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Benoit Dostie
David E. Sahn

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**Benoit Dostie**
*HEC Montréal, CIRANO, CIRPÉE and IZA Bonn*

**David E. Sahn**
*Cornell University*

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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# ABSTRACT

## Labor Market Dynamics in Romania During a Period of Economic Liberalization*

In this paper, we estimate a model of labor market dynamics among individuals in Romania using panel data for three years, 1994 to 1996. Our motivation is to gain insight into the functioning of the labor market and how workers are coping during this period of economic liberalization and transformation that began in 1990. Our models of labor market transitions for men and women examine changing movements in and out of employment, unemployment, and self-employment, and incorporate specific features of the Romanian labor market, such as the social safety net. We take into account demographic characteristics, state dependence, and individual unobserved heterogeneity by modeling the employment transitions with a dynamic mixed multinomial logit.

JEL Classification: P2, P3

Keywords: employment dynamics, Romania, multinomial logit, initial conditions, random effects

Corresponding author:

Benoit Dostie
Institute of Applied Economics
HEC Montréal
3000, chemin de la Côte-Sainte-Catherine
Montréal, H3T 2A7
Canada
E-mail: benoit.dostie@hec.ca

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http://www.worldbank.org/lsms/country/romania/rm94docs.html

# 1 Introduction

Since the end of the 1980s, Eastern Europe and the former Soviet Union have been experiencing a fundamental restructuring of their economic system toward a market economy. In Romania, prior to the current reform period, wages as well as the allocation of labor were heavily regulated.[1] It was only in 1991 that, within a broad based reform package, the government began to liberalize the labor market by allowing wage scales, hiring and promotion criteria to be determined by collective contracts between workers and managers. Still Romania's economic transition from a state-controlled to a market-oriented economy during the 1990s was slow, characterized by a lack of commitment to reform and weak economic performance (Organization for Economic Cooperation and Development (OECD) (2000)).

Svejnar (1999) surveys the principal applied labor market studies in the Central and Eastern European Countries as the countries launched the transitions from central planning to a market economies (see also Boeri and Terrell (2002)). The study of individual labor force histories can provide important insights into the effect of privatization and restructuring on the labor market. By measuring the effects of demographic characteristics, labor market conditions, and active labor market policies on individuals' labor market history, one can identify imbalances across socio-economic groups.

Most early work on labor market dynamics focused on the determinants of unemployment and in particular on the impacts of demographic characteristics and labor market policies on unemployment duration and the probability of finding a job (for example, Ham, Svejnar, and Terrell (1998) on the Slovak and Czech Republics[2], Bellmann, Estrin, and Lehmann (1995) on East Germany,

[1] See Paternostro and Sahn (1998).

[2] See also Ham, Svejnar, and Terrell (1999), Terrell and Storm (1999), Lubyova and van Ours (1997) for other works on those countries.

Micklewright and Nagy (1999) on Hungary, and Jones and Kato (1997) on Bulgaria).

In this paper, we take a broader view of the labor market and study transitions across four labor market categories: employed, self-employed, unemployed, and, in the case of the latter, distinguishing between those receiving and those not receiving unemployment benefits.[3] We also disaggregate our analysis by gender, allowing us to determine whether the patterns and behaviors observed differ for males and females. This broader perspective is important for several reasons. For example, transitions in and out of self-employment are usually found to be important in transition economies. Earle and Sakova (2000) document the rising importance of self-employment in total employment for six transition economies, and Wu (2002) also finds that rates of entry into self-employment increased in China concurrent with market liberalization. Moreover, the broader perspective allows us to identify ways in which the social safety net – more specifically, unemployment benefits or public transfers – interact with, and affect employment status. This issue is particularly important since Romania, like most countries in Eastern Europe, has a generous package of social insurance and social assistance[4] that is likely to have an impact on labor market transitions. For example, Micklewright and Nagy (1999) in Hungary find that the "most likely way to exit unemployment insurance is not by getting a job but by exhausting entitlement to benefit".

Studies of labor market dynamics usually use one of two methods. Duration models can be used if one knows how much time individuals spend in the labor market state of interest. This is the approach taken by Micklewright and Nagy

[3] Among those not receiving unemployment benefits, most have seen their benefits expire. Official policy involved the unemployed receiving benefits for nine months after loosing a job at a level equal to the minimum wage. After this period, supplementary benefits were provided up to 18 months at a level of 40 percent of the minimum wage (Sahn and Younger (2000)).

[4] Romania also has a rather large set of state transfers, beyond unemployment benefits, as discussed by Sahn and Younger (2000) and Sahn and Gerstle (2001).

(1997), Earle and Pauna (1997), Ham, Svejnar and Terrell (1998), and Ham, Svejnar and Terrell (1999), for example. Since we have no such information, we model transition probabilities between different labor market states with a discrete choice model, a modeling option also chosen by Terrell and Sorm (2000), Bellmann et al. (1995), Jones and Kato (1997), and Voicu (2005), among others.

However, the particular model we use allows us to innovate compared to the aforementioned papers by taking into account both state dependence and individual unobserved heterogeneity through the inclusion of past labor market states as explanatory variables and individual specific random effects, two characteristics that are deemed to be important in the study of labor market dynamics. In fact, use of the dynamic mixed multinomial logit permits us to allow for correlation between different labor market states both across time and at the individual level.[5]

We use three successive years of panel data from a household survey that was conducted in Romania from 1994 to 1996. It is not typical to study labor market dynamics with a household survey. However, the Romania Integrated Household Survey contains detailed data about labor market activities and various forms of social security, in addition, to insure standard questions in jointly determined household production and consumption activities. It should be interesting to compare our results to those obtained with more traditional labor force surveys.

The plan of the paper is as follows. We first provide a brief description of the data and non-parametric estimation of labor market dynamics in the form of transition matrices. We follow with a description of the statistical model employed. We then discuss the results and conclude.

[5]Voicu (2005) also also takes into account state dependence and individual unobserved heterogeneity but focuses only on employment, unemployment and non-participation. He finds, among other things, that personal characteristics have a strong influence on employment decisions and that sequential employment decisions exhibit a strong but declining persistence.

# 2 Labor Market Transitions

## 2.1 Data

For decades under totalitarian rule, the National Commission of Statistics conducted a family budget survey. It was not representative of the population, both because the original sample frame was enterprise-based, not household-based, and because there was no serious attempt to update the permanent sample of households included from one year to the next. In the early 1990s, the Romanian Integrated Household Survey (RIHS) was designed by the National Commission of Statistics to respond to the deficiencies in the sampling and questionnaire design of the Family Budget Survey. Field testing took place in early 1994, and the survey officially went into the field in April 1994. The survey was thereafter repeated from 1995 through 1997. Each year's sample is nationally and regionally representative.[6]

The RIHS is thus the first large-scale nationally representative household survey ever administrated in the country, and takes place during Romania's transition to a market economy. The survey involved a sample of 24,560 households randomly selected from all districts of Romania and the city of Bucharest. Detailed information was collected on household incomes and expenditures, labor market activity, public transfers, and a wide range of living standard indicators. The yearly Romanian household surveys included a small rotating panel of households that remained in the survey from one year to the next. By matching individuals within households that were present for two consecutive years, we were able to construct panels containing labor market information for 6168 individuals for 1994-1995 and 6918 individuals for 1995-1996.

