Is the Swiss Labor Market Segmented? An Analysis Using Alternative Approaches

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Abstract. In this paper, three common empirical methods encountered in the segmentation literature are used in order to establish whether or not the Swiss labor market is segmented: (i) a hierarchical cluster analysis; (ii) a switching model with unknown regime; and (iii) an analysis of low-wage mobility with a bivariate probit model with endogenous selection. According to method (i), segmentation can hardly be observed. Method (ii) shows that the Swiss labor market is dualistic in nature. Method (iii) reveals that a certain degree of persistence exists in low-wage jobs. Whether or not the Swiss labor market is segmented thus depends on the choice of method, i.e. on the definition and understanding of segments. In any case, none of the methods used in this study point to the existence of a large and well-defined secondary segment.

1. Introduction

The theoretical foundations of labor market segmentation date back several decades and have been a topic of analysis in several different ideological strains (see Leontaridi, 1998). In fact, the analysis of labor market segmentation originated as a criticism of the neoclassical apparatus and has been strongly influenced by institutionalists and Marxists. It was argued that neoclassical theory could not provide adequate explanations for the existence of several labor market flaws, especially wage inequality and discrimination

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(Taubman, Wachter, 1986). Labor market segmentation theory states that segmentation in the labor market is a main cause of these problems. It also postulates that the labor market is not (as is assumed in the neoclassical tradition) a homogeneous entity, but, instead, is composed of two or more independent segments. The underlying mechanisms and structures at work with regard to payment, promotion, job security, etc. differ fundamentally among segments. In its original form, labor market segmentation theory distinguished two segments: a secondary and a primary sector. This is the well-known dual labor market hypothesis. The secondary segment is characterized by low-wage jobs, no returns to human capital, and a high degree of job insecurity. The primary sector, on the other hand, is characterized by high-wage jobs, returns to human capital, large firms, and job security. Furthermore, mobility between the sectors is severely restricted, and jobs in the primary sector are rationed (due to high wages) (e.g. Doeringer, Piore, 1971). Thus, one of the main implications of labor market segmentation theory is that individuals of equal productivity will receive different wages. Although neoclassical theory also acknowledges that different segments exist according to specific socio-demographic characteristics, the main difference is that labor market segmentation theory questions the pure maximizing behavior of firms and individuals whereas neoclassical theory does not (see Sengenberger, 1987a, b; Wachter, 1974; Wagner, 1985). One implication of this is that the price mechanism does not function in all segments of the labor market. There are a number of reasons (according to labor market segmentation theory) why segmentation may occur, the main one being that the primary market substitutes market processes with institutional rules. According to Piore (1975), labor market segmentation arises due to uncertainty in the market. More specifically, the primary sector is organized in such a way as to shelter workers and firms from uncertainty, i.e. from market fluctuations.[1] This is not the case in the secondary segment, where market forces are felt. The main consequences are job rationing in the primary sector, different compensation mechanisms between the sectors, different unemployment and poverty probabilities between the sectors, and general allocative inefficiency.

In recent years an increased interest in research on labor market segmentation has taken place. One of the reasons for this resurgence is that labor market conditions deteriorated in the 1990s (Orr, 1997); poverty, welfare, and unemployment thus re-entered public debate. This is especially the case in Switzerland, where unemployment and poverty, in particular, increased in the 1990s. Labor market segmentation theory postulates that these ills are, to a certain extent, a result of segmented labor markets (for an overview see Leontaridi, 1998; Taubman, Wachter, 1986). Establishing whether or not a labor market is segmented is therefore by no means a trivial undertaking. First, it questions the (albeit simplistic) theoretical notion that only one labor market exists, in which remuneration adheres to the human capital model. Second, revealing the existence of segments with precarious employment conditions is important as this could allow for adequate (and well-directed) policy measures that may 'upgrade' these segments. Thus, knowing whether segmentation exists is essential in possibly understanding and solving many important labor market problems such as recidivist unemployment, poverty, and discrimination.

Despite the obvious benefits of knowing the existence and characteristics of different segments within a country's labor market, identifying segments is problematic. The main problem is that definitions of segments vary substantially and, once segments have been defined, proving that these segments are the results of entry barriers in certain (better) segments is often difficult. It is therefore not surprising that several methodological approaches have been developed in order to define and prove the existence of segmentation (see Leontaridi, 1998).

The aim of this paper is to apply three common empirical methods encountered in the segmentation literature in order to try and determine whether or not the Swiss labor market is segmented. First, a hierarchical cluster analysis is implemented, where jobs (characterized as industry/occupation pairs) are allocated to clusters according to a selection of explanatory variables. The approach used in this paper is similar to that of Anderson *et al*. (1987). Second, the dual labor market hypothesis is tested with the aid of a switching model with unknown regime. The same method was used by Dickens and Lang (1985). Third, low-wage mobility is analyzed using the methodology described in Stewart and Swaffield (1999), i.e. by estimating a bivariate probit model with endogenous selection.

It should be mentioned that very little research exists on labor market segmentation in Switzerland. Lewin (1982) and Meier (1983) made a first attempt at analyzing segmentation in Switzerland. However, their methodological approach and data sets were relatively elementary. Furthermore, both studies are outdated and were conducted at a time when few problems existed in relation to the labor market in Switzerland. In a more recent study, de Coulon (1999) analyzed data from the 1994 Wage Structure Survey and the 1995 Swiss Labor Force Survey in order to investigate the potential segmentation of the foreign workforce in Switzerland. Sousa-Poza (2002) analyzed the relationship between labor market segmentation and the magnitude of the wage differential with data from the 1998 Wage Structure Survey. It is argued that a typical secondary segment is more exposed to competitive market forces and/or less likely to be embedded in large internal labor markets (ILMs), which should facilitate discrimination, and that this will influence the magnitude of the gender wage gap.

Perhaps the main reason for the lack of research on labor market segmentation is that Switzerland has (at least in comparison to other countries) experienced very few problems in the past in relation to the labor market. The situation changed in the last decade, however, with the unemployment rate peaking in 1997 at 5.2 percent, i.e. its highest level since the 1930s. Moreover, Switzerland is an interesting country in which to study labor market segmentation as it has a small and open economy with weak unions and, by Continental European standards, loose employment protection legislation.[2] Thus, it is not very surprising that Switzerland also has very few labor disputes and, in an international setting, very few lost days due to strikes (see IW, 1999, p. 154). One could assume that these are ideal conditions for the development of typical secondary segments, characterized by, among other things, job insecurity and low wages.[3] In particular, the relatively weak unions in Switzerland would make us assume that ILMs are not as abundant or well developed as in other countries.[4]

The paper is structured as follows: Section 2 discusses the methodological issues, and Section 3 the data. Section 4 presents the results and Section 5 concludes.

2. Methodological issues

2.1 A cluster analysis

The most popular methods used to define segments are based on a priori allocations of jobs to segments. These allocations use job characteristics (e.g. Flatau, Lewis, 1993; Theodossiou, 1995), industry or occupational characteristics (e.g. Edwards *et al.*, 1975; Fichtenbaum *et al.*, 1994; Khandker, 1992; Osberg *et al.*, 1987), or subjective measures (e.g. Osterman, 1975). One of the main problems with *ex ante* allocations is that this allocating mechanism is rather arbitrary. One way of overcoming this arbitrary definition of segments is by performing a cluster analysis. Cluster analysis (in the context of this paper) is an approach of assigning jobs (usually on the basis of occupation and industry classifications) into relatively homogeneous groups with respect to a given set of variables. The main advantage of this method is that it can establish into how many clusters the observations fall, without having to force the data into a predetermined number of segments.[5] Such an approach has been used by Anderson *et al*. (1987), Cutcher-Gershenfeld (1991), and Drago (1995).

