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ANALYSIS OF JOB CHANGES IN POLAND USING THE BAYESIAN METHOD

1. INTRODUCTION

Employees in Poland prefer stability of employment, willingness to change job is expressed by only 15% of them, while 84% of employees are not planning to find a new employer and 69% are totally sure they are not going to search for a new employer (Public Opinion Research Centre, 2006). This situation might have been caused by the labor market organization before 1989. State-socialist work structures before economic transformation did not promote frequent job changes. The dominance of the public sector and state-controlled, regulated economy resulted in limited motivation for career mobility, as most of the work and payment conditions were defined centrally and the range of choices was largely constrained (Kryńska E., 2000).

At the same time, the comparative study of career mobility in the Federal Republic of Germany and Poland has shown that the frequency of job changes in Poland was higher in the analyzed period, which contradicts stereotypes about limited employee mobility in state-socialist societies (Mach B.W., Mayer K.U., Pohoski M., 1994). Taking into account the lack of detailed studies regarding job changes in Poland during the regulative economy period (1950-1989) (Jezierski A., Leszczyńska C., 2001), research on career mobility and the most important factors effecting it should be continued.

The retrospective survey "Family changes and Fertility Patterns in Poland"[1] performed in 1991 shows that almost 50% of respondents changed job at least once. According to the same survey, the most frequent reasons for starting work or changing job were that adult workers felt obliged to be employed for financial and family reasons and they wanted to maintain and improve standard of living, the less important factors were personal development and the need for improving qualifications. At the same time the job changes might have been effected by many other demographic and socio-economic factors. Among them age, sex, education level, place of living, having a family, number of children and socio-occupational group could be considered.

The primary objective of the work is to identify key factors influencing career mobility in Poland between the years 1950-1988 and estimate their impact on it by using Bayesian methods. In this work career mobility is expressed by the number of employment periods, except for career breaks caused by maternity leave or long-term illness.

A discussion on different forms of employee mobility during the transformation period can be found in (Kryńska E., 2000). The work concentrates on the description and analysis of work resources on regional labor markets in Poland and aims to recommend how mobility could be increased and stimulated. Mobility analysis both at intra and inter-organization level has considered the following demographic and professional features: age, sex, place of residence, education and employment status. In addition, other determinants including travel time to work, income and work experience have been included. It has been determined that the factors influencing inter-organization mobility were: sex, age, work experience, education and place of residence. However, income appeared to have the largest impact on the frequency of job changes. The methods applied in the work rely on the comparison of percentage shares. Contrary to this approach, in our work a statistical model has been applied. This allows the investigation of the joint impact of selected determinants on career mobility.

The analysis of three forms of employee mobility i.e. career mobility, inter-organizational mobility and the spatial mobility of graduates employed in the public sector on the territory of three regions has been described in (Witkowski J., 1983). The study begun

[1] Research performed by the Institute of Statistics and Demography of the Warsaw School of Economics and Central Statistical Office in 1991, as a part of European program „Family and Fertility Survey" coordinated by the Population Activity Unit Commission for Europe, UN Geneva.

in 1977 in Bialsk Podlaski region in 1977. It continued in 1978-1979 on the territory of Olsztyn and Warsaw region. Different combinations of mobility forms in terms of their frequency have been investigated. Moreover, for each of the regions and each mobility form the impact of demographic, socio-environmental and professional factors using a classical regression model has been analyzed. The main motivation for this research was to identify employee attributes that have substantial influence on career mobility in different subpopulations of highly educated employees. The question may be asked, what features influenced the career mobility of the remaining part of Polish society in the period of the state-socialism economy, as highly educated persons were only 2.7% of Polish society during this period (Census data, 1970).

The comparison of career mobility conceived as a sequence of job-shifts within and between organizations in Poland and the Federal Republic of Germany has been performed by W. Mach, K. U. Mayer and M. Pohoski (1994). In the case of Poland the survey data collected in 1972 for persons born in the period 1939-1941 has been used. The following determinants of employee mobility have been taken into account: sex, education, occupational experience, social class, firm size and industrial sector. The authors emphasize that Polish enterprises of this period, in spite of strict control through central planning and state-monopolized supply of capital, had to compete for labor power in the labor-market. The labor market was well developed and to a great extent free from any form of administrative control over the allocation of labor. At the same time, the analysis reveals significant differences in the dynamics of job changes and the scale of impact of individual factors between Poland and the Federal Republic of Germany.