In order to analyze employment transitions, we restrict our sample to individuals between the ages of 15 and 65 who were in the labor force. Students

[6] The survey was continued after 1997, but without the Labor Market module.

and housewives who report not to be searching for employment are considered to be out of the labor force. We divide those individuals into three mutually exclusive labor market states: employees, who are salaried and hourly workers for both private, and more importantly state-run and operated enterprises, including workers on state-run and operated farms; self-employed largely in small (often single person) and informal enterprises, including own-account agriculture; and unemployed. Note that we thus exclude pensioners. Labor market states frequencies for men and women present in 1994-1995 and then for those present in 1995-1996 are shown in Table 1.

The employee category comprises around three-quarters of the potential labor force for men, although only around 60 percent for women. The self-employed represent a far greater share of the working age population among women, generally, around 30 percent, and that proportion tends to be slightly higher for more recent years. Among men, the increase in the share of self-employed from the 1994-95 to the 1995-96 panel is greater than for women, although, the overall share of men who are self-employed remains far smaller than the share of women in self-employment. This rise in self-employment is mirrored by a decrease in unemployment. This seems to highlight a role for self-employment as a way to escape unemployment. However, to know if the increase in self-employment is due to people moving from unemployment or dropping out of employment, we have to look at transition tables. Those transitions tables are presented in the next section.

## 2.2 Nonparametric Analysis

Trends in labor market status can be analyzed in the context of a simple four-states Markov chain model linking labor market status in different years. To get a better picture of how the unemployed are faring and how government interventions through the provision of benefits affects labor market dynamics, we have split the unemployed into two subcategories, distinguishing between those that do, and do not receive benefits. The estimates in Tables 2 are average observed transition frequencies.

Focusing first on the role of self-employment as a potential buffer for people coming out of employment, we find that employment seems to be relatively stable on a year-to-year basis with about 94% of both men and women being able to keep their job. Among the women losing their job, more entered unemployment (3.5%) than self-employment (2.4%). More than two-thirds of those transitioning into unemployment received unemployment benefits. In contrast, the majority of men who lose their job become self-employed. This could be construed as suggesting that self-employment serves partly as a resting or interim stop for men who lose their job, but less so for women. Also, recall that overall, share of jobs in self-employment is only a small fraction of those who are employed, and that self-employment is relatively far less important for men than women. So the large share of men entering self-employment highlights the buffering role it plays when jobs are lost.

Over half of the men who were unemployed and receiving benefits are no longer unemployed one year later. Again, employment and self-employment are nearly as likely to be paths out of unemployment. For women, a slightly smaller share find work, although, interestingly, a greater share of them are employed than self-employed. Among those who were unemployed without benefits, among men, a larger share finds jobs than those who were unemployed with benefits. This conforms to our initial expectation that after benefits are depleted, people would become more desperate and stop queuing for rationed jobs and instead enter self-employment at a higher rate than those still receiving benefits. However, the effect of not having benefits as an incentive for finding work is less than expected. Interestingly, however, this incentive appears not to apply to unemployed women without benefits, for whom 44 percent find themselves in the same position a year later. Overall, these results suggest that, especially for women, even if self-employment is an exit out of unemployment, it does not appear to play a crucial role as a springboard toward employment.

Focusing next on the impact of the social safety net on labor market dynamics, we note that over one-third of the men who depart from employment do not receive benefits in the year following job loss. Those people are not caught by the social safety net. Moreover, we see that 15 percent of the unemployed men and 18 percent of the unemployed women who were unemployed with benefits exhaust their benefits without being able to find a regular job or get into self-employment. Thus, many people are initially caught by the safety net, but then exhaust their benefits before finding a job.

Tables 3 and 4 present summary statistics for our sample divided by labor market status and gender. Individuals who are employed or self-employed are older than the unemployed. The age differences are greater for women than men. This implies that unemployment tends to disproportionately afflict the young. As for education, we note that the self-employed have less schooling than those in the other categories, including the unemployed. Those employed, have the highest education, with the mean levels being nearly the same for men and women, 11.5 and 11.6 years, respectively. This mean is four years greater than women who are self-employed. It is also noteworthy that while 12 percent of the employed have higher education degrees, this is the case for less than two percent of the persons in the three other categories, both for men and women. In contrast, nearly one-third of women, and 23 percent of men who are the self-employed have less than a high school education. Interestingly, a much smaller share of men who are unemployed, both with and without benefits, as compared to women, are in the category of having low levels of education. This in part reflects the overall lower levels of education of women than men.

Also, not surprisingly, we find the share of urban residents among those employed is greater than the other categories. The difference, however, is particularly dramatic for women where 76 percent of the employed are urban, in contrast to only eight percent being self-employed. Quite interestingly, if we look at the shares of unemployed with benefits and unemployed without benefits by region, we find a higher share of the latter in urban areas. This would seem to suggest that the safety net does a better job of reaching the rural unemployed than those in urban areas. While the descriptive findings are of interest, we next estimate the labor market dynamics using a discrete choice model to assess the robustness of the non-parametric analysis.

## 3 Statistical Model

Transition matrices give a complete picture of movements across different labor market status. While it is possible to decompose those matrices along variables of interest, this would be of limited use if we did not control for other factors that affect those transition probabilities. A preferred option, which we employ in this paper, is to use a reduced-form multinomial choice model explaining the labor market state of each individual during each time period. In this way, we have a complete decomposition of the transition probabilities along covariates of interest like age, education, family composition, and region of residence.

