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Wage differentials between foreigners and locals - discrimination or unobserved skills?

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Abstract

This paper analyzes a regulated trans-border labor market segmented by skills in the Canton of Ticino (Switzerland). Swiss regulation distinguishes two types of foreign labor force, i.e. trans-border commuters with de facto free access and immigrant workers regulated by quota. While wages are generally observed to be lower for trans-border commuters than for locals, immigrant workers accomplishing difficult tasks can earn higher wages than their Swiss counterparts. This can be due to differences in unobserved skills or to regulatory discrimination.

In order to shed light on this, we analyze the labor market assuming that firms hire workers setting efficient wages according to a competitive screening model. Estimating a two step switching regression model including dummy variables for the different categories of foreign workers allows distinguish between discrimination and effects of asymmetric information.

The bilateral treaties between Switzerland and the EU will introduce free mobility abolishing the current regulation by quota. Speculations abound on the impact this might have on wages. An effect of this liberalization can only be expected if current differentials are found to be due to regulation.

1 Introduction

The access of immigrant labor force to the Swiss labor market has historically been limited by industry specific quota, and work permits for foreigners that are conceded only in absence of an equivalent Swiss supply. The only category that has not been subject to quotas are trans-border commuters; their number having been controlled via the delimitation of the border area. Since 1st June 2004 the bilateral treaty on free mobility between the European Union and Switzerland is effective. Speculations abound (especially in border regions) on the impact this might have on wages and other labor market indicators. Given that the "deregulation" concerns changes in the regulation via work permits of immigrant workers, the "natural" instrument to investigate potential impacts seems to be the wage function. This permits to identify discriminatory shifts in wages due to the specific status of immigrant workers and thus to speculate on the impacts of a free mobility.

Wage functions for Switzerland usually show a significant negative shift for the various categories of work permits for foreign labor force with respect to Swiss residents [7] [9]. This is then interpreted as institutional (regulatory) discrimination of foreigners. As a consequence, liberalization (bilateral treaties) can be expected to have an equalizing effect on wages (i.e. a negative one on the salaries of Swiss residents). This paper re-proposes the argument from a slightly different perspective. First, attention is shifted from a labor supply interpretation of the wage function in a human capital perspective to a more general argument of hedonic markets and equalizing differences [16].Second, the focus is on the demand side in so far as firms are confronted with a problem of adverse selection [1] arising from the asymmetric information on workers' skills. We consider a firm's reaction to the adverse selection problem [21] [24] as adapted by Mas-Collel et al. (1995) [16] to the labor market, considering the general case of multi-tasks firms and multiple skills of native and foreign workers.

The central idea is that wage differentials are not necessarily due to discrimination according to the type of permit, but can be the result of a successful segmentation by skills due to screening.

This paper therefore presents a model of wage formation on the Ticino labor market on the base of a selection process by skill levels and discusses the issue of discrimination and segmentation.

In the following, we present the theoretical framework and the empirical model, describe the data used and the sample characteristics. We then present and discuss the empirical findings and draw conclusions on discrimination and the possible impact of deregulation.

2 Theoretical framework

Assume that we are in a competitive labor market in which *J* identical multi-task firms produce an identical output using the same constant return to scale technology with labor (L) as the only input. Firms are risk neutral and maximize their expected profits acting as price takers (the output price p is normalized to 1). Jobs differ in the "task level" denoted by t required from worker[1]. In this contest tasks are productive, i.e. each worker with assigned productivity level θ assigned to the task t is able to produce the output $y(t,\theta)$, where $y_t(t,\theta)=\theta$ (subscripts denote partial derivatives).

Then we suppose there are *K* workers whose opportunity cost to reject the employment is zero for simplicity. Workers differ in their skills[2] unobservable by firms. There are *N* different productivity types (denoted by θ_i with i =1,…, N) included in the bounded set of possible worker productivities $\theta \in [\underline{\theta};\bar{\theta}]$ following the distribution function *f*(θ). Each type θ worker employed in a task level t faces a twice continuously differentiable cost function $c(t,\theta)$. In particular $c(0,\theta)=0$, $c_t(t,\theta)>0$, $c_{tt}(t,\theta)>0$, $c_\theta(t,\theta)>0$ for all t > 0, and $c_{t\theta}(t,\theta)<0$. Thus both the cost and the marginal cost to fulfill the task are assumed to be lower for high-ability workers.

A type θ worker who receives wage w chooses the task level t ≥ 0 in order to maximize his utility function $u(w,t|\theta)$ that we define as $u(w,t|\theta)=w-c(t,\theta)$ the difference between earnings and cost.

