e. classes are formed to have approximately equal number of observations each. The advantage of this classification is that the classes will not be sensitive to extreme values. Its backlog, however, is that it is difficult to justify the choice of "arbitrary" boundaries. The other problematic question is the number of classes to be formed. Too many or too few categories cannot give appropriate results. In the case of unemployment rate, five classes are created (table 2).

Table 2. Classes of unemployment

No.	Name of class	Class boundaries	Class midpoint	Number of observations
1	extremely low	3.25–5.80	4.525	70
2	low	5.81–7.30	6.555	76
3	medium	7.31–9.50	8.405	96
4	high	9.51–11.50	10.505	65
5	extremely high	11.51–17.72	14.615	53

Source: own compilation.

The equal distributional definition of the class boundaries has also been carried out. The number of observations belonging to the classes, however, is biased to a large extent. That is why it has been neglected and the arbitrary modification of class boundaries has been applied because of the equal number of observations.

After the classification of the counties to the given phase, the transition probabilities among the possible classes are examined. From the initial time (t_0) to the next year phase (t_1) the following probabilities can be observed. It implies that from the extremely low class of unemployment counties stayed either in the same class or had low or medium values by the next year. It is also possible to move to the other phases, but they are not present in the sample.

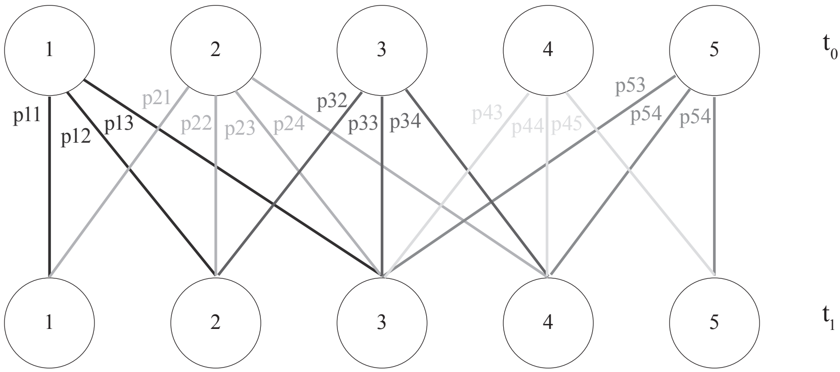

Figure 7. Probabilities in the sample from 1992 to 1993

Source: own compilation.

The next step is to find the one step transition probability matrix (table 3) with the Lagrange function presented above for the probability values. In fact, relative frequencies have to be calculated from the available 17×20 = 340 transitions ($\sum d_{ij} = 340$).

Table 3. One step transition probability matrix

Class	**1**	**2**	**3**	**4**	**5**
1	0.965	0.032	0.003	0	0
2	0.044	0.909	0.044	0.003	0
3	0	0.050	0.924	0.026	0
4	0	0	0.032	0.944	0.024
5	0	0	0.003	0.015	0.982

Source: own compilation.

It is worth interpreting the elements of the one step transition probability matrix. The probability that the counties belonging to the extremely low unemployment class are staying in the same class in the next year as well is 96.5%. The probability that they are moving to the low class is 3.2% and the probability that they are moving to the class of medium level unemployment rate is 0.3%. In the case of counties belonging to the class of low unemployment rate, the probability of moving to the extremely low class is 4.4%, so the improving labor market position can also be seen. They are staying in the same class with 90.9%, they are moving to the class of medium unemployment rate with 4.4%. A further 0.3% is the probability that they are moving to the high value class. Out of the counties belonging to the medium level unemployment rate class, the probability of moving to the low level class is 5%. The counties are staying in the same class as in the previous year with 92.4%. The probability of moving to the class of high unemployment rate is 2.6%. In the case of counties with high level unemployment rate, the probability that the situation is improving by the next period and they can move to the class of medium unemployment rate is 3.2%. 94.4% is the probability that they are staying in the same class and 2.4% is the probability that the situation is worsening and the counties are moving to the class of extremely high unemployment rate. In the case of counties with extremely high level of unemployment rate, the chance of moving to the class of medium level unemployment is 0.3% and the probability of moving to the high class is 1.5%. The probability of staying in the same class, however, is 98.2%. It is apparent that the probability of moving from a class to the other is rather low. In the bulk of the cases, counties stay in the same class in the next period, too.