It is usual to derive the multinomial logit model by defining the utility of individual $i$ for being in labor market state $j$ at time $t$ as

$$\tilde{y}_{ijt} = X_{it}\beta_j + \sum_{l=1}^{J} \gamma_{lj} d^{y}_{i(t-1)l} + \epsilon_{ijt}, \quad i = 1, ..., N, \quad j = 1, ..., J, \tag{1}$$

where $J$ is the number of possible market states, $X_{it}$ is a vector of explanatory variables for individual $i$ at time $t$, and $d^y_{i(t-1)l}$, $l = 1, ..., J$, are a set of dummy variables equal to 1 if $y_{i(t-1)} = l$. We assume $\epsilon_{i1t}, ..., \epsilon_{iJt}$ are distributed type 1 extreme value so that the usual multinomial logit model results with

$$\Pr[y_{it} = j] = \frac{X_{it}\beta_j + \sum_{l=1}^{J} \gamma_l d^y_{i(t-1)l}}{1 + \sum_{m=2}^{J} \left( X_{it}\beta_m + \sum_{l=1}^{J} \gamma_{lm} d^y_{i(t-1)l} \right)}. \tag{2}$$

For model identification, we assume $\beta_1 = 0$ and $\gamma_1 = 0$ , i.e., employment is taken to be the base category for both past and present labor market states. Note that in our case, we do not interpret the above probabilities as choices but as conditional probabilities, i.e., the probability that the individual will be in each of the labor market states conditional on observed characteristics and past labor market status.

The log-likelihood of the multinomial logit model is written

$$L = \sum_{i=1}^{N} L_i \tag{3}$$

with

$$L_i = \sum_{t=1}^{2} \sum_{j \in C_i} d_{ij} \ln \Pr[y_{it} = j] \tag{4}$$

where

$$d_{ij} = \begin{cases} 1 & \text{if individual } i \text{ choose an alternative } j \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The inclusion of past labor market states is done in order to take into account the individual's labor market history. It is well known that it is more likely that an individual will be employed if he was employed in the last period, a phenomenon known as state dependence. Theoretically, we would like to model

$$P[y_{it} = j] = P[y_{it} = j | y_{it-1}, y_{it-2}, y_{it-3}, ...] \tag{6}$$

but in what follows, we will assume

$$P[y_{it} = j] = P[y_{it} = j | y_{it-1} = k] \tag{7}$$

The implicit assumption is that transition probabilities follow a Markov process of order 1. Note also that the previous period's explanatory variables have an impact $y_{it}$ on through their effect on $y_{it-1}$.

We can also make use of the panel structure of our data set by adding a random effect to the utility functions defined above. This allows us to take into account unobserved individual heterogeneity in labor market status. This also allows us to relax the Independence of Irrelevant Alternatives (IIA) assumption imbedded in the standard multinomial logit. More specifically, we have

$$\epsilon_{ijt} = u_{ij} + v_{ijt}, \quad i = 1, ..., N, \quad j = 1, ..., J \tag{8}$$

where $u_{ij}$ are the individual-choice specific random effects. In order to make the model more tractable, we use the following simplifying assumption[7] for $u_{ij}$:

$$u_{ij} = \lambda_j \theta_i \tag{9}$$

We assume that $\theta_i$ is normally distributed with mean zero and variance equal to 1. Note that the load factor $\lambda_j$ is also set to zero for the reference category. Thus, the unobservable component for choice $j$ is given by $\lambda_j \theta_i$ where the covariance

[7] Heckman and Walker (1990) introduce unobserved heterogeneity in a similar way in a competing risk framework.

between different choices $k$ $(\lambda_k\theta_i)$and $l$ $(\lambda_l\theta_i)$ is $\lambda_k\lambda_l$. It is even possible to test the IIA hypothesis by testing the hypothesis that all parameters $\lambda_j$ are equal to zero. Since the $\theta_i$ are not given, the (unconditional) choice probabilities are obtained by integrating (7) over all values of $u_{ij}$ weighted by the density of $u_{ij}$:

$$L_i() = \int L_i(u)f(u)du \tag{10}$$

We estimate this slightly more complicated form by maximizing the marginal likelihood, integrating out the heterogeneity components, assuming joint normality. Since a closed form solution to the integral does not exist, we use Gauss-Hermite Quadrature to approximate normal integrals (e.g., Abramowitz and Stegun (1972), pp. 890 and 924).

For the first year of our panel, we do not know the previous state. Moreover, it would be wrong to assume those initial states to be exogenous. This is the usual problem of initial conditions. This problem can be viewed as a problem of endogeneity of the lagged values of the labor market status in equation (1). To solve this problem, we also estimate simultaneously a multinomial logit on the initial states where we specify the latent utility as:

$$\tilde{y}_{ijt} = X_{it}\beta_j + \epsilon_{ijt}, \quad i = 1, ..., N, \quad j = 1, ..., J \tag{11}$$

Note that this is the same as equation (1) except it is obviously impossible to include lagged values for occupations. We also decompose the error term to include an individual specific effect in the same way as in equation (8) Note that we obtain a different set of load factors $\lambda_{ICj}$ for the initial conditions, but the individual specific effect $\theta_i$ is the same. We maximize the full likelihood where we assume that every labor market status and initial states are independent conditions on a vector of heterogeneity components $u_{ij}$.

# 4 Econometric Results

The base category in the econometric models we estimate are those employed as wage workers (employed). Coefficient estimates are shown in Tables 6 and 7 for men and women, respectively. Since the sign of the coefficients are not necessarily the same as the sign of the marginal effects, we also present three additional tables to better interpret the results. Tables 8 and 9 show predicted probabilities of being in each labor market state computed at the average characteristics of men and women, respectively, and Table 10 shows predicted transition rates and simulation on those for both genders at the average characteristics of each labor market status (simple marginal effect are also available on demand)

## 4.1 Determinants of employment state

Our coefficient estimates in Tables 6 and 7 first and foremost underscore the importance of taking into account individual unobserved heterogeneity and state dependence when estimating labor market transition probabilities. The null hypothesis that all load factors are zero is rejected, and we find statistically significant effects for lagged labor market status. Once we control for observable and unobservable characteristics, our results indicate that it is much more likely to see both men and women with benefits remaining in that state, or becoming unemployed without benefits, than either moving into employment or self-employment. The magnitude of the coefficients on the unemployed with benefits indicates a slightly higher probability that they will be without benefits in the next period, both for men and women, than with benefits. Likewise, men and women who are unemployed without benefits are also far more likely to stay in that state than transition into employment.

Among those that were unemployed without benefits, as expected, the probability of finding themselves receiving benefits is much lower than in the case where the initial state was being unemployed with benefits and transitioning to not receiving benefits. Somewhat to our surprise, there is no higher likelihood of the unemployed, regardless of receiving benefits, moving into self-employment than employment among men, while unemployed women are more likely to move into employment than self-employment; and those unemployed women not receiving benefits are even less likely to take jobs as self-employed than those not receiving benefits.

Model results also indicate that those in self-employment are far more likely to remain in that state than become unemployed with benefits. In the case of women, they are also considerably less likely to transition into unemployment without benefits than remain self-employed. Both men and women are more likely to find themselves employed or unemployed without benefits in the subsequent period than either continuing as self-employed or becoming unemployed with benefits. Thus, the self-employed in general appear to be much more likely to transition into employment than the unemployed who are more likely to remain in that state than transition into employment.