The largest employee mobility in the analyzed period has been observed in the USA. The research on the career mobility of men shows the significance of education (Sicherman N., Galor O., 1990). The employees with higher education status were found to have lower number of distinct professions and therefore were less likely to change jobs and employers. Moreover, the research shows that career mobility is reduced with more work experience. In addition, in cases of higher level of experience, career mobility is more likely to occur within the firm than outside the firm. Finally, the fact that intra-organization job mobility is controlled by employers, while inter-organization changes are largely decided upon by the employees, has been emphasized (Sicherman N., Galor O., 1990). Still, both mobility forms are effected by many other factors. The identification and investigation of these factors is the objective of this work.

2. THE SCOPE OF THE ANALYSIS

The work concentrates on the career mobility in Poland in the years 1950-1988. The study has been based on the retrospective study ”Family changes and Fertility Patterns in Poland”. Our work includes all the persons who were employed at least once, except for self-employed farmers, for whom their family farms were the main source of income. The analysis takes into account the whole employment periods of the respondents during the period 1950 till 1988. The youngest respondent entered the workforce at the age of 15.

In order to consider the fact that different factors may influence job changes for young persons starting their professional careers and for more experienced employees, three groups have been investigated separately: the persons aged 18 – 30 years (1654 observations), 31 – 45 years (2779 observations) and 46 or more years (269 observations)[2]. The last group has the lowest number of observations. However, it contains the most data regarding professional career as older employees are more reluctant to change job.

The analysis of career mobility has been performed using a Bayesian generalized linear model. Because dependent variable is the number of employment periods, a Bayesian Poisson regression model has been applied. The model proposed enables the investigation of the joint influence of different factors on the number of employment periods. An important advantage of Bayesian analysis is the ability to produce reliable conclusions even in cases of a limited number of observations, as in the case of the third age group.

In order to investigate the characteristics of the group, the value of dependent variable being the number of employment periods for individual age groups has been calculated and summarized in Tab. 1. Based on this data, an observation can be made that young persons changed jobs infrequently. In market economies high career mobility among you persons had been observed in the analyzed period (Topel R.H., Ward M.P., 1992, Light A., 2005). It has been suggested that possible increases of income was the factor that stimulated job changes. After 1989, the same phenomenon was observed in Poland and the largest career mobility has been observed among young persons aged under 30 years (Kryńska E., 2000).

[2] In the remainder of the work the age groups 18– 30 years, 31-45 years and above 45 years will be called the first age group, the second and the third age group respectively.

	The number of persons			
The number of employment periods	**Total**	**Age group I**	**Age group II**	**Age group III**
1	2552	1162	1283	107
2	1335	370	883	82
3	505	86	374	45
4	186	28	139	19
5	76	7	56	13
6	30	1	29	0
7	10	0	8	2
8	4	0	3	1
9	2	0	2	0
10	2	0	2	0

Table 1. The number of employment periods for different age groups.

The primary objective of the study is the investigation of dependencies between career mobility defined as the number of employment periods and the following features of respondents: the place of residence at the moment of research, sex, education level, the intention to continue education within two years, the intention to change place of residence within two years, having a family, the number of children, socio-occupational group and the age of entering the workforce. The characteristic of independent variables that potentially have an impact on career mobility developed for all the age groups together has been discussed below.

The first variable is place of residence at the moment of examination, the values of this variable are: 1 = a big city – above 200.000 residents (32.52%), 2 = a small city (37.75%), 3 = a village (29.73%). One can expect that higher mobility will be observed for respondents living in big cities than those living in villages, it is easier to find a job in bigger cities.

Another determinant which has been taken into consideration is sex: 0 = woman (42.32%), 1 = man (57.68%). Having considered the traditional family model one can expect that higher mobility should be observed for men rather than for women.

