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Labor market segmentation using Stochastic Markov chains [1]

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Abstract: This article discusses regional labor segmentation using stochastic Markov chains. We present a formal model and derive preliminary results using the evolution of wages in Colombian urban areas. The results show that there was regional labor market segmentation in wages for university graduates during the period from 1993 to 2000, and corroborate the existence of structural changes in wages during the nineteen nineties.

Keywords: Labor market segmentation, Markov Chains, structural changes

JEL Classification: J30, J42.

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1 Computations reported in this paper were undertaken [in part] using the BACC software.

1. Introduction

Labor market segmentation exists when a different wage is paid for the same kind of work based on education, geographic region, gender, or race (Cain 1976, Gerke and Evers 1993). According to Molho (1992), individuals are trapped in segments; in some, it is possible to rise through internal markets, while in others, instability, low wages, and underemployment do not allow this. When there is labor market segmentation, discrimination and screening processes limit mobility between segments. Once wage differentials exist, geographic barriers contribute to making the process difficult to alter. According to Servo (1999), segmentation theory explains wage differentials on the basis of differences in production structure, labor markets, and the level of development in each region.

This article develops a model of wage segmentation using Markov chains and makes a non–parametric analysis of the distribution of average wages between 1985, 1993, and 2000 in Colombia. Also, in the context of Markov chains, we test the hypothesis of labor market segmentation for Colombian professional workers during that period (1985-2000). In case of the possible existence of structural changes having taken place in the nineteen nineties, a hypothesis of structural changes in the market place was tested by applying the Bayes factor to first order Markov chains.

The rest of this article is organized in the following manner: The second section presents the principal theory about labor market segmentation. The third section presents a model in which labor segmentation occurs and incorporates the structural changes in the wages. The fourth section discusses the number of modes in the sample distribution. The last section discusses the hypothesis of segmentation in the Colombian labor market. The findings of this article show a framework to model the existence of segmentation in labor market theory using Markov chains and corroborate the results for the Colombian labor market.

2. Labor market segmentation

Segmentation theory assumes the existence of two markets: a primary market with high wages, high benefits, and employment security; and a secondary market with low benefits and wages (Piore 1971, 1975; Cain 1976; Eduards *et al.* 1975; and Berger and Piore 1980). Gerke and Evers (1993) consider labor market segmentation to exist when different wages are paid for the same type of work depending on gender, location, and formal education, while Cain (1976) considers geographic regions and demographic characteristics such as gender or race. Individuals are trapped within segments, and in some it is possible to rise through internal markets, while in others, instability, low wages, and underemployment do not allow this. Discrimination and screening processes limit mobility between segments. Once wage differentials exist, geographic barriers contribute to making the process difficult to alter (Molho 1992).

Segmentation theory explains wage differentials on the basis of differences in production structure, labor markets, and the level of development in each region (Servo 1999). In this way, wages are one of the characteristics explaining the differences in regional labor markets, since transitory shocks in local markets, usually those caused by demand, have a positive impact on the wages of the workers, especially those who have more education and experience (Topel 1986).

Recently, Boyer and Hatton (1997) and Hatton and Williamson (1992) make the case that wage differences among regions or between cities and rural areas are evidence of the level of integration among labor markets. Since regional labor market segmentation involves incorporating the analysis of all cities which make up the labor market, the first step implies that, "if workers are really segmented into two distinct markets, the resulting distribution of earnings should be bimodal. That is to say, the frequency distribution of salaried professionals should be concentrated on one mode on the secondary market of low wages and on another on the primary market of elevated wages" (Macconell and Brue 1997).