Education is also an important factor in explaining labor market status. Individuals with less education are more likely to be unemployed or self-employed, as seen by the fact that all the dummy variables have negative and significant coefficients, relative to the left out category of having completed less than middle school. Comparing between unemployment and self-employment, we find that among women, but not men, more educated individuals are much more likely to be unemployed than self-employed, controlling for other covariates. This is shown by the much larger negative coefficients on higher education for self-employment than the two unemployment states, something not nearly as pronounced for men. But the most important finding overall is the importance of education in terms of being employed relative to all other states.

To illustrate the magnitude of the education effects, Tables 8 and 9 present the predicted probabilities of being in the four states. In the case of education, we find that the predicted probability of being in a state other than employed is nearly zero for those with higher education. Similarly, men with high school or professional degrees are very unlikely to find themselves self-employed or unemployed, although, this is not the case for women, where the predicted probability of not being employed is around 25 percent. Among those who have only completed primary school or less the predicted probability of being self-employed is also much higher for women than men, 0.52 and 0.36, respectively. Perhaps more troubling is the high predicted probabilities of men and women being unemployed among those who have completed less than secondary school.

In terms of the predicted effects of education, another interesting finding is the gender difference between unemployment with and without benefits. Specifically, we observe that women with primary or less education are approximately one-third more likely to not be receiving benefits than receiving benefits, while for middle and high school degree holders, their predicted probabilities of receiving benefits are slightly higher than not receiving benefits. This pattern emphasizing the importance of education in terms of the predicted probability of receiving benefits is not nearly as strong for men.

Our model results indicate an asymmetrical impact of marriage for men and women. Married men are less likely to be unemployed or self-employed than employed, but we find the opposite result for women. Not surprisingly, we also find that it is much less likely that an individual will be engaged in self-employment in urban areas relative to rural areas, especially for women. It is also the case that urban dwellers are less likely to be unemployed. Overall, the probability of being unemployed in urban areas is greater than self-employment, something that is not found in rural areas.

The negative coefficient on age suggests that older individuals are also more likely to be employed. However, the positive and significant quadratic implies a declining impact of age. Simulating the effects of age on the predicted probability of working, we find an interesting pattern that for both men and women, the probabilities of being employed is lowest among 60-year olds, implying an inverted U relationship between age and employment. In contrast for others, there is a U-shaped relationship between age and being unemployed and self employed, with the exception of women who are unemployed with no benefits.

Our models also predict that the vast majority of the urban labor force, especially among men, will be employed, as compared to less than two-thirds of the rural labor force. What is quite striking is the low predicted probability of women in rural areas being employed, 36 percent, versus 78 percent for men.

Finally, we also find that those in the labor force from larger households are more likely to be unemployed, and even more so, self-employed, relative to being employed, but the effect is statistically significant for women only. Perhaps this captures the fact that larger households also tend to have more than one person in the labor market, who both is more selective in the choice of a job, or, more able to be engaged in self-employment activities to the extent that a spouse is employed.

## 4.2 Predicted transition rates

Table 10 reports predicted transition rates from our econometric model. Those numbers, found in bold text, are computed at the average for each labor market state and can be compared to the actual observed transitions, in parenthesis, that are taken from Tables 6 (for men) and 7 (for women). The table also indicates how the transitions rates vary with the different observed characteristics of the individuals.

We first note that for individuals currently employed, predicted transition rates are reasonably close to actual transition rates. We slightly under-predict the number of “stayers,” especially for women, where the model indicates that 83.9 percent of the women remain as employed, but in fact, this is the case for 94.1 percent of them. Our prediction overshoots the actual number of individuals transitioning from employment to all other states, both for men and women. This overshooting is particularly noteworthy in the case of self-employment for women, where we predict that 11.2 percent of the women who were employed in the previous state will be self-employed in the current state, while in fact, this is only the case for 2.4 percent of the women.

The model fares much worse in predicting transitions out of the other employment states. Transitions to employment from unemployment and self-employment are systematically overestimated for both men and women. To illustrate, our model predicts that an unemployed male worker with benefits has a 74.3% chance of being employed in the next period, while the actual transition rate is just 25.9%. The prediction error is slightly smaller in the case of women (58.9% (predicted) versus 26.0% (actual)). Put another way, our model predicts that the difference in the probability of men being employed in the next period between currently employed and currently unemployed with benefits is 17% (91.3% - 74.3%) while the observed difference is 68.2% (94.1% – 25.9%). Perhaps the most acute instance of an over-prediction of the probability of currently being employed is in the case of men who were previously self-employed, predicted to be 63.1 percent. In fact, this is the case for only 10.2 percent of the men. Thus, the difference in the probability of men being employed in the next period between those that are currently employed and self employed is 28 percent, in contrast to the observed difference of 83.9 percent.

In contrast, overall probabilities of staying in current states are underestimated in all cases, both for men and women. Transitions to self-employment from unemployment, both with and without benefits, are also greatly underestimated for men, although, this is not the case for women where the difference between the actual and predicted transitions to self-employment are quite small. We also observe that transitions from self-employment to unemployment are overestimated, but again, this type of movement is relatively rare for both men and women in Romania.

Overall, it is clear that in many cases, observed characteristics in our model explain often one-third or sometimes even less of the difference in transition probabilities. The remainder of the difference is picked up by unobserved individual effects. This underlines the importance of the role of unobserved heterogeneity and the importance of taking this into account in this type of model.

## 4.3 Simulations

The interpretation of the coefficients in the nested models found in Tables 7 and 8 is inherently difficult, which often leads researchers to estimate marginal effects and instead focus on those results. However, there is also an important limitation of focusing on marginal effects: since they are averaged over all individuals in the sample, they hide important differences due to the fact that average observable characteristics of individuals in different labor market states are markedly different, and often dramatically so, as shown in the descriptive statistics presented in Tables 5 and 6.

To get a better grasp of the role of explained characteristics in the model, Table 10 displays additional simulation results. Specifically, it answers the following hypothetical question: how would transition probabilities change for the currently unemployed and self-employed if their observed characteristics were at the same level as of those currently employed.

### 4.3.1 Transitions into employment

If an unemployed male with benefits was given the average education level of an employed individual (i.e., an increase of about two years of education), his probability of transitioning into employment would move from 74.3% to 84.4% (+10.1%). The impact of education is similarly important for an unemployed individual without benefits (+9.7%).

The role of education in moving individuals from self-employment to employment is also important. More specifically, if the self-employed males had the three more years of education that are found among the employed, their probability of moving into employment would increase by 21.3 percent. And if self-employed women had the additional four years of education that is found among employed women, they would be 35 percent more likely to transition into employment.