The measure of mobility is 0.6%, which can be calculated as follows:

$$\mu(P) = \frac{n - \sum_i p_{ii}}{n-1} = \frac{5-(0.965+0.909+0.924+0.944+0.982}{5-1} = 0.069 \tag{12}$$

The measure of mobility shows the overall labor market mobility of the counties. The probability that the counties change their labor market class in the next period is 6.9%. By moving forward over time and by calculating the one step transition probability matrix, the value of the mobility measure keeps increasing.

After examining the past, it is worth examining what will happen in the future. Provisions for the future should be taken with reservations as unemployment is influenced by several factors (demand of companies for workforce, demographic processes). Expected changes for 18 years can be expressed with the 17^{th} power of the transition probability matrix (17 transition is possible in 18 years) or with the direct estimation from the data. With the calculation of the transition probabilities for the 17 years, it is possible to test the long term predicting ability of the model. It is not necessary by all means to choose 17 year long prediction, but provided that the initial data were available with 17 years transitions, it is practical to apply the same time period.

Table 4. The 17^{th} power of the one step transition probability matrix

Class	**1**	**2**	**3**	**4**	**5**
1	0.637	0.239	0.100	0.021	0.003
2	0.316	0.354	0.242	0.075	0.013
3	0.116	0.262	0.397	0.182	0.043
4	0.020	0.078	0.218	0.450	0.233
5	0.003	0.016	0.059	0.151	0.770

Source: own compilation.

Probability values show a remarkable deviation relative to the one step phase. Over 18 years, several ways are possible, any phase can be reached from any other phases. In this way, elements of the main diagonal are decreasing and elements outside the main diagonal are increasing. The measure of mobility also increases to a large extent comparing to the one step phase. This measure is 59.8% in this case. It does not provide any further information about the changes in the processes. Predictions generated on the basis of the Markov model for several years should be taken with severe reservations. 18 years later (in 2027) the probability of belonging to the class of absolutely low level unemployment rate will be 63.7%, that of belonging to the class of low level unemployment rate will be 35.4%, that of belonging to the medium class will be 39.7%, that of belonging to the high class is 45%, while the probability of belonging to the extremely high class is 77%. The probability of moving from the class of extremely low level unemployment rate to the class of low level unemployment rate will be 23.9%. A further 10% is the probability of moving to the medium class, 2.1% is the probability of moving to the high level class and 0.3% is the probability of moving to the extremely high class of unemployment. The probability that counties belonging to the low class will reach better position in the long run and will belong to the extremely low class is 31.6%. The probability of falling back to the medium class of unemployment will be 24.2%, the probability of high unemployment will be 7.5% and the probability that the counties are moving to the extremely high class is 0.13%. The probability that counties belonging to the class of medium level unemployment rate are moving to the class of extremely low level unemployment is 11.6% and the probability of moving to the low level class is 26.2%. The improvement of unemployment position can be considered to be important on the whole and also in the case of each class. In this case, the measure of mobility is 59.8%.

Table 5. Expected distribution based on the transition probability matrix

Class	**Initial distribution**	**Estimation for 2027**	**Estimation for stationary distribution**
1	0.1944	0.2273	0.2412
2	0.2111	0.2069	0.1930
3	0.2667	0.2236	0.1958
4	0.1806	0.1707	0.1585
5	0.1472	0.1716	0.2114

Source: own compilation.

In 2027, 22.73% of the counties will belong to the extremely low class of unemployment, 20.69% of them will fall into the low class, while 22.36% of them will belong to the medium class. The high class of unemployment includes 17.07% and the extremely high class includes 17.16% of the counties based on the estimation.

Stationary distribution describes the distribution of unemployment in a stationary phase (table 5), i.e. in a phase when the inflow to and the outflow from any county has the same extent and in this way the level of unemployment can be considered constant. This is the so called steady state phase. Stationary distribution mathematically means the examination of the P^n transition probability matrix that describes the long term behavior of a finite phase space Markov chain in the case of N. The limit value (limit matrix) of P^n exists, which has each row equal [Smith, Hsieh, 1997: 670].