In this paper, a hierarchical cluster analysis is implemented in order to sort jobs into clusters. These jobs are classified by industry and occupation. In the original sample, 17 industries and 45 occupations were available. This would give rise to a maximum of 765 jobs. Of these 765 industry–occupation categories, only 211 appear in the data set. The following nine variables were used to define the clusters:[6]

- Gender: labor market segregation exists in Switzerland, and typical secondary segment tasks that require low skills are often performed by women (see Sousa-Poza, 2002).
- Unemployment rate: according to labor market segmentation theory, unemployment levels in secondary segments are higher than in primary segments.
- Tenure: job fluctuations are more common in the secondary segment and, thus, tenure should be lower in these segments, on average.
- Education: a standard observation in the segmentation literature is that secondary segments are typically characterized by low levels of education, since investments in human capital are not rewarded.
- Hourly wage: secondary segment jobs have a low level of wages and a flat wage profile, while primary segment jobs have a higher level and a steep profile.
- Foreigners: foreign workers in Switzerland are most likely to be employed in typical secondary segments (see de Coulon, 1999).
- On-the-job training: primary segment jobs are often characterized by more frequent on-the-job training than jobs in the secondary segment (see Drago, 1995).
- Searching for a new job: since, according to the segmentation literature, job fluctuations are more common in the secondary

segment, one could also expect this segment to have a larger portion of workers searching for a new job.
- Absenteeism due to accident or illness: due to the often precarious working conditions in typical secondary segment jobs, one could expect higher absence due to accidents or illnesses.

The industry–occupation pairs and variable definitions are presented in the Appendix.

There are several algorithms available in conventional statistical software packages for choosing clusters. In this study, an average linkage measure between groups was used (see, for example, Jobson, 1992, p. 510). A further aspect to take into account is the decision when to stop agglomerating clusters. In this study, two conventional stopping rules were used: an upper tail rule and a moving average rule (see, for example, Jobson, 1992, p. 546).

2.2 A switching model with unknown regime

One important contribution to the empirical segmentation literature was made by Dickens and Lang (1985). They developed an innovative approach for defining segments by explicitly endogenizing segmental choice between two sectors (i.e. they proposed a test for the dual labor market hypothesis). This method has the advantage (as is also the case in the cluster analysis) that segments are treated as unknown a priori. Dickens and Lang (1985) argue that the usual a priori classifications misclassify many workers since even within the same firm (industry or occupation) one encounters both primary and secondary segment type workers. Consequently, sample separation is a priori unknown. A similar approach to that taken in Dickens and Lang (1985) has also been used by Basch and Paredes-Molina (1996), de Coulon (1999), Pailhé (2003), and Rebitzer and Robinson (1991). This model — a switching model with unknown regime — is based on the following three-equation regression model:

$$W_i = X_i'\beta_p + u_{ip}$$
$$W_i = X_i'\beta_s + u_{is}$$
$$Y_i^* = Z_i'\beta_a + u_{ia},$$

where W_i is the individual's wage, X_i and Z_i are vectors of characteristics associated with the ith individual, β_p, β_s and β_a are vectors of parameters, and u_{ip}, u_{is} and u_{ia} are normally distributed error terms. Y_i^* is a latent variable measuring the tendency for the ith individual to be in the primary segment, and the subscripts p and s indicate primary and secondary segments. The first equation depicts the wage function for primary segment workers, the second depicts the wage function for secondary segment workers, and the third equation is the switching equation. Note that Y_i^* cannot be observed, but if it is positive then the individual is in the primary segment (otherwise in the secondary segment). Thus, the individual works in the primary segment if and only if

$$u_{ia} > -Z_i'\beta_a.$$

The variables included in X are the usual human-capital variables: EDU (number of years of schooling), EXPR (number of years of job experience), and EXPR2 (experience squared). W is the natural logarithm of the hourly wage rate. The variables in Z include the variables in the wage equations and also MARRIED (dummy variable equal to one if the respondent is married) and FOREIGN (dummy variable equal to one if the respondent is a foreigner). In accordance with the segmentation theory, one would expect the probability of being in the primary segment to increase with a higher level of education, more work experience, being married,[7] and Swiss nationality.

The likelihood function for this model is the following:

$$\prod_{i=1}^{n}(\Pr[u_{ia} > Z_i'\beta_a|Z_i, X_i, u_{ip}]f(u_{ip}) + \Pr[u_{ia} \leq -Z_i'\beta_a|Z_i, X_i, u_{ip}]f(u_{is})).$$

If it is assumed that the error terms are normally distributed, then the log-likelihood function for this model is given by:

$$\prod_{i=1}^{n}\left(\left[1-F\left[\frac{\left(-Z_i'\beta_a-\dfrac{s_{pa}u_{ip}}{s_{pp}}\right)}{\left(1-\dfrac{s_{pa}^2}{s_{pp}}\right)^{\frac{1}{2}}}\right]f(u_{ip})\right]+F\left[\frac{\left(1-Z_i'\beta_a-\dfrac{s_{sa}u_{is}}{s_{ss}}\right)}{\left(1-\dfrac{s_{sa}^2}{s_{ss}}\right)^{\frac{1}{2}}}\right]f(u_{is})\right),$$

where $f(.)$ and $F(.)$ are the normal density and cumulative distributions; s_{pa} and s_{sa} are covariances between u_p and u_a and between u_s and u_a, respectively. s_{pp} and s_{ss} are variances, and s_{aa} is normalized to one. Four basic optimization algorithms were relied upon: (i)

Davidon–Fletcher–Powell (DFP); (ii) steepest ascent; (iii) Newton's; and (iv) Berndt–Hall–Hall-Hausman (BHHH).[8] Of these, the most suitable ones in the context of this study were the DFP and BHHH algorithms, the latter being the most expedient.

In order to test whether or not a two-equation model fits the data better than a single-equation model, a log-likelihood test as used by Dickens and Lang (1985) is applied here. Note that the single-equation model is nested in the switching model if the latter is constrained to yield a single-equation model. This leaves several parameters unidentified. Monte Carlo results suggest, however, that one can use a log-likelihood test to determine whether a two-equation model fits the data better than a single model by setting the degrees of freedom equal to the number of constraints plus the number of unidentified parameters (Goldfeld, Quandt, 1975). In this way, twice the difference between the log-likelihood values for the two models yields a conservative test using a chi-squared distribution.

Although this model is elegant and does not rely on a priori definitions of segments, it tests only the dual labor market hypothesis, i.e. only two segments can be distinguished. The other two methods described above do not have this limitation. In the Germanic world, in particular, the existence of more than two segments is often assumed (see Biehler, Brandes, 1981; Lutz, 1987; Sengenberger, 1987a, b).[9]

2.3 Low-wage mobility

Another way of analyzing labor market segmentation is by taking a look at wage mobility (Leontaridi, 1998). According to labor market segmentation theory, jobs in the (high-wage) primary segment are rationed and thus one should, in the presence of labor market segmentation, observe persistence in low-wage jobs. One way of analyzing this topic is with a bivariate probit model with endogenous selection as developed by Meng and Schmidt (1985) and used in the context of a low-wage mobility study by Stewart and Swaffield (1999), Cappellari (2000), and de Coulon and Zürcher (2001). More specifically, assume that individual earnings in year $t-1$ are generated by the process:[10]

$$g_1(y^*_{it-1}) = x'_{it-1}\beta^* + \varepsilon_{i1},$$

where y^*_{it-1} is hourly earnings at the survey point in year $t-1$, x_{it-1} is a vector of earnings-determining characteristics and g_1 is a suitable monotonic transformation such that ε_{i1} is distributed $N(0, 1)$. Assuming the low-pay threshold to be equal to λ_{t-1}, and defining an indicator variable $y_{it-1} = 1$ if the ith individual is low paid and $y_{it-1} = 0$ otherwise, then

$$P[y_{it-1} = 1] = P[y^*_{it-1} < \lambda_{t-1}] = \Phi\{g_1(\lambda_{t-1}) - x'_{it-1}\beta^*\},$$

where Φ is the standard normal cumulative distribution function. If one is not interested in the intercept in β^* then the model can be estimated as

$$P[y_{it-1} = 1] = \Phi\{x'_{it-1}\beta^*\}.$$

Assume that an individual's earnings in t depend on the individual's state in $t - 1$. More specifically, suppose that an individual's earnings in t depend on whether or not the individual was low paid in year $t - 1$. Assume that if $y_{it-1} = 1$, then the process determining an individual's wage is equal to

$$g_2(y^*_{it}) = z'_{it}\gamma^* + \varepsilon_{i2},$$

where z_{it} is a vector of characteristics that determine the wage change. The distribution of $(\varepsilon_{i1}, \varepsilon_{i2})$ is assumed to be bivariate standard normal with correlation ρ. The conditional probability of being low paid in year t, given being low paid in year $t - 1$, is given by

$$P[y_{it} = 1 | y_{it-1} = 1] = \frac{\Phi_2\{x'_{it-1}\beta, z'_{it}\gamma; \rho\}}{\Phi\{x'_{it-1}\beta\}}.$$