In what follows the uninformed parties (here the firms) act in order to distinguish, or screen, the various types of workers that are the

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[1] For example firms may have different production line or jobs for which higher tasks level required implies higher responsibilities, etc…

[2] In the all paper we use as synonymous skill, ability and productivity level.

informed parties on the market. Thus the task level t is used to induce workers to truly reveal their skill level.

This kind of problem has been studied as two stage game, in which in a first step firms simultaneously offer a set of contracts defined as a pair (w, t). In the second stage, given the firms' offers, workers of each type choose whether to accept a contract and, if so, which one. For simplicity, it is assumed that if a worker is indifferent between two contracts, he always chooses the one with the lower task level and that he accepts employment if he is indifferent about doing so.

While the scope of the original papers [21] [24] on the issue were to identify pure strategy subgame perfect Nash equilibria, our purpose is to define the separating equilibrium[3] in the case of many multi-task firms that try to screen multiple types of workers.

According to Mas-Colell et al. (1995) [16] a separating equilibrium can be found starting from the definition of the optimal contract $(w^*_{\underline{\theta}}, t^*_{\underline{\theta}})$ offered to the lower-ability $\underline{\theta}$ worker which is the same for the complete information case as well as for the asymmetric information case. Then, given contract $(w^*_{\underline{\theta}}, t^*_{\underline{\theta}})$ we define separating equilibrium task levels t^*_i for i>1 imposing N-1 no-deviation conditions.

Then under complete information the competitive market assumption guarantees that in equilibrium each firms earns zero profits (∏=0). This implies that firms offer contracts where wage levels are $w = y(t, \theta)$ lying on the so called break-even lines as depicted in figure 1. A break-even line identifies all contracts representing zero profits. For a specific segment there exist three break-even lines, two for the separating and one for the pooling equilibria.

Task level $t^*_{\underline{\theta}}$ solves the following utility maximization problem of a lower-skill worker:

$$\max_{t} \ u(w, t|\underline{\theta}) \quad (1)$$

FOC:

[3] Separating equilibria arise when different types of workers choose different contracts; pooling equlibria arise when different types of workers choose the same contract.

$$\partial c(t,\theta) \big/ \partial t = \underline{\theta} \quad (2)$$

Consequently from the zero profit condition we find the optimal wage $w^*_{\underline{\theta}}$ offered by firms.

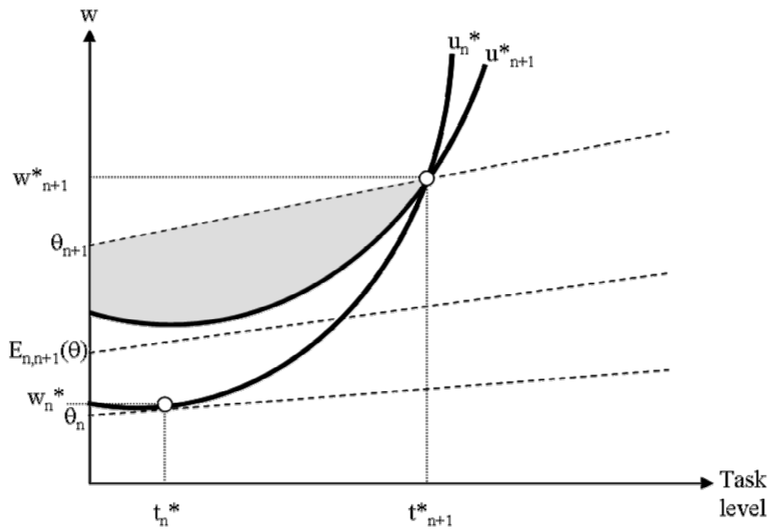
Given $(w^*_{\underline{\theta}}, t^*_{\underline{\theta}})$ the zero profit conditions $w = y(t,\theta)$, t^*_{n+1} (with n=1,…, N-1) satisfy the following system of N-1 no-deviation conditions:

$$u^*_n(w^*_{n+1}, t^*_{n+1}|\theta_n) = u^*_n(w^*_n, t^*_n|\theta_n) \quad (3)$$

These conditions imply that the type θ_n worker accepting (w^*_n, t^*_n) receives the same utility of accepting (w^*_{n+1}, t^*_{n+1}). By assumption on in case of indifference between the two contracts the type θ_n worker chooses the one that corresponds to the lower task level, and then is induced to true reveal his true type. Figure 1 shows the case of type θ_n and θ_{n+1} workers.