3. The model

Given π_{jt} as the probability that the wages for the same class of individuals in the city *j* to be found in state *t*; then, for every time period *t*, the state will be as follows:

$$\pi'_{j,t} = \pi'_{j,t-1} P = \cdots = \pi'_{j,0} P^t \qquad (3)$$

Whereas π_0 is the initial state, and *P* is a transition matrix between states. Condition 3 will be fulfilled whenever $\pi^{*\prime}_t = \lim_{t\to\infty} \pi'_t$ exists, and it is the same for all the initial states. Operating with the information offered by the transition probability matrix, the long term can be characterized by the ergodic distribution. There are multiple possible results or scenarios, from a distribution with the probabilistic mass concentrated in one state to a distribution with the probabilistic mass distributed over both ends of the distribution. If π^* exists, this will be the invariant or ergodic distribution of the P transition *P* matrix, and it should satisfy:[2]

$$\pi^{*\prime}_t = \pi^{*\prime}_t P_t \qquad (4)$$

The invariant distribution π^* in Equation 4 will show when the transitions from the cities lead to integration or segmentation in the labor market.

Definition of segmentation: If a ζ is an element in the ergodic distribution $\zeta \in \pi^*$, so $\zeta_i > \zeta_{i+1}$ and $\zeta_i < \zeta_{i-1}$. There is integration in the labor market if, and only if, there is a unique $\zeta \in \pi^*$. It must be noted that if there is more than one $\zeta \in \pi^*$ that satisfies the previous condition, there will be segmentation. The deduction is simple: a single ζ indicates an ergodic, unimodal distribution which is the result of the integration of the labor market, while more than one ζ indicates that the ergodic

[2] Note that the eigenvalues λ_1, λ_2, ..., λ_n are arranged in order so that $|\lambda_1| \geq |\lambda_2| \geq \ldots \geq |\lambda_n|$. Then if $|\lambda_1| > |\lambda_2|$, the distribution is unique.

distribution is not unimodal, thus signifying segmentation in the labor market. In order to incorporate the existence of structural changes, the notation is modified as follows:

Let S is the wages for N cities over T periods and C classes or states, and $i \in \{1,2,..,C\}$, $n \in \{1,2,..,N\}$ and $t \in \{1,2,..,T\}$. For the wages of each city, let $\delta_{int} = 1$ if the wages of the city are in class i for time period t, and zero otherwise. Let $s_{nt} \in \{1,2,..,C\}$ the class of wage to which each city belongs, and $S_{NT} = \{\{s_{nt}\}^{N}_{n=1}\}\}^{T}_{t=1}$ is the set of information in period T. Let $K_{jo} = \sum_{n=1}^{N} \sum_{t=1}^{T} \delta_{ni(t-1)}\delta_{njt}$ be defined as the total number of class i transitions in time period t-1 to class j in period t. Then matrix $K=[k_{ij}]$ will be the transition matrix. The function of probability is shown as:

$$p(S_{NT} \mid \pi_o, P) \propto \prod_{i=1}^{C} \pi_{i0}^{k_{i0}} \prod_{j=1}^{C} p_{ij}^{k_{ij}} \tag{5}$$

This shows that (5) is the kernel of the product of two multivariate and independent Beta (Dirichlet) distributions. The *prior* distributions for π_0 and P are also independent Dirichlet distributions, defined as:

$$p(\pi_0) = \left[\frac{\Gamma\left(\sum_{i=1}^{c} a_{i0}\right)}{\Pi_{i=1}^{C}\Gamma(a_{i0})}\right] \prod_{i=1}^{C} \pi_{i0}^{(a_{i0}-1)} \quad ; \; p(P) = \prod_{i=1}^{C}\left[\frac{\Gamma\left(\sum_{i=1}^{c} a_{ij}\right)}{\Pi_{i=1}^{C}\Gamma(a_{i0})}\right] \prod_{i=1}^{C} \pi_{ij}^{(a_{ij}-1)} \tag{6}$$