Clearly, if $\rho = 0$, i.e. the initial condition is assumed to be exogenous, then the problem boils down to a simple probit model defined on a sample of individuals for which $y_{it-1} = 1$. If the initial condition is assumed to be endogenous, then the problem can be modeled by a bivariate probit model with endogenous selection, as described in Meng and Schmidt (1985).[11] The log-likelihood contribution for individual i is given by

$$\begin{aligned}\ln L_i = {} & y_{it-1}y_{it}\ln\Phi_2(x'_{it-1}\beta, z'_{it}\gamma; \rho) + y_{it-1}(1 - y_{it})\ln\Phi_2(x'_{it-1}\beta, -z'_{it}\gamma; -\rho) \\ & + (1 - y_{it-1})\ln\Phi_2(-x'_{it-1}\beta).\end{aligned}$$

An important point to note in this model is that, in order to guarantee identification, some variables included in x_{it-1} must be excluded in z_{it}. The instruments should influence the initial state but not the subsequent change of state. The obvious choice for such instrumentals are parental background information (e.g. Cappellari, 2000; Stewart, Swaffield, 1999). In this paper, the following information on the respondent's childhood is used, and where 'childhood' refers to the individual's situation at the age of 15: one-parent household, father non-employed, father unskilled laborer, mother employed, mother's education low. Other variables included in x_{it-1} (and z_{it}) are: male, age, educational level, children in household, foreigner status, unskilled laborer. As in de Coulon and Zürcher (2001), two measures for the low-pay threshold are used: two-thirds and half of the median hourly wage.

3. Data

Data from the Swiss Labor Force Survey (SLFS) for the year 2000 are used for the cluster analysis and for the switching model with unknown regime. The SLFS is a nation-wide and representative survey conducted annually by the Swiss Federal Statistical Office. With telephone interviews lasting approximately 20 minutes, individuals are questioned on a number of topics related to the labor market. The first SLFS survey was conducted in 1991, and the sample size was approximately 16,000 individuals (see Bundesamt für Statistik, 1996). We restrict our analysis to salaried employees between the ages of 18 and 62.

The wage data of the SLFS have been used in numerous studies. Despite their widespread acceptance, a word of caution is warranted: the SLFS wage data are (due to the survey methodology) characterized by relatively large non-response rates and a 'heaping' on certain rounded values. Although in Sousa-Poza and Henneberger (2000) it is shown that there does not appear to be a systematic bias in the reporting of wage data (i.e. the item non-responses do not bias the estimated coefficients of the wage equations), the unit non-responses and the concentration on certain rounded values remain a potential problematic aspect of this data set. Nevertheless, for the analysis conducted in this paper no other adequate data set exists in Switzerland. Furthermore, this is not a unique problem of the SLFS, but one associated with most labor force surveys.

The analysis of wage mobility is undertaken with data from the first three waves of the Swiss Household Panel (SHP). The first wave was conducted in 1999. The SHP is a longitudinal panel survey and data are gathered annually. For the first wave, a representative sample of 5,074 households from the Swiss population was recruited and interviewed in the autumn of 1999. Our analysis is restricted to individuals aged 18–65. The sample size for the panel of individuals who reported all relevant variables for the analysis of wage mobility (especially wages) is equal to 2,030 individuals. The main advantage of the SHP compared to the SLFS is that it collects data on family-related issues such as the level of education and employment status of the respondents' parents. These are important variables which are usually needed as instruments in order to estimate the initial state.

4. Results

4.1 Cluster analysis

In this section, the results of the hierarchical cluster analysis described in Section 2.1 are presented. Corresponding to the results in Anderson *et al*. (1987), as clustering proceeded, a large cluster formed and then expanded by absorbing the other occupation–industry pairs. No clear evidence of a dual or multiple-segmented labor market exists. As was discussed above, an upper tail rule and a moving average rule were used in order to decide when to stop agglomeration in the hierarchical cluster analysis. The upper tail rule gave rise to seven clusters and the moving average rule gave rise to six clusters. The number of industry–occupation pairs in each cluster is depicted in Table 1. A more detailed description of the clusters and the industry–occupation pairs can be found in the Appendix.

In Table 2, the average characteristics of the different clusters (determined by the moving average rule) are depicted. As was mentioned above, the overwhelming majority of occupation–industry pairs were allocated to one segment. This segment therefore reflects the average labor market characteristics in Switzerland. It is interesting to note that cluster 2 does correspond to a typical secondary segment: high female participation rate, high levels of unemployment, low education, low wage rate, and a large proportion of foreign workers. However, this cluster represents only a very small fraction of the labor force. The male (albeit, very small) cluster 3 also has some typical characteristics of a secondary segment:

Table 1. Observed clusters according to two stopping rules

Cluster number[a]	Number of industry–occupation pairs	Cluster number[b]	Number of industry–occupation pairs
1	196	1	196
2	5	2	5
3	1	3	1
4	4	4	4
5	1	5	1
6	1	6	4
7	3		

Notes: [a] Stopping rule according to the upper tail rule.
[b] Stopping rule according to the moving average rule.

relatively low wages, low average tenure, low education, and a large proportion of foreign workers.[12]

Thus, the evidence obtained with this method is that the Swiss labor market is not partitioned into more than one large segment. Note that different subsets of the dependent variables and different algorithms for choosing the clusters were also applied. In no case could a clear segmentation into two or more (numerically) meaningful clusters be observed. This conclusion is in accordance with the observation made by Anderson *et al.* (1987).

4.2 A switching model with unknown regime

The results of the switching model with unknown regime for the male sample are depicted in Table 3. The results correspond in part to those of de Coulon (1999), who estimated a similar model with data from the 1995 SLFS. The results in Table 3 show that Swiss (as opposed to foreign) males are more likely to be in the primary segment. The other coefficients in the switching equation are not significant — despite having the expected sign — at conventional levels. The log-likelihood test reveals that the two-equation model clearly fits the data better than the single-equation model (99 percent critical value of a chi-squared distribution with 13 degrees of freedom is equal to 4.107). The coefficients of the wage equations for the two segments correspond to those of similar studies. More specifically, the intercepts are larger in the secondary sector than in the primary sector,[13] and returns to schooling and

Table 2. Average characteristics of clusters

Cluster number	Male	Unemployment	Tenure	Schooling	Hourly wage	Foreigners	Training	Seeking employment	Absence due to illness, injury	Observations in underlying sample
1	0.55	0.01	8.89	11.26	37.05	0.12	0.11	0.06	0.02	12,515
2	0.27	0.12	10.20	9.50	26.39	0.26	0.07	0.05	0.00	77
3	1.00	0.00	5.63	9.82	25.62	0.47	0.18	0.06	0.00	17
4	0.81	0.03	12.84	10.25	40.01	0.08	0.08	0.02	0.09	68
5	0.80	0.10	9.48	13.25	144.85	0.20	0.20	0.20	0.00	10
6	0.44	0.03	8.08	15.15	51.97	0.14	0.10	0.24	0.01	63

Note: Results based on a moving average stopping rule.

Table 3. Switching regression model — males

	OLS	Primary	Secondary	Selection
Constant	2.578***	2.473***	2.678***	0.449**
	(0.029)	(0.207)	(0.282)	(0.205)
Schooling (years)	0.060***	0.078***	0.044***	0.002
	(0.002)	(0.012)	(0.020)	(0.015)
Experience	0.024***	0.032***	0.016	0.015
	(0.002)	(0.010)	(0.017)	(0.013)
Exp.^{2} × 10^{-2}	–0.034***	–0.059**	–0.013	–0.034
	(0.004)	(0.023)	(0.039)	(0.028)
Foreigner				–0.052***
				(0.047)
Married				0.014
				(0.012)
Covariance with switching error		0.565***	0.452***	
		(0.095)	(0.097)	
Standard error	0.359***	0.320***	0.205**	[a]
		(0.108)	(0.088)	
N	4,089	4,089		
Log-likelihood	–2,159	–1,704		
Adj. R^2	0.235			

Notes: ***, ** and *: significant at the 1 percent, 5 percent and 10 percent levels, respectively. Standard errors in parentheses.
[a] Normalized to 1.

experience are higher in the primary segment than in the secondary segment. Similar results and the same argumentation as in the male sample can also be observed in the female sample (see Table 4). In both the male and the female samples, the log-likelihood statistic clearly indicates that the two-equation model fits the data better than the single-equation model. Although such a result would suggest a dualistic labor market, it can be seen that the estimated wage functions for the secondary segment do not resemble typical secondary-segment remuneration practices since returns to schooling (although being smaller in the primary segment) are by no means insignificant.