We can suppose that education is one of the most important factors influencing the chance to find and keep a job, moreover a higher level of education should result in increased chances for an occupational promotion. Education variable takes the following values 1= higher (10.91%), 2 = post-secondary (5.19%), 3 = secondary professional (22.97%), 4 = secondary general (8.32%), 5 = basic vocational (38.09%), 6 = primary school (14.53%).

In order to investigate whether the respondents who continue education, have higher mobility rates, the intention to continue education within the next two years has been included. The variable takes the following values: 1 = yes or I am studying at the moment (5.74%), 2 = I do not know (5.66%), 3 = No (88.6%).

Finding a job or a willingness to change it may require changing place of residence. Thus the persons considering the latter change should have higher career mobility rates too. The intention to change place of residence within the next two years is the next variable to consider. As in the previous case the interpretation of its values is as follows: 1 = yes or I am in the process of changing my place of residence (6.47%), 2 = I do not know (8.02%), 3 = no (85.52%).

Furthermore, on one hand the persons having their own families and/or children can be more likely to change jobs, as they want to improve the standard of living. On the other hand, the responsibility for their families may cause the anxiety to change job. Thus, having a family has been selected as the next variable to consider with the following interpretation of answers 0 = no (13.76%), 1 = yes (86.24%). Consequently, the number of children has been added as one more variable, with four categories used: 0 (19.37%), 1 (23.76%), 2 (38.54%), 3 or more (18.33%)

Frequency of job changes might be also dependent on the sector. Thus, the socio-occupational group a respondent belonged to at the moment of entering the workforce has been added. The following classes have been identified 5 = factory workers and similar professions (25.41%), 4 = employees of transport, trade and services (19.33%), 3 = experts in engineering and non-engineering professions (19.54%), 2 = clerks (15.33%), 1 = remaining employees (20.37%)

Finally, one can assume that the persons who start their professional careers earlier, change jobs more frequently before they reach stability. Therefore, the age of entering workforce has been added too. The minimal age was 15 years; the maximal value reported in the survey was 43 years.

3. THE METHOD

In this paper we have used a Bayesian Poisson regression model. The Bayesian methods offer an alternative approach to frequentist analysis and actually are equivalent to classical methods. The Bayesian methods combine subjective prior knowledge with the information from the data by using Bayes' theorem. The advantages of using Bayesian methods are discussed in many works (Bolstad W.M., 2007 and Gelman A., Carlin J.B., Stern H.S., Rubin D.B., 2000). These advantages include the possibility of incorporating information not contained in the data set, a natural interpretation of credible interval.

Moreover inference based on a small sample proceeds in the same manner as if one had a large sample.

Let $\mathbf{Y}$ denote the samples space, Θ the parameters space, a $\{P_\theta : \theta \in \Theta\}$ the family of probability distributions on $\mathbf{Y}$. In Bayesian analysis we additionally assume the existence of a probability measure defined on the class of all measurable subsets of Θ. This distribution we call a prior distribution of parameter θ[3], it expresses the degree of our belief about parameter before we examine the data (Silvey S.D., 1978). The main disadvantage of Bayesian analysis is lack of any information on how to select a prior. But if the result of an experiment provides enough information, then any changes in the prior distribution do not result in significant changes in posterior distribution (Silvey S.D., 1978).

Consider the estimation of an unknown parameter θ from data $\mathbf{y} = \{y_1, \ldots y_n\}$, let $p(\theta)$ be a prior distribution of parameter θ, moreover let $p(\mathbf{y} \mid \theta)$ be the distribution of $\mathbf{y}$ given θ. Moreover the joint density function can be written as a product $p(\mathbf{y} \mid \theta)p(\theta)$. Then using Bayes' theorem, conditional distribution of parameter θ is defined as follows:

$$p(\theta \mid \mathbf{y}) = \frac{p(\mathbf{y} \mid \theta)p(\theta)}{p(\mathbf{y})},$$

where $p(\mathbf{y})$ denotes the marginal distribution of $\mathbf{y}$, which is given by $p(\mathbf{y}) = \sum_i p(\mathbf{y} \mid \theta_i)p(\theta_i)$, in the case of discrete θ and $p(\mathbf{y}) = \int_\Theta p(\mathbf{y} \mid \theta)p(\theta)d\theta$, in the case of continuous θ. This conditional distribution $p(\theta \mid \mathbf{y})$ of the parameter θ is called the posterior distribution of this parameter. Inferences in Bayesian statistics follow from posterior distributions obtained in this way.