Another important factor in explaining transitions from unemployment to employment is age. Remember that unemployed individuals are on average five years younger than employed individuals. Increasing the age of men by five years raises their probabilities of moving into a job as an employee by 10.4 and 8.9 probability points for the unemployed with and without benefits, respectively.

Similarly, recall that the proportion of unemployed individuals living in an urban setting is much lower than for employed individuals. If the share of currently unemployed males was the same as the share of males currently employed living in urban areas the probability of the currently unemployed moving into an employed state would increase by 10.9 and 6.3 probability points, respectively, for those with and without benefits.

While the impact of education is similarly as important for women as it is for men, it should be noted that for women, age and living in an urban setting are much more important in explaining transitions from unemployment to employment than education. For example, for women unemployed with benefits, the impact of reaching the education level of employed women raises their probability of transiting into employment by 10.0 probability points, and moving into an urban area raises it by 22.0 probability points. We also note the great importance of whether a self-employed person, especially among women, resides in rural or urban areas for the probability of transitioning into employment. Increasing the probability of a self-employed woman being urban from the present level of 8% to the 76%, which is the probability observed among the employed, would increase their transition probabilities by 20.3%. Finally, state dependence is also important in explaining transitions from self-employment to employment, especially among men.

#### 4.3.2 Transitions into unemployment

The model predicts that unemployed men with benefits have an 8.9% chance of staying unemployed (with benefits) and 5.8% chance remaining unemployed while losing their benefits. Both those probabilities are higher for women at 13.7% and 7.1%, respectively. While education is most effective in reducing the probability of staying unemployed (with benefits) for men (-4.7 relative to the base probability of 8.9), for women, state dependence and age play the most important role (- 5.7 and -5.3, respectively, relative to the base probability of 13.7). In the case of unemployment without benefits, the most important determinant is age for both genders. Because unemployed without benefits are on average four years younger than employed individuals, their predicted probability of staying in this state is double what it would be if they were older (6.4 instead of 3.4 for men and 8.2 instead of 4.3 for women). Finally, looking at unemployed receiving benefits transitioning into not receiving benefits, we see, not surprisingly, that state dependence plays an important role. But among other characteristics, we see a meaningful impact of household composition on the probability of keeping benefits for men (picking up the fact that employed individuals are more likely to be married).

The simulations also show the particular role state dependence plays for unemployed individuals as it is the most important determinant of the probability of staying unemployed with no benefits. Eliminating state dependence would diminish the probability of staying unemployed with no benefits by 4.0 and 5.7 probability points for men and women, respectively. Compared to the base predicted transition rates of 7.2% and 8.9%, these are economically significant numbers.

### 4.3.3 Transitions into self-employment

The most important finding is that the model predicts that women are generally approximately twice as likely to transition from unemployment to self-employment as are men. We also find that individuals living in an urban setting are much less likely to make this transition, and the negative geographical effect is particularly high for women. Age and education also play an important role for both men and women in terms of the probability of transitioning into self-employment. If, for example, unemployed women without benefits had the same age and education characteristics of the older and more educated women who are employed, it would roughly reduce by three quarters the probability of their transitioning into self-employment.

## 5 Conclusion

In this paper we evaluate how employment transitions interact with the social safety net in Romania, particularly the benefits received through unemployment insurance. We use a three-year individual panel from 1994 to 1996, a period subsequent to the early stages of economic liberalization in Romania.

We first compute transition matrices that give a complete picture of the mobility process between different labor market states, distinguishing the experience of men and women. We thereafter take into account demographic characteristics, state dependence, and individual unobserved heterogeneity by modeling the employment transitions with a dynamic mixed multinomial logit with endogenous initial conditions.

We find that both unobserved heterogeneity and state dependence are important determinants of transition probabilities. However, unobserved heterogeneity seems to play a much bigger role as observed characteristics, and past labor market states explain in many cases only one-third or sometimes even less of the difference in transition probabilities, the rest being picked up by unobserved heterogeneity.

Our analysis indicates a relatively stable labor market, especially among those employed as wage workers. Employed individuals tend to be older and are more likely to live in urban areas. Education is also paramount in terms of being employed. Among those who lose their job, most transition into being unemployed, and a large portion do so without receiving benefits. Those not receiving benefits are more likely to be younger, male, and living in urban areas, suggesting that the social safety net is functioning better in rural areas for workers with longer duration of employment. Moreover, for unemployed women, education is a more important predictor of whether they will receive benefits.

Among those that find themselves unemployed, age, gender and education have a large impact on their probability of transitioning out of unemployment, especially in terms of moving into self-employment. Older and more educated women, for example, are much more likely to exit unemployed for self-employment. It is also of interest that the unemployed receiving and not receiving benefits have a similar likelihood of becoming self-employed, relative to becoming employed. This seems to suggest that self-employment is not primarily a stopping point between unemployment and becoming employed. We also note that women are much more likely overall to transition out of unemployment into self-employment. State dependence is important, although surprisingly, somewhat stronger for unemployed not receiving benefits. We also note that a large share of those unemployed who do receive benefits, exhaust them prior to finding work, either as a wage worker or being self-employed.

Like being unemployed, we find individuals with less education are more likely to be self-employed than employed. Among women, but not men, the self-employed also have less education than not just the employed, but the unemployed are less educated as well. Self-employment is also of greater importance in rural areas, especially among women, and education is particularly important in explaining transitions into employment. .

An assumption we are unable to test within our model is the hypothesis that only the past labor market status has an impact on the current labor market status. To test this assumption would require a much longer panel or detailed information about the length of time spend in each labor market status. Another useful distinction our data does not allow for is the one between formal and informal work. It is expected transition rates would differ between these categories, and it is possible our modeling of unobserved heterogeneity picks up some of those differences.

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Table 1: Frequencies - Labor Market Status

| | 1994 | | | | 1995 | | | |
|---|---|---|---|---|---|---|---|---|
| | Men | | Women | | Men | | Women | |
| Employed | 2503 | 74.5% | 1672 | 59.5% | 2485 | 74.0% | 1677 | 59.7% |
| Unemployed | 336 | 10.0% | 361 | 12.9% | 280 | 8.3% | 304 | 10.8% |
| Self-Emp. | 520 | 15.5% | 777 | 27.6% | 594 | 17.7% | 828 | 29.5% |
| | 3359 | 100.0% | 2809 | 100.0% | 3359 | 100.0% | 2809 | 100.0% |
| | 1995 | | | | 1996 | | | |
| | Men | | Women | | Men | | Women | |
| Employed | 2779 | 74.5% | 1946 | 61.1% | 2784 | 74.6% | 1985 | 62.3% |
| Unemployed | 320 | 8.6% | 329 | 10.3% | 224 | 6.0% | 237 | 7.4% |
| Self-Emp. | 633 | 17.0% | 911 | 28.6% | 724 | 19.4% | 964 | 30.3% |
| | 3732 | 100.0% | 3186 | 100.0% | 3732 | 100.0% | 3186 | 100.0 |