4.3 Low-wage mobility

The cross-tabulation for low-wage mobility between the years 1999 and 2001 is shown in Tables 5 and 6. Table 5 uses the '50 percent of the median hourly wage' criterion as the low-pay thresh-

Table 4. Switching regression model — females

	OLS	**Primary**	**Secondary**	**Selection**
Constant	2.562***	2.366***	2.800***	0.340
	(0.033)	(0.233)	(0.173)	(0.296)
Schooling (years)	0.055***	0.055***	0.050***	–0.011
	(0.003)	(0.019)	(0.013)	(0.024)
Experience	0.019***	0.026**	0.013	0.022
	(0.002)	(0.013)	(0.011)	(0.018)
Exp.^{2} × 10^{-2}	–0.031***	–0.058	–0.010	–0.034
	(0.006)	(0.037)	(0.032)	(0.052)
Foreigner				–0.041***
				(0.060)
Married				0.007
				(0.032)
Covariance with switching error		0.722***	0.814***	
		(0.119)	(0.001)	
Standard error	0.419***	0.530***	0.663**	[a]
		(0.171)	(0.001)	
N	3,908	3,908		
Log-likelihood	–2,148	–1,684		
Adj. R^2	0.125			

Notes: ***, ** and *: significant at the 1 percent, 5 percent and 10 percent levels, respectively. Standard errors in parentheses.
[a] Normalized to 1.

Table 5. Cross-tabulations of low wages in 1999 and 2001 — 50 per cent of median hourly wages

	High wage 2001	**Low wage 2001**
High wage 1999	Observed: 1,802 (97.2%)	Observed: 52 (2.8%)
	Expected: 1,742 (95.0%)	Expected: 112 (5.0%)
Low wage 1999	Observed: 105 (59.7%)	Observed: 71 (40.3%)
	Expected: 165 (93.8)	Expected: 11 (6.2%)

Note: Pearson χ^2 = 398.

old. Nearly 60 percent of all individuals who had low-paid jobs in 1999 managed to change their status between 1999 and 2001. If the '67 percent of the median hourly wage' criterion is used (see Table 6) to define low-paid jobs, then about 44 percent manage to exit low payment. These results show that a fair share of mobility out of low-paid jobs exists, and that upward mobility is much more likely

Table 6. Cross-tabulations of low wages in 1999 and 2001 — 67 per cent of median hourly wages

	High wage 2001	**Low wage 2001**
High wage 1999	Observed: 1,588 (94.2%) Expected: 1,444 (85.6%)	Observed: 98 (5.8%) Expected: 242 (14.4%)
Low wage 1999	Observed: 151 (43.9%) Expected: 295 (85.7%)	Observed: 193 (56.1%) Expected: 49 (14.3%)

Note: Pearson $\chi^2 = 588$.

than downward mobility. Nevertheless, the chi-squared statistic clearly shows that state dependency exists, with more workers staying in low-paid employment than statistically expected.

Table 7 depicts the results of the bivariate probit model with endogenous selection. In addition, the table shows the results of the standard probit model estimated on the sample of individuals who were in low employment in 1999. The dependent variable in this case is equal to one if the respondent also had a low-paid job in 2001; otherwise it is equal to zero. A first point to note is that most estimated coefficients are not significant at conventional levels. This can arise if the exit from low-paid employment is largely idiosyncratic. It must be stressed, however, that the sample size is relatively small, which could also be influencing the significance levels.[14]

If half of the median hourly wage is taken as the low-pay threshold, then the null hypothesis that $\rho = 0$ cannot be rejected, in which case no sample-selection bias arises, i.e. the standard probit model can be estimated. If two-thirds of the median hourly wage is taken, then the null hypothesis is rejected, although only at the 10 percent level. The negative coefficient of ρ is analogous to the negative correlation found between the change in earnings between $t - 1$ and t and the level of earnings at $t - 1$ (Stewart, Swaffield, 1999). As is relatively standard in these models, a low education hinders an exit out of low-paid employment. The negative coefficients of the firm-size and public-employment variables are also often encountered in other studies. In general, the differences between the exogenous and endogenous specifications are not very dramatic. The results also highlight the fact that wage mobility does not (with the exception of public-sector employees) depend on industry.

De Coulon and Zürcher (2001) analyzed low-wage mobility in Switzerland with pooled data from the SLFS (1992–98) and using

Table 7. Determinants of low-wage mobility: $P[\text{low-wage}_{t+1} \mid \text{low-wage}_t]$

	1/2 Median		2/3 Median	
	Exogenous	**Endogenous**	**Exogenous**	**Endogenous**
Constant	–0.094	–0.315	0.660**	0.652**
	(0.359)	(0.215)	(0.275)	(0.270)
Male	–0.024	–0.063	–0.142	–0.037
	(0.243)	(0.265)	(0.177)	(0.187)
Age	–0.006	–0.017	–0.014**	–0.002
	(0.009)	(0.013)	(0.006)	(0.010)
Low education	1.115**	1.315***	0.803**	0.547*
	(0.456)	(0.454)	(0.313)	(0.323)
Child in household	–0.065	–0.111	–0.111	–0.269
	(0.224)	(0.241)	(0.180)	(0.189)
Foreigner	0.150	0.099	–0.102	–0.745
	(0.300)	(0.290)	(0.225)	(0.213)
Unskilled laborer	–0.426	–0.458	0.252	0.258
	(0.490)	(0.454)	(0.357)	(0.337)
Part time	0.046	0.110	0.238	0.170
	(0.270)	(0.278)	(0.190)	(0.191)
Firm fewer than 20 employees	0.154	0.163	0.189	0.171
	(0.221)	(0.226)	(0.165)	(0.163)
Firm more than 100 employees	–0.736**	–0.788*	–0.637***	–0.529**
	(0.353)	(0.451)	(0.202)	(0.213)
Manufacturing	–0.351	–0.376	–0.157	–0.122
	(0.328)	(0.356)	(0.237)	(0.232)
Construction	0.064	0.034	–0.260	–0.200
	(0.567)	(0.692)	(0.465)	(0.541)
Hotels, restaurants, catering	–0.124	–0.134	0.686	0.570
	(0.493)	(0.457)	(0.430)	(0.461)
Real estate, IT	–0.367	–0.326	–0.416*	–0.386
	(0.344)	(0.366)	(0.246)	(0.236)
Public administration	–0.189	–0.279	–0.628***	–0.527**
	(0.340)	(0.370)	(0.226)	(0.244)
ρ		0.327		–0.380*
		(0.310)		(0.212)
Log-likelihood	–107	–561	–205	–920
N	176	2,030	344	2,030

Notes: ***, ** and *: significant at the 1 per cent, 5 per cent and 10 per cent levels, respectively. Standard errors in parentheses.

the same methodological approach as in this paper. Their study had the advantage that, due to the pooling of the SLFS, the sample size was substantially larger. This most probably explains their generally more significant results. However, due to the lack of parental background information, they used nationality, complementary income, and presence of children in the household as instruments. Although their instruments appear to be valid, it seems difficult to accept that at least nationality and children do not influence *changes* in *gross* hourly wages.[15] The advantage of the SHP is that it does provide information on parental background. Despite these differences, the results are not all that different. They also show that, depending on the threshold used, between 56 and 64 percent of low-paid workers manage to exit low-paid employment within a 3 year timespan, which corresponds well to the results obtained in this study.