It means:

$$\lim_{n\to\infty} P^n = \Pi = \begin{bmatrix} \underline{\pi} \\ M \\ \underline{\pi} \end{bmatrix} \tag{13}$$

In the case of any p_0 initial distribution, the above described equation has the following form:

$$\lim_{n\to\infty} p_0 P^n = p_0 \Pi = \underline{\pi} \tag{14}$$

It implies that the initial distribution loses its importance gradually. Let $\underline{\pi}$ be a limit distribution, i.e. in the case of any p_0 initial distribution:

$$\lim_{n\to\infty} p_0 P^n = \underline{\pi} \tag{15}$$

In this case:

$$\underline{\pi} = \lim_{n\to\infty} p_0 P^n = \lim_{n\to\infty} p_0 P^{n+1} = \lim_{n\to\infty} p_0 P^n P = \underline{\pi} P \tag{16}$$

The $\underline{\pi}$ distribution is called stationary (or equilibrium) distribution if

$$\underline{\pi} = \underline{\pi} P \tag{17}$$

The transition probability matrix composed based on unemployment data tries to quantify the processes of unemployment mobility between 1992 and 2009. The prediction generated with the use of the matrix gives estimation for the distribution that takes shape provided that the observed processes of the past are continuing. A backlog of the method is that it is not suitable for the prediction of turning points or breaking points in unemployment. It only projects the trends based on the observed sample for the future. It makes the prediction statically.

Conclusion

The paper models the labor market processes, especially unemployment in the Hungarian counties with Markov chain. The prediction of the model has to be taken with reservations as Markov chain model oversimplifies processes. As a result, long term mobility is systematically overestimated. At the same time, the novelty of the results is that similar long term labor market predictions are rarely generated. Labor market is sensitive to changes that cannot be forecasted for the future. Events changing labor market participation that cannot be foreseen can happen anytime – these cannot be taken into consideration in Markov model. Literature includes the application of Hidden Markov Model (HMM) and mover-stayer model that are refined versions of the basic Markov model. A possible continuation of the research is the application of these models to the labor market and its indicators.

I think that one of the most important problems is unemployment also in Hungary. Each member of the area has to cooperate in order to decrease unemployment. The efficiency of local initiatives can be completed only with extended partnership. That is why traditional forms and institutions of cooperation have to be exceeded. Partners can be local and national institutions, national or regional administrative institutions, the private sector, civil organizations, chambers. The most important aim is that these organizations present a united front against unemployment and work out an action plan supporting this front. In regional policy, it is the development of infrastructure that has a dominant role. It can increase the demand side of employment, which, based on keynesianism, can extend internal market and thus can contribute to the foundation of new enterprises. Aiming the improvement of labor productivity, measures to develop enterprises develop the set of means: they increase skills, develop technology and ensure capital. Measures to attract foreign investors, however, trusting in the self-regulation of the market, try to support it to solve the problems of regional employment. Hungarian employment policy is definitely defined from social aspect. Its main aim is to support the unemployed by social transfers. The unemployed is not involved in the economic life of the regions, which should be changed. Interventions in regional and employment policies, that can strengthen each other, are necessary to handle the problem of high unemployment level.

Regional realignment is becoming more and more important in the future and it is not possible any more to talk about homogenous counties, so the relative position of the areas are going to change as well. In the case of unemployment, however, a bit more favorable situation is expected. Prediction based on Markov model shows that the number of counties belonging to the original five categories of unemployment will have been changed by 2027. More counties are belonging to the category of extremely low unemployment, while there will be less counties in the middle class and more counties in the class of extremely high unemployment comparing to the initial situation. It predicts a bit more balanced unemployment situation in the future as the current one. At the same time, however, it is not possible to draw far-reaching conclusions because of the static nature of the forecast. In order to break out of the current unemployment situation, both the regional and employment policies have to be reconsidered and the measures to apply have to be harmonized as the current situation is not going to work out by itself. I am optimistic about the future and I am definitely positive that it is possible to break out of the current position. It only requires thinking over what is possible to do, something that is not only an activity for a show, but a measure leading to real results.

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