In (6) the *prior* distributions are parametrized by the vector $a_0 = [a_{10},\ldots,a_{C0}]'$ and the matrix $A = [a_{ij}]$ (Geweke 2003). Thus, the conjectures have a notional interpretation of the sample. Assuming that the *prior* distributions are independent, the posterior distribution will be:

$$p(\pi_0, P \mid S_{NT}) \propto \left[\frac{\Gamma\left(\sum_{i=1}^{c} a_{i0}\right)}{\Pi_{i=1}^{C}\Gamma(a_{i0})}\right] \prod_{i=1}^{C} \pi_{i0}^{(k_{i0}+a_{i0}-1)} \prod_{i=1}^{C}\left\{\left[\frac{\Gamma\left(\sum_{j=1}^{C} a_{ij}\right)}{\prod_{j=1}^{C}\Gamma(a_{ij})}\right]\right\} \prod_{j=1}^{C} \pi_{ij}^{(k_{ij}+a_{ij}-1)} \tag{7}$$

In equation (7) posterior distributions can be analyzed both for invariant distribution and the differences between invariant distribution and any other set of distributions (for example, a distribution showing integration or segmentation in the labor market). Next, let model M_j, j=1...J be defined as describing a set of observations S_{NT} in which the marginal probability for model j is shown by:

$$p(S_{NT} \mid M_{jN}) = \int_{\rho} p(S_{NT} \mid \pi_0, P, M_j) p(\pi_0, P \mid M_j) d(\pi_0, P)$$

$$\rho = \left\{ (\pi_{j0}, p_{ij}) : 0 \leq \pi_{j0} \leq 1, 0 \leq p_{ij} \leq 1; \ \sum_{j=1}^{C} \pi_{jo} = 1, \sum_{j=1}^{s} p_{ij} = 1 \ \ \forall i = 1, \ldots C \right\} \qquad (8)$$

If there are two independent transition matrices, with each one built for a different time period, then the marginal probability of a model including two transition matrices of this type will be the product of the marginal probability of the two models with a transition (Landon-Lane and Quinn 1999). Thus, the existence of structural change can be defined using the Bayes factor (Geweke 2003) of the model without structural change versus the model with structural change, as follows:

$$B_{CH,NCH} = \frac{p(S_{NT} \mid M_{CH,N})}{p(S_{NT} \mid M_{NCH,N})} \qquad (9)$$

Where CH indicates structural change and NCH absence of structural change. Bayes factor shows the likelihood of the model with structural changes versus the model without structural change (Jeffreys 1961).

4. Regional distribution of wages in Colombia

One of the main characteristics of labor market segmentation is that distribution is not unimodal. This can be concealed within any parametric estimate of the function of density. A non-parametric estimate of the function of density does not imply any assumption of wage distribution, although it does require choosing a method for smoothing the data. One of the most commonly used methods is the histogram, but its main difficulty is the need to choose the origin (Silverman 1986). For this reason, the smoothed kernel method is used here. According to this methodology, the following function of density is estimated:

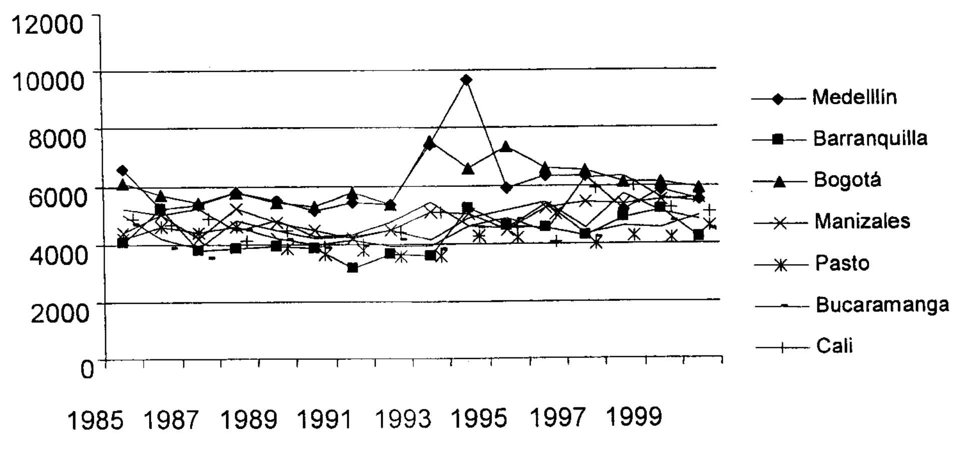
$$\hat{f}(w) = \frac{1}{nh} \sum_{i=1}^{n} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{w - w_i}{h}\right)^2} \qquad (1)$$

