The Moroccan Labour Market in Transition:

A Markov Chain Approach

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Abstract

This study uses data from the 2009 Follow-up of Moroccan Vocational Training Graduates – Class of 2006 – to examine the labour market transitions between the states of employment, unemployment, and inactivity using a Markov chain approach. We estimate labour market transition matrix that is related by means of a multivariate logistic link to various variables. We find evidence that mobility patterns are fairly similar which confirm the static nature of the Moroccan labour market. Gender, age, Regional unemployment rate and Training operator are observed to display significant effects on mobility patterns.

Mathematics Subject Classification: 91B60, 46N10, 65F30

Keywords: Optimization CG, Markov process, labour market

1 Introduction

The analysis of transitions between labour market states is crucial to understanding the complex phenomenon of unemployment. Several attempts have been made to model labour mobility using Markov transition process. To name a few, Bosch and Maloney (2010) estimate a continuous time Markov process on panel data from Argentina, Brazil and Mexico. Fabrizi and Mussida (2009)

In this study, we propose a Markov chain approach allowing the estimation of the transition probabilities given specific characteristics.

This study uses data from the Follow-up of Moroccan Graduates – Class of 2006 – survey. For each graduate, a retrospective time calendar records the labour force status in each month during the three-year period following graduation, for a total of 37 months of observation.

In order to examine the nature of labour mobility patterns, we estimate six multinomial logit models for six labour market transitions by adopting a number of characteristics as explanatory variables (Alvarez et al., 2008; Tansel and Kan, 2012).

The remainder of the paper proceeds as follows. In the next section, we describe the methodology of Markov transition analysis. Results of Markov transition analysis are presented in Sections 3. Finally, Section 4 provides the concluding remarks.

2 Methodology

Let \( i \in \Omega = \{E, CH, O\} \) where E, CH, O denote respectively employment, unemployment and inactivity. We assume a stochastic movement over time from one state to another which is generated by a stationary time-homogenous Markov process. The Markov chain process is characterized by a transition matrix \( \theta \).

\[
\theta = \begin{bmatrix}
\theta_{EE} & \theta_{ECH} & \theta_{EO} \\
\theta_{CHE} & \theta_{CHCH} & \theta_{CHO} \\
\theta_{OE} & \theta_{OCH} & \theta_{OO}
\end{bmatrix}
\]

The stationary vector \( \pi = (\pi_i)_{i \in E} \) satisfies the usual conditions \( \pi = \pi \theta \) and \( \sum_{i=1}^{3} \pi_i = 1 \) and is given by:

\[
\pi_E = \frac{\text{Num}_E(\theta)}{\text{Den}(\theta)} = \frac{\theta_{OE} \theta_{CHE} + \theta_{CHE} \theta_{OCH} + \theta_{OE} \theta_{CHO}}{\text{Den}(\theta)}
\]
The Moroccan labour market in transition

\[ \pi_{CH} = \frac{\text{Num}_{CH}(\theta)}{\text{Den}(\theta)} = \frac{\theta_{OE} \theta_{ECH} + \theta_{ECH} \theta_{OCH} + \theta_{EO} \theta_{OCH}}{\text{Den}(\theta)} \]

\[ \pi_{O} = \frac{\text{Num}_{O}(\theta)}{\text{Den}(\theta)} = \frac{\theta_{ECH} \theta_{CHO} + \theta_{EO} \theta_{CHE} + \theta_{EO} \theta_{CHO}}{\text{Den}(\theta)} \]

When \( \text{Den}(\theta) = \text{Num}_{E}(\theta) + \text{Num}_{CH}(\theta) + \text{Num}_{O}(\theta) \)

The transition probabilities are parameterized as a function of individuals' characteristics and labour market conditions using a multivariate logistic link \( Y := Y(\theta) \):

\[ Y_{ECH} := \ln\left( \frac{\theta_{ECH}}{\theta_{EE}} \right) \]

\[ Y_{EO} := \ln\left( \frac{\theta_{EO}}{\theta_{EE}} \right) \]

\[ Y_{CHE} := \ln\left( \frac{\theta_{CHE}}{\theta_{CHCH}} \right) \]

\[ Y_{CHO} := \ln\left( \frac{\theta_{CHO}}{\theta_{CHCH}} \right) \]

\[ Y_{OE} := \ln\left( \frac{\theta_{OE}}{\theta_{OO}} \right) \]

\[ Y_{OCH} := \ln\left( \frac{\theta_{OCH}}{\theta_{OO}} \right) \]

where \( Y_{ij} := \beta_{ij}^{(0)} + \sum \beta_{ij}^{(m)} X_{m} \quad i, j \in \Omega = \{ E, CH, O \} \)