These results on low-wage mobility are, on the one hand, difficult to reconcile with the existence of a secondary labor market segment, in which certain unskilled laborers in certain groups of the population — such as foreigners and women — are barred from entering the primary segment. On the other hand, the estimated coefficient for the firm-size, public-sector employee, and education variables are compatible with labor market segmentation theories. In general, however, the reasons for wage mobility appear to be very idiosyncratic, which is in itself compatible with segmentation theory. Ultimately, the question of whether or not entry barriers exit remains unanswered.

5. Summary and concluding comments

The aim of this paper was to determine whether or not the Swiss labor market is segmented. In other words, do distinct labor markets exist, which exhibit different characteristics, such as length of tenure, socio-demographic composition and the like? Furthermore, does the human-capital model apply equally well to all segments? And, is wage mobility restricted in any way? Three common methodological approaches encountered in the segmentation literature were used in order to try to answer these questions: (i) a hierarchical cluster analysis; (ii) a switching model with unknown regime; and (iii) an analysis of low-wage mobility. The somewhat unsatisfactory (although by no means surprising) answer to the question posed in the title of this paper is that it depends very much on the method being used, i.e. on the understanding and definition of segmentation.

The results of the cluster analysis show quite clearly that segmentation did not occur. Although the cluster analysis gave rise to (at the most) seven clusters, well over 98 percent of all Swiss salaried employees fell into the same cluster. In only one of these clusters could something resembling a secondary segment be identified. This segment, however, covers only a small fraction of the Swiss labor force. The switching model with unobserved regime revealed that a dual labor market specification fits the data considerably better than a single-equation model. This conclusion applies to both the male and female samples. Although such a result would suggest a dualistic labor market, it was also shown that the estimated wage functions for the secondary segment did not resemble typical secondary-segment remuneration practices, since returns to schooling (although being substantially smaller in the primary segment) were by no means insignificant. An analysis of low-wage mobility showed that, over a 3 year period, a fair share of persistency in low-wage jobs exists. Nevertheless, upward mobility is much more likely than downward mobility. Although some variables such as educational level and firm size can account for part of the inclination to remain in low-paid employment, it is fair to state that a large degree of idiosyncrasy remains. Whether or not entry barriers are the reason for persistence in low-wage employment remains open.

Although the answer to the question posed in the title of this paper is partially driven by the choice of method, this paper does show that, with the common methods implemented here, the existence of a relatively large and well-defined typical secondary segment in the *male* sample does not appear to exist. Although the analysis conducted in this paper cannot definitely conclude that a secondary segment does not exist in the Swiss male labor market, the methods used here find little evidence for a *pronounced typical* secondary segment. This finding in no way contradicts a casual observer's sense of reality. It is interesting to note, however, that in the *female* sample the evidence is not as clear cut. The hierarchical cluster analysis does identify one (albeit small) women-dominated cluster, which strongly resembles a typical secondary segment. Considering the fact that women are more likely than men to perform low-skill-requirement tasks, it should also be more likely to encounter women in a typical secondary segment.

Appendix

The industry–occupation pairs used in the hierarchical cluster analysis are depicted in Table A1.

Table A1. Industry–occupation pairs used in the cluster analysis

CLU6	INDUST	OCCUP	MALE	UNEMPL	TEN_Y	EDU_Y	HWAGE	FOREIG	TRAIN	LOOK	LESSW	*N*	CLU7
1	1.00	1.00	0.62	0.00	19.63	9.50	23.68	0.01	0.05	0.02	0.04	331	1
1	1.00	2.00	0.69	0.00	12.44	10.06	25.53	0.05	0.07	0.06	0.01	122	1
1	4.00	3.00	0.74	0.00	10.19	10.18	27.66	0.21	0.10	0.08	0.03	62	1
1	4.00	4.00	0.38	0.00	15.17	9.07	25.68	0.31	0.01	0.00	0.03	68	1
1	4.00	5.00	0.94	0.11	6.99	9.44	30.18	0.28	0.06	0.00	0.00	18	1
1	4.00	6.00	0.88	0.00	10.10	9.88	26.76	0.24	0.08	0.05	0.03	59	1
1	4.00	7.00	0.64	0.00	9.25	9.71	30.83	0.21	0.00	0.00	0.00	14	1
1	4.00	8.00	0.76	0.03	9.40	9.63	25.50	0.30	0.06	0.06	0.01	269	1
1	4.00	9.00	0.88	0.03	12.27	10.01	30.41	0.17	0.10	0.06	0.01	184	1
1	4.00	10.00	0.94	0.02	10.05	9.99	24.83	0.18	0.07	0.06	0.02	101	1
1	4.00	11.00	0.68	0.01	12.04	10.38	30.34	0.10	0.09	0.06	0.01	68	1
1	4.00	12.00	0.66	0.00	12.82	10.14	35.05	0.17	0.08	0.05	0.02	93	1
1	4.00	13.00	0.97	0.00	7.86	15.17	47.66	0.17	0.13	0.04	0.01	98	1
1	4.00	14.00	0.89	0.01	10.98	10.90	33.16	0.17	0.14	0.07	0.01	178	1
1	4.00	15.00	0.52	0.04	7.52	10.77	40.95	0.04	0.09	0.09	0.04	56	1
1	4.00	16.00	0.72	0.01	9.61	11.06	39.12	0.17	0.11	0.08	0.00	90	1
1	4.00	18.00	0.52	0.04	5.16	13.48	41.06	0.04	0.13	0.04	0.00	23	1
1	4.00	19.00	0.85	0.00	15.99	13.02	57.81	0.08	0.08	0.10	0.00	71	1
1	4.00	20.00	0.81	0.02	9.95	12.30	47.26	0.07	0.16	0.05	0.02	58	1
1	4.00	21.00	0.14	0.01	9.79	10.32	28.32	0.11	0.10	0.07	0.03	231	1
1	4.00	23.00	0.55	0.00	10.11	11.31	56.40	0.07	0.15	0.05	0.04	74	1
1	4.00	24.00	0.70	0.03	6.28	11.52	38.24	0.17	0.20	0.03	0.00	30	1
1	4.00	25.00	0.74	0.01	10.87	9.67	26.16	0.21	0.03	0.09	0.06	68	1

1	4.00	27.00	0.90	0.00	15.06	12.40	66.96	0.10	0.10	0.00	0.00	10	1
1	4.00	28.00	0.61	0.00	8.12	13.88	37.03	0.16	0.11	0.08	0.00	38	1
1	4.00	29.00	0.65	0.00	11.27	10.64	32.63	0.09	0.09	0.04	0.02	46	1
1	4.00	31.00	0.20	0.00	9.47	9.40	68.19	0.10	0.20	0.10	0.00	10	1
1	4.00	36.00	0.65	0.00	12.67	10.00	34.02	0.06	0.06	0.00	0.06	17	1
1	4.00	43.00	0.96	0.00	12.95	15.67	48.87	0.22	0.09	0.04	0.00	23	1
1	4.00	44.00	0.63	0.03	9.87	9.66	25.20	0.18	0.04	0.09	0.01	80	1
1	5.00	6.00	1.00	0.00	11.16	10.50	26.80	0.07	0.00	0.00	0.00	15	1
1	5.00	8.00	0.92	0.00	10.33	10.08	30.60	0.00	0.00	0.17	0.00	12	1
1	5.00	14.00	0.85	0.00	15.04	11.00	39.12	0.00	0.20	0.15	0.00	20	1
1	5.00	21.00	0.20	0.00	11.73	9.90	41.90	0.10	0.10	0.10	0.00	10	1
1	6.00	5.00	1.00	0.00	10.00	9.89	31.58	0.27	0.04	0.05	0.00	163	1
1	6.00	6.00	0.98	0.02	10.01	9.97	25.87	0.23	0.03	0.06	0.04	297	1
1	6.00	8.00	0.96	0.00	10.81	9.50	28.14	0.28	0.04	0.00	0.00	25	1
1	6.00	10.00	1.00	0.00	9.64	10.58	33.71	0.17	0.04	0.00	0.00	24	1
1	6.00	13.00	1.00	0.04	11.02	15.37	43.30	0.04	0.19	0.04	0.04	27	1
1	6.00	14.00	0.94	0.00	10.82	9.95	30.75	0.21	0.06	0.03	0.01	71	1
1	6.00	19.00	0.82	0.00	14.17	11.52	43.99	0.05	0.09	0.05	0.00	22	1
1	6.00	21.00	0.16	0.00	8.63	10.54	32.75	0.06	0.07	0.04	0.02	96	1
1	6.00	23.00	0.40	0.00	10.29	11.25	40.52	0.00	0.10	0.10	0.00	10	1
1	6.00	25.00	0.95	0.00	12.26	10.00	29.58	0.21	0.00	0.16	0.00	19	1
1	7.00	2.00	0.38	0.09	8.33	10.38	21.65	0.12	0.12	0.09	0.03	34	1
1	7.00	3.00	0.68	0.00	8.82	9.84	27.53	0.13	0.08	0.04	0.03	72	1
1	7.00	4.00	0.29	0.00	8.99	9.46	19.76	0.25	0.04	0.04	0.04	28	1
1	7.00	5.00	1.00	0.00	7.65	10.45	29.01	0.27	0.09	0.18	0.00	11	1
1	7.00	6.00	1.00	0.00	8.07	10.43	29.49	0.30	0.10	0.07	0.03	30	1
1	7.00	8.00	0.93	0.01	11.44	10.02	26.38	0.19	0.09	0.03	0.01	150	1
1	7.00	9.00	0.89	0.11	13.13	10.46	31.47	0.25	0.14	0.00	0.04	28	1
1	7.00	10.00	0.82	0.00	9.20	11.77	16.15	0.27	0.00	0.00	0.00	11	1
1	7.00	13.00	0.90	0.00	5.31	14.26	45.20	0.10	0.10	0.00	0.00	21	1
1	7.00	14.00	0.92	0.03	9.06	11.07	37.50	0.14	0.17	0.06	0.00	36	1
1	7.00	15.00	0.21	0.02	7.01	9.90	23.17	0.12	0.06	0.06	0.01	557	1
1	7.00	16.00	0.46	0.01	10.22	10.64	30.19	0.11	0.10	0.07	0.01	283	1
1	7.00	18.00	0.47	0.00	7.49	11.23	35.06	0.09	0.13	0.06	0.00	32	1