In (1) the choice of the bandwith (*h*) affects the distribution in different ways, as an *h* which is too small will generate an excessive number of peaks, so that the true structure of the data cannot be clearly distinguished; this phenomenon is called *undersmoothing*. On the contrary, an overly large *h* creates *oversmoothing*, so that features which could have been present in the data (e.g. multimodal structures) remain concealed. Underlying these facts is the traditional trade-off between bias and variance that correlates directly with the amount of smoothing: more h, less variance and more bias, and vice versa.

The existing methods for determining the value of h in (1) can be classified into the two following categories: first and second generation. The first were proposed before 1990 and have been discussed the most in the literature. Among these are the theories known as *rules of thumb* (Silverman 1986), least *squares cross-validation* (hLSCV), and *biased cross-validation* (hBCV). The second generation methods fall into two groups: the *solve-the-equation plug-in approach* and *smoothed bootstrap*.

The data were taken from the National Household Survey by the Colombian National Administrative Department of Statistics (DANE) for the third quarter from 1985 to 2000. Using these, a series of average hourly wages was built based on the figures for wages of Colombian professionals – those with a university degree or higher, i.e., those with sixteen or more years of education -- in the cities of Bogotá, Bucaramanga, Barranquilla, Cali, Manizales, Medellin, and Pasto. The wages obtained were deflated with the Consumer Price Index for the middle class. Excluded from the sample were: self-employed individuals, employers, and those who did not report wages. This selection is due to the fact that for the selected workers, the diploma they earned in a city could be used by the companies as a signaling or screening mechanism, thereby reducing mobility, following regional segmentation theory (Molho 1992, Taubman and Wachter 1986, Mora 2003, 2008). The evolution of wages is shown in the following figure:

Figure 1. Wages by Cities



Source: Author's calculations using NHS-DANE.

Figure (1) shows how, from 1993 on, there is a change in their evolution. The changes which began in the early the nineteen nineties, such as the liberalization of the economy and the labor market reform, produced a greater concentration of income because of the increase in the demand for highly qualified workers, based on technical change biased in their favor (Santa María 2001, Arango and Uribe 2004), along with the expansion in the number of universities offering professional degree programs (Mora 2003).

Therefore, the technical change which occurred in the nineteen nineties could have produced a structural change in the evolution of wages in Colombia. The results obtained using a Gaussian kernel and 100 points for the *h* were as follows:

Table 1. h- Index

Year/Method	Least Squares CV	Biased CV	Silverman's rule of thumb	Park and Marron plug-in	Sheather and Jones plug-in
1985	1044.7	1044.7	692.385	1020.45	774.428
1993	1949	1958.63	1169.18	1768.79	1288.97
2000	431.753	431.753	408.265	541.431	422.237

Source: Author's calculations using NHS-DANE.