In this paper we use a Poisson regression model, which we estimate using a Bayesian approach. This model belongs to the class of generalized linear models, which allow examining influence of continuous and discrete predictors on a dependent variable. Distribution of a dependent variable belongs to the exponential family of distribution functions, moreover independent variables can have a nonlinear influence on the dependent variable (Nelder J.A., Wedderburn R.W.M., 1972, McCullagh P., Nelder J.A., 1989 and Dobson A.J., 1991).

If probability distribution of a dependent variable y has probability distribution from a family of distributions of the exponential form, then we can write

[3] Parameter θ is treated as a random variable or random vector with a certain distribution.

$$f(y;\theta,\phi)=\exp\left\{\frac{y\theta-b(\theta)}{a(\phi)}+c(y,\phi)\right\},$$

where a, b and c are established functions, θ is canonical parameter, and ϕ is scale parameter.

If $\theta=\ln\lambda$, $\phi=1$, $a(\phi)=\phi$, $b(\theta)=\lambda$ and $c(y,\phi)=-\ln(k!)$, we obtain the Poisson distribution

$$f(k;\lambda)=\frac{\lambda^k}{k!}e^{-\lambda},\ k=0,1,2,3,\dots,\ \lambda>0.$$

Depending on the distribution of a dependent variable we can use different link functions, a standard link function for the Poisson distribution is the logarithmic function.

The Bayesian analysis of Poisson regression models has been discussed in many works (Doss H., Narasimhan B., 1994, Dey D.K., Ghosh S.K., Mallick B.K., 2000, Gelman A., Carlin J.B., Stern H.S., Rubin D.B., 2000, and Bolstad W.M., 2007). In (El-Sayyad G. M., 1973) a comparison of a Bayesian and a classical approach to Poisson regression can be found. The author remarks that whereas Bayesian approximation is suitable both for estimation and test of significance of parameters, the classical method is not always suitable for estimation of parameters.

Let variable y_i, $i=1,2,\dots n$ has Poisson distribution with mean λ_i. If a link function is logarithm, then $\ln(\lambda_i)=\sum_{j=1}^{k}x_{ij}\beta_j$, where x_{ij} are independent variables, $\boldsymbol{\beta}=(\beta_1,\dots,\beta_k)$ is a vector of unknown parameters. Therefore $\lambda_i=\exp\left(\sum_{j=1}^{k}x_{ij}\beta_j\right)$. Then the likelihood function of parameters vector $\boldsymbol{\beta}$ is given by

$$L(\boldsymbol{\beta};\mathbf{y})=\left(\prod_{i=1}^{n}y_i!\right)^{-1}\exp\left(-\sum_{i=1}^{n}\exp\left(\sum_{j=1}^{k}x_{ij}\beta_j\right)+\sum_{j=1}^{k}\beta_j\sum_{i=1}^{n}x_{ij}y_i\right).$$

Examples of prior distributions for parameters of generalized linear models can be found in (Dey D.K., Ghosh S.K., Mallick B.K., 2000). Usually we choose normal distributions with zero mean and any variance. In Bayesian inference special role is played by non-informative priors, which have minimal impact on a posterior distribution. Sometimes distributions, which are sufficiently non-informative can be used. In the case of a normal distribution we use zero mean and any large number for variance. For parameters $\beta_1,\dots,\beta_k$ we take the normal prior distributions with mean m_j and variance σ_j^2, the joint density of $\beta_1,\dots,\beta_k$ is given by

$$p(\beta_1,\ldots,\beta_k)=\prod_{j=1}^{k}\frac{1}{\sigma_j\sqrt{2\pi}}\exp\left(-\frac{1}{2\sigma_j^2}(\beta_j-m_j)^2\right).$$

Therefore, the posterior distribution can be written in a closed form, up to a constant proportionality

$$p(\beta_1,\ldots,\beta_k \mid \mathbf{y})\propto \exp\left(-\sum_{j=1}^{k}\frac{1}{2\sigma_j^2}\beta_j^2+\sum_{j=1}^{k}\left(\frac{m_j}{\sigma_j^2}+\sum_{i=1}^{n}x_{ij}y_i\right)\beta_j-\sum_{i=1}^{n}\exp\left(\sum_{j=1}^{k}x_{ij}\beta_j\right)\right).$$