Table 2: Average Transition Rates

| | Current Status | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Men | | | | | Women | | | | |
| Prev. Status | 1 | 2 | 3 | 4 | | 1 | 2 | 3 | 4 | |
| 1-Emp. | 94.1 | 1.8 | 1.0 | 3.1 | 100 | 94.1 | 2.4 | 1.1 | 2.4 | 100 |
| | *94.4* | *34.4* | *22.8* | *12.4* | | *93.0* | *29.6* | *16.0* | *4.9* | |
| 2-Unemp. | 25.9 | 31.6 | 15.0 | 27.5 | 100 | 26.0 | 34.0 | 18.3 | 21.7 | 100 |
| with ben. | *2.1* | *48.2* | *27.6* | *8.8* | | *3.3* | *55.0* | *34.4* | *5.7* | |
| 3- Unemp. | 30.2 | 10.2 | 30.6 | 28.9 | 100 | 27.7 | 9.6 | 43.6 | 19.1 | 100 |
| w/o ben. | *1.4* | *8.7* | *31.6* | *5.2* | | *1.7* | *7.2* | *38.4* | *2.3* | |
| 4-Self-Emp. | 10.2 | 2.1 | 3.6 | 84.2 | 100 | 4.5 | 1.4 | 1.7 | 92.5 | 100 |
| | *2.2* | *8.7* | *18.0* | *73.7* | | *2.1* | *8.3* | *11.2* | *87.1* | |
| | *100* | *100* | *100* | *100* | | *100* | *100* | *100* | *100* | |

Table 3: Variable Definitions

| Name | Definition |
|---|---|
| Age | Age in years |
| Age squared | Age squared in year divided by 100 |
| Less than middle school | Dummy variable: 1 if did not complete middle school |
| Completed middle school | Dummy variable: 1 if completed middle school |
| High school degree | Dummy variable: 1 if completed high school |
| Professional degree | Dummy variable: 1 if has a professional degree |
| Higher education degree | Dummy variable: 1 if has a a higher eduction degree |
| Married | Dummy variable: 1 if married |
| Separated | Dummy variable: 1 if separated or divorced |
| Household size | Number of individuals in household |
| Urban | Dummy variable: 1 if lives in a urban area |

Table 4: Summary Statistics - Men

| Status | Employed | | Unemployed with benefits | | Unemployed w/o benefits | | Self-Employed | | All | |
|---|---|---|---|---|---|---|---|---|---|---|
| N | (N=5269) | | (N=276) | | (N=228) | | (N=1318) | | (N=7091) | |
| | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. |
| Age | 39.67 | 9.63 | 36.32 | 11.70 | 35.31 | 11.20 | 40.78 | 12.95 | 39.61 | 10.52 |
| Years of education | 11.48 | 2.96 | 9.80 | 2.72 | 10.18 | 2.82 | 8.40 | 3.01 | 10.80 | 3.19 |
| Less than middle school | 0.03 | 0.18 | 0.09 | 0.28 | 0.11 | 0.32 | 0.23 | 0.42 | 0.07 | 0.26 |
| Completed middle school | 0.17 | 0.38 | 0.25 | 0.44 | 0.18 | 0.39 | 0.38 | 0.48 | 0.22 | 0.41 |
| High school degree | 0.26 | 0.44 | 0.28 | 0.45 | 0.28 | 0.45 | 0.16 | 0.37 | 0.24 | 0.43 |
| Professional degree | 0.42 | 0.49 | 0.37 | 0.48 | 0.40 | 0.49 | 0.22 | 0.42 | 0.38 | 0.48 |
| Higher education degree | 0.12 | 0.32 | 0.00 | 0.06 | 0.02 | 0.15 | 0.01 | 0.10 | 0.09 | 0.29 |
| Married | 0.86 | 0.35 | 0.66 | 0.47 | 0.57 | 0.50 | 0.71 | 0.45 | 0.81 | 0.39 |
| Separated | 0.02 | 0.13 | 0.02 | 0.13 | 0.05 | 0.22 | 0.03 | 0.18 | 0.02 | 0.14 |
| Household size | 3.85 | 1.37 | 4.17 | 1.84 | 4.07 | 1.77 | 4.09 | 1.90 | 3.91 | 1.52 |
| Urban | 0.62 | 0.48 | 0.40 | 0.49 | 0.57 | 0.50 | 0.15 | 0.36 | 0.53 | 0.50 |

Table 5: Summary Statistics - Women

| Status | Employed | | Unemployed with benefits | | Unemployed w/o benefits | | Self-Employed | | All | |
|---|---|---|---|---|---|---|---|---|---|---|
| N | (N=2662) | | (N=291) | | (N=250) | | (N=1792) | | (N=5995) | |
| | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. | Mean | Std.Dev. |
| Age | 39.12 | 8.55 | 33.41 | 10.34 | 31.65 | 8.94 | 43.22 | 11.67 | 39.15 | 10.17 |
| Years of education | 11.59 | 2.73 | 10.42 | 2.27 | 10.61 | 2.42 | 7.43 | 2.77 | 10.25 | 3.29 |
| Less than middle school | 0.02 | 0.14 | 0.04 | 0.20 | 0.06 | 0.24 | 0.32 | 0.46 | 0.11 | 0.31 |
| Completed middle school | 0.19 | 0.40 | 0.26 | 0.44 | 0.21 | 0.41 | 0.47 | 0.50 | 0.28 | 0.45 |
| High school degree | 0.42 | 0.49 | 0.46 | 0.50 | 0.49 | 0.50 | 0.13 | 0.34 | 0.34 | 0.47 |
| Professional degree | 0.24 | 0.43 | 0.24 | 0.43 | 0.24 | 0.43 | 0.08 | 0.27 | 0.19 | 0.39 |
| Higher education degree | 0.12 | 0.33 | 0.00 | 0.06 | 0.00 | 0.06 | 0.00 | 0.03 | 0.08 | 0.26 |
| Married | 0.80 | 0.40 | 0.62 | 0.49 | 0.68 | 0.47 | 0.89 | 0.31 | 0.81 | 0.39 |
| Separated | 0.07 | 0.25 | 0.09 | 0.29 | 0.06 | 0.24 | 0.03 | 0.16 | 0.06 | 0.23 |
| Household size | 3.61 | 1.31 | 3.88 | 1.49 | 4.13 | 1.64 | 4.03 | 1.79 | 3.77 | 1.51 |
| Urban | 0.76 | 0.42 | 0.54 | 0.50 | 0.67 | 0.47 | 0.08 | 0.27 | 0.54 | 0.50 |