Table 1 show that the Silverman method reports the lowest *h*. In order to check whether the data show an integration mode in the labor market - or more than one mode, and, therefore, segmentation, we use the technique proposed by Silverman (1981): Consider the problem of testing the null hypothesis that density *f* has *k* modes, versus the alternative that *f* has more than *k* modes. Let $\hat{h}_k$ be the critical bandwith; that is, the smallest value of *h* so that $\hat{f}(x;h)$ has *k* modes. A high value of $\hat{h}_k$ with respect to $\hat{h}_{k+1}$ indicates that a great deal of smoothing is needed to create and estimate a density with only *k* modes. The procedure used by Silverman (1981) uses the bootstrap technique to evaluate the significance of an observed value of $\hat{h}_k$, and is based on the level of significance which is achieved, the ASL:

$$ASL_{bootstrap} \equiv Prob\ \{\hat{h}_k^* > \hat{h}_k\}, \qquad (2)$$

In Equation 2, $\hat{h}_k^*$ is the lowest value of *h*, so that the density in the sample obtained by the bootstrap method has *k* modes. This test begins with the fact that for a Gaussian kernel, the number of zeros in all the derivatives of the estimated density decreases monotonically over the bandwidth. This property of monotonicity appears to be unique when the kernel is Gaussian (Babaud *et al.* 1986, Minnotte and Scott 1993). Thus, when using a Gaussian kernel, 100 replicas, and an average of 30 histogram changes, and choosing the smallest *h* in Table 2, the results are as follows:

Table 2. Number of modes

Year	Number	P-Value
1985	1	0.12
1993	1	0.06
2000	1	0.07

Source: Author's calculations using NHS-DANE.

According to Martínez –Ramírez *et al.* (1998), and Salgado-Ugarde (1997), with a *p*-value greater than 0.1, the hypothesis that the distribution is unimodal is acceptable. Therefore, from Table 2, it can be concluded that the distribution in the years 1993 and 2000 is not unimodal.

5. Labor market segmentation in Colombia

Arango and Posada (2001) suggest the possibility of segmentation in the Colombian labor market based on a discussion of the unemployment rate. García et al. (2007) discuss segmentation comparing Mincer regressions for the formal and informal sectors, and García et al. (2008) also use Mincer regressions which incorporate differences among cities and sectors.

Other articles consider that the regional labor market segmentation in Colombia arises if there is no cointegration among wages, because in a segmented market, regional wage differentials increase over time (Nupia 1997, Jaramillo *et al.* 2000, Gálvis 2002). Because of the notion of complete convergence, convergence can lead to the exclusion of a significant part of the market, as in Gálvis (2002) who excludes 29% of the labor market.

In order to calculate (4), the wages of each city were discretized based on the national mean for each of the cities. Using this method, they were discretized into three states, since this is the minimum value which allows for segmentation to appear when there is an ergodic distribution. There is no rule that establishes how many states should be taken or how the discretization process should be carried out. Mora and Nuñez (2009), in particular, show how discretization by quantiles can lead to bi-stochastic matrices, and Durlauf and Quah (1999) show that there are problems of robustness in classifications arrived at by percentiles in the case of worldwide convergence in incomes. The states are constructed as follows: the value is 1 if the wages are between 0 and 0.9 of the national mean, 2 if they are greater than or equal to 0.9 and lower than 1.01, and, 3 if they are greater than 1.01 of the national mean. The results were:

Table 3. Transition Matrix (1985-2000)

State	1	2	3
1	0,5882	0,2942	0,1176
2	0,3	0,5333	0,1667
3	0,0732	0,122	0,8048
Ergodic	0,2871	0,2912	0,4217

Source: Author's calculations using NHS-DANE.

As shown in Table 3, the results for the period (1985-2000) suggest that there was no segmentation in the Colombian labor market. However, these results don't take into account the possible existence of structural changes in the nineteen nineties. To prove the existence of structural change in the evolution of professional wages in Colombia, two models are proposed, i.e. one composed only of one transition matrix between 1985 and 2000 (Table 3), and another composed of two transition matrices: between 1985-1992 and between 1993-2000. The transition matrices which were obtained are:

Table 4. Transition Matrix by periods

1985 - 1992			
State	1	2	3
1	0,5385	0,3077	0,1538
2	0,1764	0,6471	0,1765
3	0,1053	0,1579	0,7368
Ergodic	0,2331	0,3775	0,3894

1993 - 2000			
State	1	2	3
1	0,5789	0,3158	0,1053
2	0,4546	0,3636	0,1818
3	0,0526	0,1053	0,8421
Ergodic	0,305	0,2285	0,4665

Source: Author's calculations using NHS-DANE.