In the Bayesian inference about the parameter vector $\boldsymbol{\beta}=(\beta_1,\ldots,\beta_k)$, we seek the conditional distribution of the parameter of interest given the observed data, which is derived from the joint posterior distribution by integrating out all other parameters. Only in the simplest examples the marginal posterior distribution can be obtained analytically, usually we use a simulation method for sampling from posterior distribution and computing posterior quantities of interest - Markov chain Monte Carlo (MCMC) methods are frequently used for such simulations. The MCMC techniques construct an ergodic Markov chain with the stationary distribution, which in Bayesian statistics is called the posterior distribution of the model parameters. The best known sampling method is Metropolis algorithm and Metropolis-Hastings algorithm. A Gibbs sampler is a special case of the Metropolis-Hastings sampler, it has been used to obtain a sample from the posterior distribution in this paper.

The important part of Bayesian analysis is assessing the convergence of a Markov chain. In theory, if the Markov chain is allowed to run for an infinite number of iterations, then the chain reaches stationarity. The assessment of convergence is important, but there are no conclusive tests for the convergence of Markov chains, many diagnostic tools verify only necessary but not a sufficient condition. The most known statistical diagnostic tests are: Gelman and Rubin diagnostics, (Gelman A., Rubin D. 1992, Brookes S., Gelman A., 1998), Geweke diagnostics (Geweke J., 1992), Heidelberger and Welch diagnostics (Heidelberger P., Welch P., 1981, 1983) and Raftery and Lewis diagnostics (Raftery A., Lewis S., 1992, 1995).

4. THE ESTIMATION OF MODELS

Estimation and verification of all the models has been performed using SAS system. In Bayesian estimation, Markov chain Monte Carlo methods have been applied. First, Poisson regression models have been estimated using classical approach, then based on standard measures of fit and the correlation between variables the best model has been selected.

Taking into account the characteristics of the variable and preliminary simulations, in case of the third age group, the following variables have been skipped: the intention to continue education within the next two years, the intention to change place of residence within the next two years and having a family. The two remaining models include all the variables listed in the introduction of the work.

In order to obtain objectively correct results, we have used a priori distributions that have a minimal impact on a posteriori distribution. Therefore, non-informative independent normal prior distributions with zero mean and variance of 10^6 have been used for all regression parameters to estimate all the models:

$$p(\boldsymbol{\beta}) \sim N\left(\mathbf{0}, 10^6 \mathbf{I}\right)$$

Moreover, to minimize the effect of initial values on the posterior inference the number of burn-in iterations has been set to 2000, and the number of iterations after the burn-in to 10000.

Estimated models have been evaluated to assess the convergence of generated Markov chains. For the third model, the number of the posterior samples was not sufficient, and the sampler had to be run longer (100000) to reach stationarity of the Markov chain.

Inference in Bayesian analysis under unchecked convergence for all model parameters may result in wrong conclusions. Using Geweke's test (Geweke J., 1992) we have found that there is no indication that the Markov chain has not converged for all the parameters of investigated models, at the significance level 0.05 (Table 2.). Thus, it can be assumed that the obtained posterior samples are appropriate for statistical inference.