The set of contracts (w^*_θ, t^*_θ) for $\theta > \underline{\theta}$ are solutions of the system of no-deviation conditions (eq. 3)

Figure 1: Separating equilibrium between two worker types



In the separating equilibrium depicted in figure 1 no firm can earn strictly positive profits by deviating in a manner that attracts only high-ability or only low-ability workers, or in a manner that attracts all workers to a single pooling contract. In fact pooling equilibrium is possible only if the break-even pooled line lies in the shaded area of the figure 1. Then condition for the existence of the separating equilibrium between each two workers types implies that the expected productivity value between type θ_n and θ_{n+1} workers is less or equal to the utility level of type θ_{n+1} worker accepting the contract (w^*_{n+1}, t^*_{n+1}):

$$E_{n,n+1}(\theta) \leq u^*_{n+1}(w^*_{n+1}, t^*_{n+1} | \theta_{n+1}) \quad (4)$$

Readjusting we obtain the following condition:

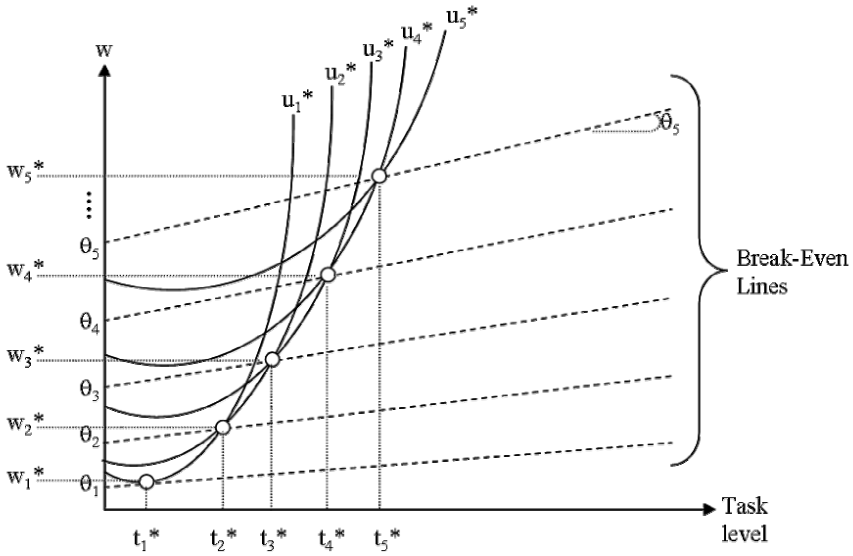
$$\lambda \leq \frac{u^*_{n+1} - \theta_n}{\theta_{n+1} - \theta_n} \quad (5)$$

where $\lambda = \dfrac{f(\theta_{n+1})}{f(\theta_n) + f(\theta_{n+1})}$ is the proportion of worker type θ_{n+1}.

Condition (5) tells us that the existence of a separating equilibrium between two worker types depends on their respective frequencies, the differences of the productivities and the utility value of the worker type considered.

Now assume that we are able to screen all K workers. The separating equilibrium in which firms offer a set of contracts (w^*_θ, t^*_θ) for each worker of type $\theta \in [\underline{\theta}; \overline{\theta}]$ that he accepts is as depicted in the figure 2

Figure 2: Separating equilibrium of N types of worker



Foreign workers discrimination:

Suppose that there is an observable subsample of foreigners in the *K* workers. Foreign workers behave as natives, they maximize their utility function that differ on the natives by an additional cost of moving g(d) that includes psychological cost of migration and travel costs as explained by Borjas (1987) [2]. This cost increases with distance d and has the effect of shifting the utility function downward:

$$u(w, t|\theta) = w - c(t, \theta) - g(d) \quad (6)$$

Furthermore, because we assume that workers react to real wages (no money illusion) immigrant workers will evaluate their utility indexing the nominal wages with their cost of living and moving costs.

Assuming local relative price level as p=1, we distinguish two foreign price cases relative to Switzerland low (p_L<p) and high (p_H>p) cost of living in home country.

Consequently when firms define optimal separating equilibrium, they offer contracts to type θ foreign workers (w_θ^*, t_θ^*), that consider the origin country's price level and moving cost g(d).

For the optimal task t_θ^* the real wage at price p_i where i=L, H is

$$\frac{w_\theta^*}{p_i} - \frac{g(d)}{p_i} \qquad (7)$$

which corresponds to two cases:

$$\frac{w_\theta^*}{p_i} - \frac{g(d)}{p_i} - w_\theta^* \begin{cases} > 0 \\ < 0 \end{cases} \qquad (8)$$

Equation (8) gives, for a foreign worker at given optimal task, the difference between the optimal wage in real terms in the origin country and the optimal wage received in the host country. If this difference is positive, i.e. if foreign workers earn more in real terms in the host country with respect to the origin country, then firms could adjust wages downward, while if the difference is negative firms could adjust wages upward.