Table A1. Continued

CLU6	INDUST	OCCUP	MALE	UNEMPL	TEN_Y	EDU_Y	HWAGE	FOREIG	TRAIN	LOOK	LESSW	*N*	CLU7
1	7.00	19.00	0.64	0.02	11.73	11.70	51.50	0.14	0.12	0.03	0.05	66	1
1	7.00	20.00	0.56	0.05	7.43	11.61	35.56	0.09	0.17	0.05	0.01	75	1
1	7.00	21.00	0.17	0.03	8.32	10.66	32.42	0.07	0.10	0.07	0.01	229	1
1	7.00	23.00	0.44	0.02	9.32	11.02	41.10	0.08	0.14	0.06	0.04	50	1
1	7.00	24.00	0.97	0.03	4.49	12.43	37.60	0.03	0.24	0.13	0.00	38	1
1	7.00	25.00	0.72	0.06	11.19	9.73	23.98	0.13	0.06	0.08	0.00	53	1
1	7.00	26.00	0.13	0.06	8.21	10.66	22.68	0.13	0.06	0.06	0.00	16	1
1	7.00	29.00	0.38	0.00	9.84	10.72	23.57	0.07	0.17	0.14	0.07	29	1
1	7.00	30.00	0.00	0.00	6.22	8.68	20.72	0.18	0.18	0.18	0.00	11	1
1	7.00	31.00	0.56	0.06	8.64	9.92	25.84	0.33	0.06	0.06	0.00	18	1
1	7.00	33.00	0.26	0.00	4.01	8.53	22.48	0.26	0.00	0.11	0.00	19	1
1	7.00	35.00	0.14	0.00	10.31	12.34	26.46	0.05	0.14	0.03	0.03	58	1
1	7.00	36.00	0.62	0.00	10.17	11.00	33.91	0.00	0.15	0.00	0.00	13	1
1	7.00	41.00	0.36	0.09	7.62	11.68	43.87	0.18	0.27	0.09	0.00	11	1
1	7.00	44.00	0.77	0.02	6.24	9.57	25.07	0.35	0.03	0.14	0.00	66	1
1	8.00	15.00	0.00	0.00	5.71	10.10	20.57	0.13	0.07	0.07	0.00	15	1
1	8.00	16.00	0.25	0.00	7.65	9.75	22.33	0.17	0.17	0.08	0.08	12	1
1	8.00	21.00	0.27	0.09	4.60	11.59	85.27	0.09	0.09	0.00	0.00	11	1
1	8.00	30.00	0.16	0.06	5.11	9.24	19.90	0.23	0.03	0.07	0.01	166	1
1	8.00	31.00	0.47	0.04	6.86	9.92	23.59	0.18	0.03	0.13	0.01	161	1
1	8.00	33.00	0.10	0.00	7.20	7.10	33.90	0.10	0.10	0.00	0.10	10	1
1	9.00	8.00	0.97	0.03	9.81	10.78	31.36	0.10	0.17	0.03	0.03	30	1
1	9.00	9.00	1.00	0.00	10.21	10.47	33.32	0.17	0.06	0.06	0.00	18	1
1	9.00	13.00	1.00	0.00	9.06	15.13	48.15	0.16	0.05	0.00	0.00	19	1
1	9.00	15.00	0.64	0.09	4.98	10.77	36.57	0.00	0.55	0.09	0.00	11	1
1	9.00	16.00	0.43	0.00	7.50	11.64	31.10	0.21	0.00	0.21	0.00	14	1
1	9.00	18.00	0.24	0.03	6.52	11.29	29.68	0.24	0.14	0.07	0.00	29	1
1	9.00	19.00	0.90	0.00	9.62	12.24	38.90	0.10	0.10	0.05	0.00	21	1
1	9.00	20.00	0.55	0.05	7.32	11.50	40.50	0.10	0.00	0.05	0.00	20	1
1	9.00	21.00	0.17	0.04	8.77	10.28	25.59	0.07	0.12	0.07	0.01	69	1

1	9.00	23.00	0.67	0.00	7.98	10.94	38.55	0.11	0.11	0.00	0.00	27	1
1	9.00	24.00	0.85	0.00	7.94	12.23	42.78	0.08	0.08	0.15	0.08	13	1
1	9.00	25.00	0.81	0.01	12.35	10.33	34.72	0.08	0.08	0.07	0.03	265	1
1	9.00	26.00	0.45	0.00	12.73	10.25	32.23	0.06	0.08	0.03	0.03	187	1
1	9.00	33.00	0.19	0.00	16.36	8.44	26.41	0.38	0.00	0.13	0.00	16	1
1	9.00	44.00	0.82	0.06	10.58	10.94	29.57	0.12	0.00	0.00	0.00	17	1
1	10.00	13.00	0.92	0.00	7.37	14.71	51.58	0.25	0.08	0.17	0.00	12	1
1	10.00	16.00	0.48	0.04	8.80	11.43	41.71	0.04	0.22	0.04	0.00	23	1
1	10.00	17.00	0.51	0.02	9.07	11.15	38.70	0.08	0.10	0.03	0.00	244	1
1	10.00	18.00	0.75	0.01	7.91	12.06	50.21	0.09	0.20	0.06	0.03	129	1
1	10.00	19.00	0.95	0.00	10.55	14.65	83.65	0.10	0.20	0.00	0.00	20	1
1	10.00	20.00	0.47	0.00	7.85	11.23	51.49	0.00	0.13	0.07	0.00	15	1
1	10.00	21.00	0.23	0.02	7.40	10.80	30.63	0.08	0.15	0.07	0.02	171	1
1	10.00	23.00	0.67	0.00	6.59	12.69	57.43	0.11	0.28	0.06	0.06	18	1
1	10.00	24.00	0.88	0.00	7.65	11.96	48.86	0.20	0.18	0.06	0.00	51	1
1	10.00	27.00	0.67	0.00	4.86	15.46	57.47	0.08	0.17	0.00	0.00	12	1
1	10.00	43.00	0.83	0.00	8.60	15.38	74.46	0.00	0.33	0.00	0.00	12	1
1	11.00	4.00	0.40	0.00	7.10	9.80	23.49	0.30	0.00	0.10	0.00	10	1
1	11.00	6.00	0.93	0.00	13.74	10.53	38.16	0.20	0.00	0.07	0.00	15	1
1	11.00	8.00	0.93	0.00	10.67	11.25	33.90	0.07	0.07	0.14	0.00	14	1
1	11.00	9.00	0.73	0.00	12.79	9.91	26.71	0.00	0.09	0.09	0.00	11	1
1	11.00	11.00	0.69	0.00	7.52	10.58	39.38	0.00	0.08	0.08	0.00	13	1
1	11.00	12.00	0.50	0.06	11.35	9.94	28.57	0.22	0.11	0.00	0.06	18	1
1	11.00	13.00	0.93	0.00	10.26	15.25	41.55	0.11	0.13	0.08	0.03	133	1
1	11.00	14.00	0.82	0.01	8.12	10.80	28.51	0.08	0.07	0.07	0.03	107	1
1	11.00	15.00	0.33	0.06	3.64	10.78	28.93	0.06	0.17	0.00	0.00	18	1
1	11.00	16.00	0.75	0.00	7.09	11.36	37.00	0.06	0.08	0.03	0.03	36	1
1	11.00	18.00	0.66	0.01	7.19	12.81	56.03	0.07	0.16	0.05	0.02	134	1
1	11.00	19.00	0.75	0.05	7.60	13.50	57.18	0.14	0.05	0.05	0.00	44	1
1	11.00	20.00	0.57	0.00	4.20	12.60	41.88	0.03	0.26	0.11	0.00	35	1
1	11.00	21.00	0.12	0.01	6.48	10.71	32.73	0.06	0.08	0.06	0.01	217	1
1	11.00	23.00	0.45	0.00	7.51	10.95	37.77	0.05	0.15	0.03	0.04	74	1
1	11.00	24.00	0.84	0.00	5.42	12.32	46.25	0.12	0.11	0.08	0.04	90	1