Geweke diagnostics						
	Model 1		**Model 2**		**Model 3**	
Parameter	z	Pr>|z|	z	Pr>|z|	z	Pr>|z|
Intercept	1.7706	0.0766	-0.4246	0.6711	-0.3870	0.6988
the age of entering workforce	-1.7582	0.0787	1.2593	0.2079	0.4554	0.6488
the place of residence 1	0.0945	0.9247	-0.0221	0.9824	0.9330	0.3508
the place of residence 2	0.3604	0.7185	0.0707	0.9436	0.5169	0.6052
Sex	-0.2516	0.8014	0.1251	0.9004	-0.1919	0.8478
Education 1	1.6843	0.0921	-0.5534	0.5800	-0.7691	0.4418
Education 2	0.4203	0.6743	-0.2240	0.8228	-0.8972	0.3696
Education 3	0.5818	0.5607	-0.2258	0.8214	-0.5364	0.5917
Education 4	0.3358	0.7370	-0.3680	0.7129	-0.7419	0.4581
Education 5	-0.0827	0.9341	0.5831	0.5598	-0.8717	0.3834
the intention to continue education 1	0.7909	0.4290	0.6769	0.4985	-	-
the intention to continue education 2	-0.3544	0.7230	-0.5715	0.5676	-	-
the intention to change place of residence 1	-0.0123	0.9902	-0.9828	0.3257	-	-
the intention to change place of residence 2	0.1440	0.8855	0.1328	0.8943	-	-
having a family 0	-0.6881	0.4914	-0.9292	0.3528	-	-

the number of children 0	-0.5110	0.6094	-0.6137	0.5394	-0.7172	0.4733
the number of children 1	0.2329	0.8159	1.3219	0.1862	-1.7120	0.0869
the number of children 2	0.3141	0.7535	0.9697	0.3322	-1.3768	0.1686
the socio-occupational group 1	0.4726	0.6365	0.5704	0.5684	0.0924	0.9263
the socio-occupational group 2	-0.0883	0.9296	0.1756	0.8606	0.0887	0.9293
the socio-occupational group 3	-0.2216	0.8246	0.1405	0.8883	0.0751	0.9401
the socio-occupational group 4	0.4223	0.6728	0.1036	0.9175	0.2504	0.8023

Table 2. Source: our calculations.

The results of model estimation have been summarized in tables 3, 4 and 5. Each of the tables contains mean values and highest probability density intervals ($\alpha = 0.05$), based on 10000th a priori samples for the first two models and 100000th sample for the third model, for all model parameters.

Model 1 (I group: 18 – 30 years)				
Parameter	**Mean**	**Highest Probability Density Interval**		**Exp(Mean)**
Intercept	1.0639	0.0267	1.9806	2.898
the age of entering workforce	-0.1436	-0.1905	-0.0895	0.866
the place of residence 1	0.4101	0.2100	0.6067	1.507
the place of residence 2	0.1333	-0.0636	0.3211	1.143
Sex	0.7896	0.5911	0.9905	2.203
Education 1	0.0580	-0.5566	0.6548	1.060
Education 2	0.3491	-0.1431	0.8547	1.418
Education 3	0.1502	-0.1695	0.4937	1.162
Education 4	0.0624	-0.4241	0.5154	1.064
Education 5	0.1038	-0.1657	0.3960	1.109
the intention to continue education 1	-0.1365	-0.4719	0.2014	0.872
the intention to continue education 2	-0.0929	-0.3909	0.1712	0.911
the intention to change place of residence 1	-0.2551	-0.5391	0.0137	0.775
the intention to change place of residence 2	-0.1525	-0.3897	0.1034	0.859
having a family 0	0.0801	-0.2828	0.4515	1.083
the number of children 0	-0.7932	-1.1759	-0.3854	0.452
the number of children 1	-0.2824	-0.5516	-0.0138	0.754
the number of children 2	-0.0270	-0.2987	0.2336	0.973
the socio-occupational group 1	0.4118	0.1998	0.6184	1.510
the socio-occupational group 2	0.3482	-0.0127	0.7077	1.417
the socio-occupational group 3	0.2443	-0.0970	0.5664	1.277
the socio-occupational group 4	0.3168	0.1038	0.5343	1.373

Table 3. Source: our calculations.

Model 2 (II group: 31 – 45 years)				
Parameter	**Mean**	**Highest Probability Density Interval**		**Exp(Mean)**
Intercept	1.0018	0.5233	1.4423	2.723
the age of entering workforce	-0.1013	-0.1179	-0.0829	0.904
the place of residence 1	0.1877	0.0829	0.2941	1.206
the place of residence 2	0.1156	0.0113	0.2208	1.123
Sex	0.5441	0.4540	0.6354	1.723
Education 1	0.3603	0.1718	0.5656	1.434
Education 2	0.1518	-0.0823	0.3862	1.164
Education 3	0.1704	0.0228	0.3108	1.186