Table 6: Coefficients - Dynamic Mixed Multinomial Logit with Endogenous Initial Conditions - Men

| | 4-States Model | | |
|---|---|---|---|
| Status | Unemp. | | Self-Emp. |
| | with ben. | no ben. | |
| Unemp. with ben[t-1] | 1.026 *** | 1.136 *** | -0.391 |
| | (0.358) | (0.343) | (0.370) |
| Unemp. no ben.[t-1] | -0.126 | 1.641 *** | -0.080 |
| | (0.374) | (0.380) | (0.407) |
| Self-Emp[t-1] | -2.304 *** | -0.685 | -0.772 ** |
| | (0.392) | (0.451) | (0.339) |
| Age | -0.499 *** | -0.395 *** | -0.626 *** |
| | (0.097) | (0.104) | (0.112) |
| Age squared | 0.629 *** | 0.488 *** | 0.783 *** |
| | (0.117) | (0.131) | (0.135) |
| Middle school | -3.857 *** | -4.146 *** | -4.816 *** |
| | (0.795) | (0.802) | (0.911) |
| High school degree | -5.354 *** | -5.489 *** | -7.147 *** |
| | (0.836) | (0.857) | (0.958) |
| Professional degree | -5.600 *** | -5.458 *** | -7.475 *** |
| | (0.870) | (0.907) | (1.013) |
| Higher education | -10.143 *** | -8.228 *** | -10.487 *** |
| | (1.426) | (1.220) | (1.259) |
| Married | -2.433 *** | -2.523 *** | -2.638 *** |
| | (0.592) | (0.608) | (0.696) |
| Separated | -0.463 | 0.308 | -0.239 |
| | (0.669) | (0.686) | (0.776) |
| Household size | 0.166 | 0.152 | 0.171 |
| | (0.124) | (0.118) | (0.148) |
| Urban | -3.767 *** | -2.840 *** | -5.953 *** |
| | (0.473) | (0.455) | (0.637) |
| Constant | 12.305 *** | 9.816 *** | 16.546 *** |
| | (1.860) | (1.978) | (2.013) |
| $\lambda$ | 5.342 *** | 4.871 *** | 7.175 *** |
| | (0.496) | (0.655) | (0.562) |
| $\lambda_{IC}$ | 4.309 *** | 4.117 *** | 6.541 *** |
| | (0.313) | (0.365) | (0.371) |

ln-L = -6709.73

NOTE: Huber Corrected Standard Errors in Parenthese

Statistical significance: *=10%; **=5%; ***=1%

Table 7: Coefficients - Dynamic Mixed Multinomial Logit with Endogenous Initial Conditions - Women

| | 4-States Model | | |
|---|---|---|---|
| Status | Unemp. | | Self-Emp. |
| | with ben. | no ben. | |
| Unemp. with ben[t-1] | 1.015 *** | 1.237 *** | -0.734 ** |
| | (0.293) | (0.352) | (0.371) |
| Unemp. no ben.[t-1] | -0.554 | 1.726 *** | -0.968 * |
| | (0.427) | (0.514) | (0.522) |
| Self-Emp[t-1] | -1.519 *** | -0.314 | -0.777 * |
| | (0.383) | (0.520) | (0.429) |
| Age | -0.911 *** | -0.835 *** | -1.420 *** |
| | (0.147) | (0.199) | (0.193) |
| Age squared | 1.145 *** | 1.007 *** | 1.850 *** |
| | (0.187) | (0.252) | (0.253) |
| Middle school | -2.552 *** | -3.325 *** | -4.883 *** |
| | (0.566) | (0.648) | (0.702) |
| High school degree | -5.382 *** | -5.949 *** | -10.049 *** |
| | (0.739) | (0.993) | (1.102) |
| Professional degree | -4.986 *** | -5.613 *** | -9.696 *** |
| | (0.773) | (1.011) | (1.037) |
| Higher education | -11.533 *** | -11.487 *** | -18.757 *** |
| | (1.429) | (2.174) | (1.746) |
| Married | 0.688 ** | 1.100 *** | 2.598 *** |
| | (0.347) | (0.382) | (0.533) |
| Separated | 0.478 | 0.448 | 1.161 |
| | (0.505) | (0.564) | (0.820) |
| Household size | 0.156 * | 0.243 ** | 0.481 *** |
| | (0.091) | (0.108) | (0.120) |
| Urban | -4.869 *** | -4.055 *** | -10.237 *** |
| | (0.598) | (0.837) | (0.957) |
| Constant | 20.027 *** | 17.924 *** | 31.018 *** |
| | (3.042) | (4.258) | (3.804) |
| $\lambda$ | 4.059 *** | 3.870 *** | 6.964 *** |
| | (0.457) | (0.723) | (0.671) |
| $\lambda_{IC}$ | 4.655 *** | 4.944 *** | 7.532 *** |
| | (0.398) | (0.489) | (0.584) |

ln-L = -5506.20
NOTE: Huber Corrected Standard Errors in Parentheses
Statistical significance: *=10%; **=5%; ***=1%

Table 8: Predicted Probabillities

| | 4-States Model: Men | | | |
|---|---|---|---|---|
| Status | Empl. | Unemp. | | Self-Emp. |
| | | with ben. | no ben. | |
| *Average* | 0.84 | 0.03 | 0.04 | 0.09 |
| *Previous state* | | | | |
| Empl. | 0.84 | 0.04 | 0.02 | 0.10 |
| Unemp. with ben. | 0.81 | 0.09 | 0.04 | 0.06 |
| Unemp. no ben. | 0.81 | 0.03 | 0.07 | 0.08 |
| Self-Emp. | 0.88 | 0.01 | 0.01 | 0.09 |
| *Age* | | | | |
| 25 | 0.82 | 0.04 | 0.04 | 0.10 |
| 40 | 0.90 | 0.02 | 0.03 | 0.05 |
| 60 | 0.73 | 0.07 | 0.04 | 0.16 |
| *Education* | | | | |
| Primary or lower | 0.41 | 0.11 | 0.12 | 0.36 |
| Middle school | 0.82 | 0.05 | 0.04 | 0.10 |
| High school degree | 0.93 | 0.02 | 0.02 | 0.03 |
| Professional degree | 0.93 | 0.02 | 0.02 | 0.02 |
| Higher education | 0.99 | 0.00 | 0.00 | 0.00 |
| *Rural/Urban* | | | | |
| Rural | 0.78 | 0.05 | 0.04 | 0.12 |
| Urban | 0.96 | 0.01 | 0.02 | 0.01 |