Table 4 shows that in the first period there was integration in the labor market, while in the second period, there was segmentation in the labor market. Then a calculation was made of the mobility in the distribution of the wages based on the work of Shorrocks (1978). A mobility index *M* is a map of the space from the transition matrices to the real numbers. Shorrocks (1976, 1978) shows that a mobility index should satisfy monotonicity, immobility, and strict immobility. Geweke *et al.* (1986) also establish that any index should satisfy the criterion of convergence. In this way the mobility between states can be calculated using the following indicators:

$$M_1(P) = \frac{n - tr(P)}{n-1} \; ; \; M_2(P) = 1 - |\, Det(p) \,| \qquad (10)$$

As shown by Geweke *et al.* (1986), both M_1 and M_2 meet this criterion. The results were:

Table 5. Mobility index

Variable/ Index	M1	M2
1985-1992	0,5388	0,7987
1993-2000	0,6077	0,9487

Source: Author's calculations using NHS-DANE.

Table 5 shows that mobility for the period (1993-2000) is greater than that for 1985-1992. These results could show that structural change caused greater movement dynamics between classes among the most qualified workers.

In order to calculate the existence of structural change using the Bayes factor, a determination of *prior* conjectures for the initial state was made. This determination started by considering the number of degrees of freedom *i* as a notional data set, in which there is a determined number of cities, in the artificial data, which move from state *i* to state *j* (Geweke 2003, Landon-Lane and Quinn 1999, 2000). The initial parameters for π_0 reflect the *prior* conjecture that any city in the sample has equal probability of belonging to any state. The assumptions made here imply that two of the seven cities are in each initial state of the *prior* conjecture. Three *prior* conjectures were considered: Integration into one of the three states, segmentation, and a mixed conjecture implying integration for the entire period and integration for the period of 1985 to 1992, and segmentation for the period of 1993-2000 (see Appendix).

Then the Bayes factor (Equation 9) was calculated with 5,000 samples taken independently in accordance with Equation 8. The results were:

Table 6. Bayes Factor

$\frac{p(S_{NT} \mid M_{CH,N})}{p(S_{NT} \mid M_{NCH,N}}$	Integration to S_1	Integration to S_2	Integration to S_3	Segmentation	Mixture
University	34,5351106	34,2902844	34,1804633	31,69276167	31,239681

Source: Author's calculations using NHS-DANE.

Table 6 shows the result of the calculation of the Bayes factor with various integration hypotheses: S_1 when there is integration to the first state, S_2 when there is integration to the second state, and, finally, S_3 when there is integration to the third state. The fourth column shows the results of the Bayes factor when there is segmentation, while the last column shows the results of the Bayes factor based on the conjecture involving mixed assumptions (integration and segmentation). Values lower than 10 indicate strong evidence in favor of NCH, while values higher than 10 indicate strong evidence in favor of CH. The results in Table 10 show strong evidence of a model with two transitions, including structural changes in the nineteen nineties, versus a single-transition model. This result is solid even when the modification proposed by Kass and Raftery is used (1995).

6. Conclusions

This article discusses the use of Markov chains to model the segmented labor market. This approach allows us to explore the ergodic distribution and test the existence of structural change in the wages.

In order to discuss the segmentation in the labor market, we tested the number of modes in the distribution of wages among different cities in Colombia, and found that distribution was unimodal in 1985, but it was not in 1993 and 2000. This is the first indicator of the existence of segmentation by regions in the Colombian labor market. In order to reach long-term conclusions, a first-order Markov chain was calculated for the period of 1985-2000. The results show integration in the labor market. The results change substantially after incorporating the effect of structural changes which occurred in the labor market in the nineteen nineties. This was a change which, furthermore, caused a greater dynamic of movement between states, which can be observed using the mobility indicators. The effect of this structural change contrasts with the Bayes factor, which shows evidence in favor of the two-transition model over the single-transition model. Thus, we can conclude that for the second half of the nineteen nineties there was segmentation for professionals in the Colombian labor market.