Table A1. Continued

CLU6	INDUST	OCCUP	MALE	UNEMPL	TEN_Y	EDU_Y	HWAGE	FOREIG	TRAIN	LOOK	LESSW	*N*	CLU7
1	11.00	25.00	0.52	0.04	9.61	9.43	28.16	0.11	0.07	0.04	0.00	27	1
1	11.00	26.00	0.09	0.00	4.11	10.86	26.63	0.00	0.09	0.00	0.00	11	1
1	11.00	27.00	0.78	0.00	7.40	14.84	41.41	0.09	0.17	0.09	0.02	54	1
1	11.00	28.00	0.29	0.00	8.74	14.18	51.16	0.24	0.06	0.06	0.00	17	1
1	11.00	29.00	0.61	0.00	12.55	11.18	27.35	0.11	0.21	0.03	0.03	38	1
1	11.00	33.00	0.29	0.02	5.34	9.25	25.02	0.31	0.09	0.11	0.04	94	1
1	11.00	41.00	0.45	0.00	3.27	11.91	57.94	0.09	0.09	0.09	0.00	11	1
1	11.00	43.00	0.85	0.00	5.59	16.66	41.30	0.21	0.06	0.12	0.03	34	1
1	11.00	44.00	0.67	0.05	9.35	10.02	27.05	0.05	0.00	0.10	0.05	21	1
1	12.00	13.00	0.91	0.00	10.20	15.80	50.70	0.04	0.09	0.09	0.04	23	1
1	12.00	14.00	0.79	0.00	9.58	10.79	34.65	0.05	0.32	0.05	0.05	19	1
1	12.00	18.00	0.53	0.00	5.73	12.79	64.08	0.00	0.16	0.11	0.05	19	1
1	12.00	20.00	0.58	0.02	8.90	12.10	45.37	0.03	0.23	0.05	0.02	60	1
1	12.00	21.00	0.21	0.04	8.60	10.36	31.88	0.03	0.12	0.07	0.03	153	1
1	12.00	22.00	0.47	0.00	10.67	11.60	40.69	0.03	0.09	0.08	0.00	116	1
1	12.00	23.00	0.50	0.00	12.69	10.53	69.40	0.00	0.33	0.00	0.00	18	1
1	12.00	24.00	0.72	0.00	9.91	12.86	43.81	0.11	0.33	0.00	0.06	18	1
1	12.00	27.00	0.79	0.01	10.97	12.26	39.33	0.01	0.08	0.05	0.01	145	1
1	12.00	28.00	0.60	0.00	6.94	14.50	36.68	0.10	0.10	0.10	0.00	10	1
1	12.00	33.00	0.27	0.06	8.23	9.14	25.77	0.21	0.03	0.09	0.03	33	1
1	12.00	39.00	0.31	0.12	5.49	12.06	34.95	0.04	0.35	0.19	0.00	26	1
1	12.00	41.00	0.25	0.08	7.46	14.46	85.74	0.08	0.17	0.08	0.00	12	1
1	12.00	43.00	0.80	0.00	10.67	16.00	52.41	0.00	0.20	0.07	0.00	15	1
1	12.00	44.00	0.94	0.00	14.12	11.19	33.37	0.06	0.13	0.00	0.00	16	1
1	13.00	13.00	0.85	0.00	5.49	16.27	46.81	0.23	0.00	0.08	0.00	13	1
1	13.00	21.00	0.03	0.03	7.53	10.13	32.41	0.06	0.29	0.06	0.00	31	1
1	13.00	33.00	0.44	0.00	11.12	9.14	28.94	0.21	0.00	0.05	0.00	43	1
1	13.00	39.00	0.42	0.00	7.90	13.21	31.10	0.16	0.16	0.11	0.05	19	1
1	13.00	41.00	0.39	0.00	9.48	14.32	44.87	0.05	0.25	0.08	0.01	481	1

1	13.00	42.00	0.24	0.01	9.29	12.66	37.68	0.01	0.34	0.06	0.02	180	1
1	14.00	12.00	0.33	0.00	8.55	11.79	41.17	0.17	0.08	0.00	0.00	12	1
1	14.00	14.00	0.82	0.00	8.35	11.45	37.84	0.18	0.18	0.00	0.00	11	1
1	14.00	16.00	0.30	0.00	16.05	10.90	56.10	0.00	0.00	0.10	0.00	10	1
1	14.00	18.00	0.60	0.00	4.94	10.57	30.52	0.07	0.13	0.07	0.00	15	1
1	14.00	19.00	0.75	0.00	11.60	12.83	55.10	0.00	0.08	0.00	0.00	12	1
1	14.00	20.00	0.38	0.00	6.87	12.15	38.33	0.15	0.23	0.23	0.00	13	1
1	14.00	21.00	0.06	0.05	7.98	10.68	44.42	0.04	0.15	0.11	0.00	94	1
1	14.00	23.00	0.45	0.00	4.53	12.00	50.39	0.09	0.09	0.18	0.00	11	1
1	14.00	30.00	0.06	0.00	5.72	10.08	22.36	0.22	0.00	0.06	0.06	18	1
1	14.00	31.00	0.32	0.00	8.63	9.68	25.90	0.21	0.13	0.11	0.00	56	1
1	14.00	32.00	0.00	0.05	7.24	9.46	29.72	0.16	0.05	0.08	0.03	37	1
1	14.00	33.00	0.20	0.00	8.20	8.36	20.98	0.42	0.07	0.11	0.02	45	1
1	14.00	34.00	0.00	0.00	13.26	8.67	21.31	0.20	0.07	0.00	0.00	15	1
1	14.00	35.00	0.30	0.02	7.25	14.16	43.46	0.08	0.23	0.07	0.03	198	1
1	14.00	36.00	0.27	0.00	8.97	12.12	41.14	0.12	0.24	0.05	0.04	209	1
1	14.00	37.00	0.08	0.01	6.92	10.70	28.58	0.17	0.18	0.05	0.02	275	1
1	14.00	38.00	0.11	0.01	8.09	10.10	28.90	0.17	0.13	0.04	0.03	279	1
1	14.00	39.00	0.22	0.02	5.80	11.43	31.15	0.11	0.21	0.09	0.02	211	1
1	14.00	41.00	0.22	0.04	6.55	13.21	44.08	0.11	0.17	0.09	0.02	54	1
1	14.00	43.00	0.50	0.00	7.74	14.39	39.76	0.11	0.22	0.06	0.00	18	1
1	15.00	2.00	0.64	0.00	7.22	10.75	25.02	0.00	0.05	0.00	0.05	22	1
1	15.00	6.00	1.00	0.09	11.98	10.77	26.96	0.00	0.00	0.00	0.00	11	1
1	15.00	8.00	0.86	0.00	11.74	9.93	31.90	0.29	0.00	0.00	0.00	14	1
1	15.00	11.00	0.70	0.00	4.55	10.05	20.01	0.10	0.00	0.20	0.00	10	1
1	15.00	13.00	0.70	0.10	7.32	13.15	80.62	0.00	0.10	0.10	0.00	10	1
1	15.00	15.00	0.07	0.00	5.85	9.37	39.28	0.05	0.12	0.05	0.00	41	1
1	15.00	18.00	0.39	0.00	4.49	11.65	34.35	0.13	0.09	0.17	0.00	23	1
1	15.00	19.00	0.55	0.00	9.17	13.08	46.75	0.05	0.15	0.05	0.00	20	1
1	15.00	20.00	0.50	0.00	8.77	12.25	43.13	0.08	0.08	0.04	0.00	24	1
1	15.00	21.00	0.09	0.01	6.23	10.66	32.73	0.06	0.11	0.03	0.02	90	1
1	15.00	22.00	0.18	0.00	5.76	9.77	21.76	0.09	0.09	0.09	0.00	11	1
1	15.00	27.00	0.74	0.00	6.46	12.98	35.98	0.04	0.09	0.09	0.00	23	1
1	15.00	28.00	0.48	0.01	8.58	12.70	39.10	0.08	0.14	0.08	0.01	73	1