Table 9: Predicted Probabillities

| | 4-States Model: Women | | | |
|---|---|---|---|---|
| Status | Empl. | Unemp. | | Self-Emp. |
| | | with ben. | no ben. | |
| *Average* | 0.61 | 0.05 | 0.06 | 0.28 |
| *Previous state* | | | | |
| Empl. | 0.61 | 0.04 | 0.02 | 0.33 |
| Unemp. with ben. | 0.58 | 0.11 | 0.05 | 0.26 |
| Unemp. no ben. | 0.60 | 0.03 | 0.10 | 0.27 |
| Self-Emp. | 0.64 | 0.02 | 0.02 | 0.32 |
| *Age* | | | | |
| 25 | 0.54 | 0.06 | 0.10 | 0.30 |
| 40 | 0.69 | 0.03 | 0.06 | 0.22 |
| 60 | 0.40 | 0.07 | 0.02 | 0.51 |
| *Education* | | | | |
| Primary or lower | 0.25 | 0.09 | 0.14 | 0.52 |
| Middle school | 0.51 | 0.05 | 0.06 | 0.38 |
| High school degree | 0.76 | 0.05 | 0.07 | 0.12 |
| Professional degree | 0.73 | 0.05 | 0.08 | 0.14 |
| Higher education | 0.99 | 0.00 | 0.00 | 0.00 |
| *Rural/Urban* | | | | |
| Rural | 0.36 | 0.11 | 0.08 | 0.46 |
| Urban | 0.87 | 0.02 | 0.08 | 0.04 |

Table 10: Predicted transition rates by gender

| Current Status | Empl. | | | | Unemp. with ben. | | | | Unemp. no ben | | | | Self-Emp. | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Men | | Women | | Men | | Women | | Men | | Women | | Men | | Women | |
| Employed (base) | **91.3** | (94.1) | **83.6** | (94.1) | **2.4** | (1.8) | **3.6** | (2.4) | **1.2** | (1.0) | **1.7** | (1.1) | **5.0** | (3.1) | **11.2** | (2.4) |
| Unemp. with ben. | **74.3** | (25.9) | **58.9** | (26.0) | **8.9** | (31.6) | **13.7** | (34.0) | **5.8** | (15.0) | **7.1** | (18.3) | **11.0** | (27.6) | **20.3** | (21.7) |
| ... state dep. | 76.2 | *+1.9* | 61.1 | *+2.2* | 6.6 | *-2.3* | 8.4 | *-5.3* | 2.7 | *-3.1* | 2.9 | *-4.2* | 14.4 | *+3.4* | 27.6 | *+7.3* |
| ... age | 84.7 | *+10.4* | 75.4 | *+16.5* | 5.4 | *-3.5* | 8.0 | *-5.7* | 4.0 | *-1.8* | 3.8 | *-3.3* | 5.9 | *-5.1* | 12.7 | *-7.6* |
| ... education | 84.4 | *+10.1* | 68.9 | *+10.0* | 5.2 | *-4.7* | 12.7 | *-1.0* | 4.7 | *-1.1* | 6.8 | *-0.3* | 5.7 | *-5.3* | 11.6 | *-8.7* |
| ... hh composition | 81.9 | *+7.6* | 58.4 | *-0.5* | 6.4 | *-2.5* | 12.5 | *-1.2* | 3.4 | *-2.4* | 7.3 | *+0.2* | 8.3 | *-2.7* | 21.8 | *+1.5* |
| ... rural/urban | 85.2 | *+10.9* | 80.9 | *+22.0* | 5.9 | *-3.0* | 9.2 | *-4.5* | 6.0 | *+0.2* | 7.2 | *+0.1* | 2.8 | *-8.2* | 2.7 | *-17.6* |
| Unemp. no ben. | **77.2** | (30.2) | **67.6** | (27.7) | **6.4** | (10.2) | **8.2** | (9.6) | **7.2** | (30.6) | **8.9** | (43.6) | **9.2** | (29.9) | **15.2** | (19.1) |
| ... state dep. | 78.5 | *+1.3* | 69.4 | *+1.8* | 6.2 | *-0.2* | 6.6 | *-1.6* | 3.2 | *-4.0* | 3.2 | *-5.7* | 12.0 | *+2.8* | 20.1 | *+4.9* |
| ... age | 86.1 | *+8.9* | 81.8 | *+14.2* | 3.4 | *-3.0* | 4.3 | *-3.9* | 5.1 | *-2.1* | 4.4 | *-4.5* | 5.5 | *-3.7* | 9.5 | *-5.7* |
| ... education | 86.9 | *+9.7* | 77.1 | *+9.5* | 4.1 | *-2.3* | 6.7 | *-1.5* | 4.6 | *-2.6* | 6.5 | *-2.4* | 4.4 | *-4.8* | 9.7 | *-5.5* |
| ... hh composition | 85.3 | *+8.1* | 67.7 | *+0.1* | 3.8 | *-2.6* | 8.3 | *-0.1* | 4.1 | *-3.1* | 9.4 | *+0.5* | 6.7 | *-2.5* | 14.6 | *-0.6* |
| ... rural/urban | 83.5 | *+6.3* | 81.0 | *13.4* | 5.1 | *-3.3* | 6.4 | *-1.8* | 7.5 | *+0.3* | 9.6 | *+0.7* | 3.8 | *-5.4* | 3.1 | *-12.1* |
| Self-employed | **63.1** | (10.2) | **15.0** | (4.5) | **4.2** | (2.1) | **3.7** | (1.4) | **4.3** | (3.6) | **3.3** | (1.7) | **28.3** | (84.2) | **78.0** | (92.5) |
| ... state dep. | 57.0 | *-6.1* | 12.3 | *-2.7* | 9.4 | *+5.0* | 5.4 | *+1.7* | 3.5 | *-0.8* | 1.9 | *-1.4* | 30.0 | *+1.7* | 80.4 | *+2.4* |
| ... age | 74.6 | *+11.5* | 26.2 | *+11.2* | 2.9 | *+1.3* | 3.5 | *-0.2* | 4.1 | *-0.2* | 3.1 | *-0.2* | 18.4 | *-9.9* | 67.2 | *-11.8* |
| ... education | 87.9 | *+24.8* | 47.8 | *+32.8* | 2.3 | *-1.9* | 5.1 | *+1.4* | 2.8 | *-1.5* | 4.2 | *+0.9* | 7.0 | *-21.3* | 43.0 | *-35.0* |
| ... hh composition | 69.4 | *+6.3* | 17.0 | *+2.0* | 3.0 | *-1.2* | 4.0 | *+0.3* | 2.9 | *-1.4* | 3.3 | *0.0* | 24.7 | *-3.6* | 75.7 | *-2.3* |
| ... rural/urban | 83.4 | *+20.3* | 59.9 | *+44.9* | 2.5 | *-1.7* | 3.8 | *+0.1* | 4.7 | *+0.4* | 5.6 | *+2.6* | 9.3 | *-19.0* | 30.7 | *-47.3* |

Observed transition rates in parentheses