Finally, the results of this article show the importance of the regional characteristics that influence human capital such as quality of university education and the mechanisms through which higher education is used to signal or screen workers in the cities which limits their integration to the labor market and this is the main problem faced by working professionals in Colombia (Mora 2003, Mora and Muro 2008).

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Annex

A1. Assumptions of integrated labor market.

P (1985-2000)			E(P)			Ergodic
1	0,5	0,5	0,5013	0,2484	0,2503	0,5012
1	0,5	0,5	0,5016	0,2492	0,2492	0,2493
1	0,5	0,5	0,5006	0,2512	0,2492	0,2495
P (1985-1992)			E(P)			Ergodic
1,2	0,4	0,4	0,6006	0,1994	0,2000	0,6007
1,2	0,4	0,4	0,6015	0,2000	0,1985	0,1999
1,2	0,4	0,4	0,6003	0,2013	0,1984	0,1994
P (1993-2000)			E(P)			Ergodic
1,6	0,2	0,2	0,8002	0,0997	0,1001	0,8003
1,6	0,2	0,2	0,8016	0,0994	0,0990	0,0998
1,6	0,2	0,2	0,7990	0,1015	0,0995	0,0999

Source: Author's calculations.

In table A1 the sum in each file of P(·) is equal two notional cities. E(P) is obtained using 5,000 draws of independent Dirichlet functions; and the Ergodic is the limit distribution of the Markov chain. The results show integration to first state. We make similar computations for integration to second and third states.

A.2. Assumptions of segmented labor market.

P (1985-2000)			E(P)			Ergodic
0,8	0,4	0,8	0,3998	0,2010	0,3992	0,4002
0,8	0,4	0,8	0,4012	0,1983	0,4005	0,1997
0,8	0,4	0,8	0,4000	0,1991	0,4009	0,4001
P (1985-1992)			E(P)			Ergodic
0,9	0,2	0,9	0,4501	0,0995	0,4504	0,4495
0,9	0,2	0,9	0,4509	0,0993	0,4498	0,0998
0,9	0,2	0,9	0,4487	0,1002	0,4511	0,4507
P (1993-2000)			E(P)			Ergodic
0,7	0,6	0,7	0,3484	0,3014	0,3502	0,3493
0,7	0,6	0,7	0,3496	0,2996	0,3508	0,3000
0,7	0,6	0,7	0,3498	0,2990	0,3512	0,3507

Source: Author's calculations.

A.3. Assumptions of mixture (Integration – segmentation)

P (1985-1992 – Integration to third state)			E(P)			Ergodic
0,25	0,25	1,5	0,1249	0,1254	0,7497	0,1739
0,6	0,4	1	0,3001	0,1998	0,5001	0,1864
0,3	0,4	1,3	0,1505	0,1991	0,6504	0,6397
P (1993-2000 – Segmentation)			E(P)			Ergodic
0,8	0,4	0,8	0,4012	0,1989	0,3999	0,4014
0,7	0,5	0,8	0,3491	0,2496	0,4013	0,1877
0,85	0,3	0,85	0,4256	0,1484	0,4260	0,4109

Source: Author's calculations

Table A.3 followed the conjectures of the distribution in Table 4. The sum in each file of P(·) is equal to two notional cities. As below, E(P) is obtained using 5,000 draws of independent Dirichlet functions; and the Ergodic is the limit distribution of the Markov chain. The limit distribution shows the assumptions of integrated labor market in the period from 1985 to 1992 and segmentation in the period from 1993 to 2000.

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