Education 4	0.0163	-0.1808	0.2030	1.016
Education 5	-0.1090	-0.2287	0.00815	0.897
the intention to continue education 1	-0.0137	-0.2032	0.1921	0.986
the intention to continue education 2	0.0258	-0.1738	0.2297	1.026
the intention to change place of residence 1	0.0314	-0.1521	0.2205	1.032
the intention to change place of residence 2	-0.0177	-0.2024	0.1647	0.982
having a family 0	0.2352	-0.0858	0.5249	1.265
the number of children 0	-0.0650	-0.3325	0.1822	0.937
the number of children 1	-0.00014	-0.1184	0.1245	1.000
the number of children 2	-0.0411	-0.1373	0.0626	0.960
the socio-occupational group 1	0.3796	0.2572	0.4939	1.462
the socio-occupational group 2	0.2447	0.0887	0.4182	1.277
the socio-occupational group 3	0.0506	-0.1023	0.2085	1.052
the socio-occupational group 4	0.2257	0.0982	0.3529	1.253

Table 4. Source: our calculations.

Model 3 (III group: 46 or more years)				
Parameter	**Mean**	**Highest Probability Density Interval**		**Exp(Mean)**
Intercept	1.3168	0.3700	2.2676	3.731
the age of entering workforce	-0.1119	-0.1588	-0.0625	0.894
the place of residence 1	0.1826	-0.1897	0.5570	1.200
the place of residence 2	0.2968	-0.0534	0.6414	1.346
Sex	0.4834	0.1864	0.7759	1.622
Education 1	0.6860	0.1598	1.2028	1.986
Education 2	0.4669	-0.3383	1.2436	1.595
Education 3	0.3920	-0.0268	0.8085	1.480
Education 4	0.2719	-0.3921	0.9480	1.312
Education 5	-0.1844	-0.5389	0.1644	0.832
the number of children 0	0.4057	-0.0718	0.8790	1.500
the number of children 1	-0.0324	-0.3583	0.3032	0.968
the number of children 2	-0.2805	-0.5858	0.0295	0.755
the socio-occupational group 1	0.3419	-0.0380	0.7139	1.408
the socio-occupational group 2	0.3722	-0.1450	0.9035	1.451
the socio-occupational group 3	0.3015	-0.1767	0.7848	1.352
the socio-occupational group 4	0.2720	-0.1116	0.6588	1.313

Table 5. Source: our calculations.

In the case of the first model, basing on the highest probability density interval (Bolstad W.M., 2007), statistically significant are the age of entering workforce and at least one level of the following predictors: the place of residence, sex, the number of children and the socio-occupational group. As far as the second model is concerned, the following determinants are statistically significant: the age of entering workforce and at least one level of the following variables: place of residence, sex, education, socio-occupational group. The results of the third model show that place of residence, number of children and socio-occupational group are not statistically significant, in the case of the remaining predictors at least one level is statistically significant.

5. CONCLUSIONS

The analysis of career mobility has been performed for three age groups. In spite of the small size of the third age group, a Bayesian approach enabled a result comparison. When modeling the number of employment periods, the following determinants have been concerned: the place of residence, sex, education level, the intention to continue education within two years, the intention to change place of residence within the two years, having a family, the number of children, socio-occupational group and the age of entering workforce.

Results confirm the previous expectation that higher career mobility should be observed in big cities rather than in rural areas. Higher economic growth and a number of different enterprises could have resulted in an increased number of career opportunities. Moreover, this difference is even larger for young persons. Employees aged under 31 located in big cities changed their jobs 51% more frequently than respondents of the same age group from villages. In the case of the second age group (31 – 45 years), this difference is still observed but to a lesser degree – only 21%. The difference between small cities and villages for the second age group is 13%. For the remaining age groups this difference is not statistically significant. These results suggest other dependencies than those shown in (Kryńska E., 2000). The latter work also included farmers and concluded that career mobility in rural areas is much higher than in big cities. When comparing these results, one has to take into account that what we considered was the place of residence at the time the survey was carried out. At the same time, intensive migration from rural to urban areas took place in the period 1950-1989. Until 1980 an ever growing migration balance to the urban areas has been observed. The economic crises of the eighties resulted in substantial reduction of spatial mobility (Kotowska I.E., 1999). Even though career mobility is partly related to spatial mobility, our research has not confirmed that the persons planning to change place of residence had higher career mobility.