Table A1. Continued

CLU6	INDUST	OCCUP	MALE	UNEMPL	TEN_Y	EDU_Y	HWAGE	FOREIG	TRAIN	LOOK	LESSW	*N*	CLU7
1	15.00	29.00	0.52	0.02	10.30	12.13	29.13	0.18	0.17	0.09	0.05	66	1
1	15.00	31.00	0.06	0.00	5.64	10.50	19.46	0.12	0.00	0.00	0.00	17	1
1	15.00	33.00	0.13	0.00	6.82	8.88	22.75	0.25	0.02	0.07	0.05	60	1
1	15.00	34.00	0.18	0.02	10.13	10.16	24.85	0.17	0.11	0.05	0.06	130	1
1	15.00	36.00	0.09	0.00	6.76	11.45	33.94	0.09	0.36	0.00	0.00	11	1
1	15.00	39.00	0.10	0.03	6.71	10.22	22.24	0.03	0.07	0.10	0.07	29	1
1	15.00	40.00	0.47	0.00	10.94	13.72	110.57	0.08	0.24	0.03	0.00	38	1
1	15.00	41.00	0.36	0.00	5.93	11.67	54.55	0.09	0.18	0.11	0.00	44	1
1	15.00	44.00	0.47	0.00	3.68	10.68	33.67	0.18	0.12	0.00	0.06	17	1
1	16.00	2.00	0.90	0.00	20.76	9.00	24.79	0.00	0.00	0.00	0.00	10	1
1	16.00	32.00	0.00	0.00	10.01	8.68	26.62	0.12	0.24	0.02	0.00	41	1
1	16.00	33.00	0.10	0.00	9.02	8.52	27.99	0.27	0.02	0.06	0.00	51	1
1	16.00	39.00	0.00	0.00	3.03	9.63	52.16	0.04	0.12	0.08	0.04	26	1
2	4.00	33.00	0.30	0.10	10.65	8.10	26.26	0.30	0.00	0.05	0.00	20	2
2	6.00	33.00	0.21	0.14	6.09	8.79	21.59	0.43	0.07	0.00	0.00	14	2
2	7.00	12.00	0.45	0.18	10.93	10.14	31.76	0.36	0.09	0.18	0.00	11	2
2	15.00	4.00	0.09	0.09	12.45	10.41	18.93	0.18	0.18	0.00	0.00	11	2
2	15.00	16.00	0.29	0.10	10.89	10.07	33.39	0.05	0.00	0.00	0.00	21	2
3	6.00	9.00	1.00	0.00	5.63	9.82	25.62	0.47	0.18	0.06	0.00	17	3
4	9.00	6.00	1.00	0.10	11.72	10.65	34.25	0.00	0.20	0.00	0.10	10	4
4	9.00	14.00	0.89	0.00	16.16	10.96	37.03	0.18	0.11	0.04	0.07	28	4
4	11.00	34.00	0.70	0.00	11.52	10.20	24.32	0.00	0.00	0.00	0.10	10	4
4	15.00	25.00	0.65	0.00	11.95	9.20	64.45	0.15	0.00	0.05	0.10	20	4
5	10.00	41.00	0.80	0.10	9.48	13.25	144.85	0.20	0.20	0.20	0.00	10	5
6	13.00	36.00	0.21	0.00	8.03	13.45	53.64	0.32	0.26	0.21	0.05	19	6
6	13.00	43.00	0.65	0.05	8.68	17.25	41.09	0.15	0.15	0.25	0.00	20	7
6	15.00	23.00	0.46	0.08	10.13	13.00	73.87	0.08	0.00	0.31	0.00	13	7
6	15.00	43.00	0.45	0.00	5.46	16.91	39.27	0.00	0.00	0.18	0.00	11	7

- CLU6: cluster number (moving average stopping rule);
- INDUST: industry code (17 values);
- OCCUP: occupation code (45 values);
- MALE: proportion of males;
- UNEMPL: proportion unemployed;
- TEN_Y: years of tenure;
- EDU_Y: years of schooling;
- HWAGE: hourly wage;
- FOREIG: proportion of foreign workers;
- TRAIN: proportion receiving training;
- LOOK: proportion looking for a new job;
- LESSW: proportion of individuals who worked less in the previous week due to accident or illness;
- *N*: number of observations;
- CLU7: cluster number (upper tail rule).

Notes

[1] An issue also put forward by Galbraith (1967).

[2] In fact, according to the OECD, Switzerland has the least strict employment protection legislation among the Continental European countries that it analyzes. Among the non-Continental European countries analyzed, only the USA and Great Britain have looser employment protection legislation (see OECD, 1999).

[3] On the issue of job stability and security in Switzerland, see Sousa-Poza (2004).

[4] 'The early ILM literature suggested that the formation and character of ILMs reflected the influence of unions' (Creedy, Whitfield, 1988, p. 248).

[5] 'The problem with [such a priori methods] is that the sample separation is unknown in general. If we have wage data and other observable traits such as schooling and experience we do not know "a priori" which observations belong to which market' (Basch, Paredes-Molina, 1996, p. 300f.).

[6] Each variable was scaled to have the same mean and variance, in order to avoid inordinate weights being given to any variable.

[7] Since family formation is usually associated with stable earnings of at least one partner. Secondary-segment jobs are often assumed to be unstable.

[8] These optimizations were conducted with LIMDEP V. 7.0 (see Greene, 1995).

[9] '. . . we do not propose that the labor market consists of exactly two distinct segments. Only that dualism is a useful simplification' (Dickens, Lang, 1988, p. 131).

[10] The following is based on Stewart and Swaffield (1999) who, to my knowledge, were the first to implement this model for an analysis of wage mobility.

[11] See also Heckman (1981).

[12] At this stage it is worthwhile pointing out that if something akin to a secondary segment were to exist in Switzerland, then it would most probably be dominated by either female or foreign workers. One drawback of the SLFS is that foreign workers (and especially those in typical secondary employment) are, due to the survey methodology, underrepresented. Either foreign workers are difficult

to locate (due to their seasonal fluctuations in and out of the country), or their poor command of the language hinders their participation in the survey. For a detailed analysis of the labor market situation of foreigners in Switzerland, see de Coulon (1999).

[13] The usual explanation for this observation is that workers in the primary segment receive more on-the-job training than workers in the secondary segment, thereby justifying the lower wages at the beginning of their career.

[14] It is interesting to note that the results are very similar to those of Cappellari (2000), who used data from the Bank of Italy's Survey on Household Income and Wealth for the years 1993–95. The sample size in the probit model with endogenous selection is equal to 2,148 observations.

[15] With regard to the presence of children, the effect on gross hourly wages could be influenced by child subsidies (so-called 'Kinderzulagen'). Furthermore, as some degree of wage discrimination exists with foreigners, one should be cautious about the use of nationality as an instrument.

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