To deduce transition matrix elements we use the following inverse mapping:

\[ \theta_{EE} = \frac{1}{1 + e^{Y_{ECH} + e^{Y_{EO}}}} \]

\[ \theta_{ECH} = \frac{e^{Y_{ECH}}}{1 + e^{Y_{ECH} + e^{Y_{EO}}}} \]

\[ \theta_{EO} = \frac{e^{Y_{EO}}}{1 + e^{Y_{ECH} + e^{Y_{EO}}}} \]

\[ \theta_{CHE} = \frac{e^{Y_{CHE}}}{1 + e^{Y_{CHE} + e^{Y_{CHO}}}} \]

\[ \theta_{CHCH} = \frac{1}{1 + e^{Y_{CHE} + e^{Y_{CHO}}}} \]

\[ \theta_{CHO} = \frac{e^{Y_{CHO}}}{1 + e^{Y_{CHE} + e^{Y_{CHO}}}} \]

\[ \theta_{OCH} = \frac{e^{Y_{OCH}}}{1 + e^{Y_{CHO} + e^{Y_{OCH}}}} \]

\[ \theta_{OO} = \frac{1}{1 + e^{Y_{OCH} + e^{Y_{OCH}}}} \]

**Likelihood maximization**

The individuals' contributions to the likelihood function represent the product of the probability to occupy the initial state and the transition probabilities corresponding to the individual's history (Amemya, 1985)
We estimate the parameters by maximizing the likelihood function in two steps: A first step consists in initializing the parameters $\beta$ and a second phase reserved to calculate the parameters using an iterative method.

**Initialization:** We estimate the transition probabilities non-parametrically by calculating the ratio of all transitions from $i$ to $j$ to the number of transitions which start in $i$, $\hat{\theta}_{ij}^{(0)} = \frac{\#(i \rightarrow j)}{\#i}$.

After, we set the initial estimator to be: $\hat{\beta}_{ij}^{(0)} = \ln\left(\frac{\hat{\theta}_{ij}^{(0)}}{\hat{\theta}_{ii}^{(0)}}\right)$. The covariates' coefficients are set to 0: $\beta_{ij} = 0$

**Updates:** Among a panoply of nonlinear optimization methods, we adopt the iterative method: Conjugate Gradient "CG" to calculate the parameters $\beta$. This method is applied to solve different types of nonlinear unconstrained optimization problems in engineering fields and nonlinear regression (Shewchuk, 1994). The conjugate gradient method requires a memory capacity which is not enormous, and is characterized by strong properties of global and local convergence (Hager & Zhang, 2005). The conjugate gradient method is based on the search for successive directions that are similar to an ellipse axes. Three various formulas of directions research are implemented: Fletcher-Reeves, Polak-Ribiere or Beale-Sorenson. In our case, we propose to apply the first formula.

### 3 Results

We report in table 1. the maximum likelihood estimators and their standard errors. It is noteworthy that regional unemployment rate is significant in the model. It represents the influence of exogenous macroeconomic or country-specific conditions in the individual labor dynamics. There is a positive effect of age in all the transitions. Females and graduates from public schools are more prone that men to move out of the labor market.
Table 1: Maximum likelihood estimation:

<table>
<thead>
<tr>
<th></th>
<th>ECH</th>
<th>EO</th>
<th>CHE</th>
<th>CHO</th>
<th>OE</th>
<th>OCH</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>-4.231</td>
<td>-6.084</td>
<td>-3.444</td>
<td>-5.030</td>
<td>-5.774</td>
<td>-5.510</td>
</tr>
<tr>
<td></td>
<td>-9.159</td>
<td>-12,945</td>
<td>-7,594</td>
<td>-10,971</td>
<td>-12,254</td>
<td>-11,725</td>
</tr>
<tr>
<td><strong>Gender (Ref.=Male)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.071</td>
<td>0.179*</td>
<td>0.058</td>
<td>0.152*</td>
<td>0.144*</td>
<td>0.128</td>
</tr>
<tr>
<td></td>
<td>1.063</td>
<td>2.638</td>
<td>0.865</td>
<td>2.248</td>
<td>2.128</td>
<td>1.902</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>0.124*</td>
<td>0.162*</td>
<td>0.100*</td>
<td>0.133*</td>
<td>0.160*</td>
<td>0.155*</td>
</tr>
<tr>
<td></td>
<td>8,434</td>
<td>11,034</td>
<td>6,980</td>
<td>9,335</td>
<td>10,792</td>
<td>10,440</td>
</tr>
<tr>
<td><strong>Training level (Ref.=Specialisation)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Qualification</td>
<td>0.063</td>
<td>0.114</td>
<td>0.050</td>
<td>0.094</td>
<td>0.101</td>
<td>0.094</td>
</tr>
<tr>
<td></td>
<td>0.691</td>
<td>1,212</td>
<td>0.550</td>
<td>1,006</td>
<td>1,090</td>
<td>1,017</td>
</tr>
<tr>
<td>Technician</td>
<td>-0.057</td>
<td>-0.044</td>
<td>-0.042</td>
<td>-0.034</td>
<td>-0.058</td>
<td>-0.060</td>
</tr>
<tr>
<td></td>
<td>-0.571</td>
<td>-0.432</td>
<td>-0.425</td>
<td>-0.337</td>
<td>-0.573</td>
<td>-0.598</td>
</tr>
<tr>
<td>Specialized technician</td>
<td>-0.027</td>
<td>-0.012</td>
<td>-0.020</td>
<td>-0.009</td>
<td>-0.022</td>
<td>-0.024</td>
</tr>
<tr>
<td></td>
<td>-0.228</td>
<td>-0.097</td>
<td>-0.169</td>
<td>-0.072</td>
<td>-0.181</td>
<td>-0.202</td>
</tr>
<tr>
<td><strong>Regional unemployment rate</strong></td>
<td>0.055*</td>
<td>0.086*</td>
<td>0.047*</td>
<td>0.073*</td>
<td>0.078*</td>
<td>0.073*</td>
</tr>
<tr>
<td></td>
<td>4,277</td>
<td>6,560</td>
<td>3,635</td>
<td>5,620</td>
<td>5,979</td>
<td>5,640</td>
</tr>
<tr>
<td><strong>Satisfaction with the training received (Ref.= not at all satisfied)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Very satisfied</td>
<td>0.027</td>
<td>0.098</td>
<td>0.019</td>
<td>0.083</td>
<td>0.076</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>0.157</td>
<td>0.550</td>
<td>0.109</td>
<td>0.465</td>
<td>0.432</td>
<td>0.377</td>
</tr>
<tr>
<td>Somewhat satisfied</td>
<td>0.047</td>
<td>0.200</td>
<td>0.041</td>
<td>0.172</td>
<td>0.142</td>
<td>0.120</td>
</tr>
<tr>
<td></td>
<td>0.282</td>
<td>1,151</td>
<td>0.245</td>
<td>0.994</td>
<td>0.829</td>
<td>0.703</td>
</tr>
<tr>
<td><strong>Training operator (Ref.=Private schools)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public schools</td>
<td>0.071</td>
<td>0.239*</td>
<td>0.060</td>
<td>0.204*</td>
<td>0.178*</td>
<td>0.154*</td>
</tr>
<tr>
<td></td>
<td>0.967</td>
<td>3,173</td>
<td>0.817</td>
<td>2,717</td>
<td>2,387</td>
<td>2,068</td>
</tr>
<tr>
<td><strong>Parent's labour force status (Ref.=Not employed)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>-0.019</td>
<td>-0.053</td>
<td>-0.016</td>
<td>-0.045</td>
<td>-0.042</td>
<td>-0.037</td>
</tr>
<tr>
<td></td>
<td>-0.196</td>
<td>-0.532</td>
<td>-0.158</td>
<td>-0.454</td>
<td>-0.420</td>
<td>-0.373</td>
</tr>
</tbody>
</table>

Significant coefficients at: *5% confidence level.

\[ \theta = \begin{bmatrix} 0.37 & 0.32 & 0.31 \\ 0.33 & 0.34 & 0.33 \\ 0.32 & 0.32 & 0.36 \end{bmatrix} \]

Activity rate A: \( A = \pi_E + \pi_{CH} \) Measures the proportion of unemployed and employed graduates.
Unemployment rate: \( CH = \pi_{CH}/(\pi_{CH} + \pi_E) \). Measures the proportion of unemployed graduates.

Inertia: \( I = 1/3 \text{ trace } (\Theta) \) it measures the proclivity of the current employment state to perpetuate in time.

Give-up rate: \( Ab = \frac{\theta_{CHO}}{\theta_{CHCH} + \theta_{CHO}} \). is the probability for the unemployed that a transition to inactivity occurs before a transition to employment.

Net Outflow: \( F_S = \pi_E \theta_{EO} - \pi_o \theta_{OE} \) is The difference between the proportion of the graduates who leave employment for inactivity and inactive graduates who succeed to get a job.

Reliability: \( R = \frac{\theta_{EO}}{1 - \theta_{EE}} \) The probability that a graduate move from inactivity to employment before being unemployed.

Table 2. Labor market indicators:

<table>
<thead>
<tr>
<th>A</th>
<th>CH</th>
<th>I</th>
<th>Ab</th>
<th>F_S</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.67</td>
<td>0.50</td>
<td>0.39</td>
<td>0.49</td>
<td>0.03</td>
<td>0.5</td>
</tr>
</tbody>
</table>

We report In table 2. labour indicators. Activity rate is about 67% and unemployment rate is about 50%. We notice an important level of Inertia (about 40%). In the other hand the job reliability is about 50%. However, The net Outflow is around 3% and the give-up rate is about 50% which reflect the rigid nature of inactive state. these findings depict that the Moroccan labor market has a relatively static nature.

4 Conclusion

In this paper we examine the mobility in the labour market of Moroccan vocational training graduates. Results show that Regional unemployment rate is significant in the model and there is a positive effect of age in all the transitions.
Furthermore females and graduates from public schools are more prone than men to move out of the labor market. Having computed the transition probabilities matrix, we identify that the transition probabilities are fairly similar. The most discernible conclusion is the static nature of the Moroccan labour market throughout the period considered.

References


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