The education variable has turned out to be statistically insignificant in the first age group. In case of all respondents aged over 30 years, career mobility of individuals who had higher education was larger. In the second age group the graduates aged 31-45 had the number of employment periods higher by 43%, while the persons having a secondary professional education higher by 19% comparing to those who have attended primary schools only. This tendency is even more evident, when the persons aged over 45 years with higher education status are compared with the respondents with the lowest education status i.e. having at best primary school. The persons from the first group have changed jobs almost twice as frequently as the persons from the least educated group. Thus, previous assumptions that university degree may increase the chances for finding potentially better job have been confirmed. At the same time some researchers (Mach B. W., Mayer K. U., Pohoski M., 1994) analyzing the period discussed, notice the positive impact of a university degree on career development, but indicate that this impact is observed within the same organization only. What should be emphasized, however, is that graduation did not always mean promotion or a higher salary. In fact, in some cases university graduates earned less than individuals with basic vocational training. As far as our analysis is concerned, the intention to continue education has not been found to have significant impact on career mobility.

The labor market before the transformation period in Poland was characterized by high participation of women in the workforce. Economic necessity, the ideology of equal rights of women and full employment policy contributed to the rapid growth of occupational activity of women (Frątczak E., 1999). Our research confirms the previous assumption that the sex of the respondent plays an important role in career mobility, but the scale of this impact was also dependant on the age. Men aged below 31 changed jobs more then twice as frequently than women of the same age. For men aged over 31 years this difference was only 60-70%. Significant differences are quite obvious, as women usually decide to bear a child when aged under 30. Also results of other research (Mach B. W., Mayer K. U., Pohoski M., 1994) show a higher number of employment periods for men as opposed to the women.

The higher reluctance to change jobs observed among women might be due to the role that they play in their families. Women more frequently take care of children, so they do not want to change job, as this could mean that they would have less time for their families. Another reason might be discrimination against women in the labor market, as women are promoted less frequently, even if they are better educated and have more professional experience then men.

Poland in the state-socialism period was characterized by a relatively high fertility rate and occupational activity. Our research has not confirmed remarkable dependencies between the number of children and the number of employment periods in the case of persons aged over 30. However, lower career mobility has been observed for young persons who did not have any children or had a single child. A lack of noticeable relation between fertility and career mobility might be caused by the fact that, during the state-socialism economic period, some of the role of parents was transferred from parents to the state, thanks to wide access to social services (nursery schools, kindergartens, schools, extracurricular activities).

In every age group, the respondent's age when entering the workforce had significant impact on career mobility. Persons starting employment later had a lower number of jobs. The scale of job changes did not depend on the age of a respondent. The respondents, who entered the workforce at an older age, were probably more anxious about successfully dealing with work responsibilities, because of insufficient experience, as the age of entering employment partly reflects professional experience.

The socio-occupational group that a respondent belonged to at the beginning of his/her professional life has an impact on career mobility. This impact strongly differs depending on the age group. In case, of persons aged below 46 years we have determined that the persons from lower socio-economic group working in industrial and related professions had lower career mobility rates. Moreover, the respondents employed in commerce, services and transport, changed jobs 30% more frequently then workers in industrial and related sectors. The features of the jobs in these sectors might have played an important role in this case. This does not contradict results of previous studies (Mach B.W., Mayer K.U., Pohoski M., 1994) that show particularly high mobility rates in the mining and steel industry, but only within the same organizations.

To sum up, the Bayesian approach used in this study allowed us to investigate dependencies between selected demographic and socio-economic factors and career mobility. Employee mobility is a very wide research topic, usually investigated for specific regions and social groups.

The results of employment mobility studies for the state-socialism period of the Polish economy are frequently divergent (Mach B.W., Mayer K.U., Pohoski M., 1994, Kryńska E., 2000). This clearly shows that social, demographic and economic processes of the analyzed period have not been fully investigated yet. At the same time, the outcomes of further studies of this period may help to model and promote career mobility nowadays.

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