Starting from the equation (8) the corrected wage term is:

$$g(d) + w_\theta^*(p_i - 1) \qquad (9)$$

where i=L, H.

Equation (9) tells us that moving cost and high cost of living in origin country (p_H) are positively related to the correction term.

3 The empirical model

In this paper the relevance of the immigrant worker status for wage discrimination is measured via market wage adjustments deviating from optimal contracts for natives. The focus is on the estimation of the wage function. According to the above, immigrant workers with a specific permit will take different salaries from resident workers only due to compensation of moving cost and adjustment to real wages. In other words: if skill driven nominal wage differentials can be isolated, remaining wage differentials will have to be explained on an ad-hoc basis as long as the p_i in origin county could be measured.

The formulation of the empirical model contains a further challenge: the level of skills is multidimensional and not directly observable. What is observable on the labor market are equilibrium wages, task levels required by firms, education, experience, tenure, professions, industries, hierarchical levels, etc. All these variables are usually included together with further individual characteristics in the wage function (omission of selection bias). The market will therefore reveal implicit prices for these multiple characteristics. From a firm's perspective, the characteristics of the individuals (e.g. education) are only signals for underlying level of skills.

Therefore, the level of skills required by firms becomes the driver of market segmentation in our empirical model. Firms define the level of skills required by the production context for a specific job[4]. They are willing to pay higher wages for higher skills not observable by them. This will induce them to identify specific market segments through a specific screening mechanism as exposed above. This will translate on the labor market into higher bids for the same level of a characteristic (e.g. years of schooling) in the high skill segment.

Given this constellation it seems useful to rely upon a two stage switching regression model for the empirical analysis of the implicit prices of characteristics in a labor market segmented by skill levels. The switching function will model the attribution of jobs to required skills levels and hence to segments. Hedonic wage functions for each segment will then be used to estimate the implicit price of characteristics in the different segments.

As skill is an ordered phenomenon an ordered probit procedure is applied to estimate the attribution of jobs to the skill levels. The ordered probit equation that determines the firm's probability to express a labor demand for worker type θ_i is:

$$\theta_i^* = z'_i \gamma + u_i \qquad (10)$$

[4] Our data contains a skills variable where for example highest skills required are defined as "job that implies the most demanding activities and the most difficult tasks" see appendix A.

Where θ_i^* describes the skill demanded by firms on the labor market, z_i' is a vector of characteristics describing the production context, γ is the associated coefficient vector to be estimated and u_i is a normally distributed error with mean zero and variance σ_u^2.

θ_i^* is not directly observable, so what we do observe is the task level t_i required by firm in order to screen workers, a multinomial ordered choice variable taking the value 1, 2, 3 and 4 where value 1 corresponds to the lower task and 4 the higher task, and each t_i detects a corresponding skill segment (i.e. to t_i = 1 corresponds the low skill segment, … , to t_i = 4 corresponds the higher skill segment), formally:

$$t_i = \begin{cases} 1 & \text{if} \quad \theta_i^* \le L_1 \\ 2 & \text{if} \quad L_1 < \theta_i^* \le L_2 \\ 3 & \text{if} \quad L_2 < \theta_i^* \le L_3 \\ 4 & \text{if} \quad \theta_i^* > L_3 \end{cases} \qquad (11)$$

L_1, L_2 and L_3 are limit points to be estimated by the ordered probit model.

As said before our focus is on the estimation of four wage functions, one for each segment of the labor market defined by the task level offered by firms:

$$\begin{array}{llll} \text{Regime 1} & \ln w_i = x'_{1i}\beta_1 + \varepsilon_{1i} & \text{iff} & u_i \le L_1 - z'_i\gamma \\ \text{Regime 2} & \ln w_i = x'_{2i}\beta_2 + \varepsilon_{2i} & \text{iff} & L_1 - z'_i\gamma < u_i \le L_2 - z'_i\gamma \\ \text{Regime 3} & \ln w_i = x'_{3i}\beta_3 + \varepsilon_{3i} & \text{iff} & L_2 - z'_i\gamma < u_i \le L_3 - z'_i\gamma \\ \text{Regime 4} & \ln w_i = x'_{4i}\beta_4 + \varepsilon_{4i} & \text{iff} & u_i > L_3 - z'_i\gamma \end{array} \qquad (12)$$

Regime 1 is the wage function for low skill segment, regime 2 for medium-low skill segment, regime 3 for medium-high skill segment and regime 4 for the high skill segment.

lnw_i is the natural logarithm of the wage observed for the individual i employed in the task segment t_i, x_i' is a matrix of socio-economic characteristics and of job descriptors of observation i in the tradition of Mincer (1974) [17], β_t is the associated coefficient vector and ε_{ti} is a normally distributed error relative to the task segment t and individual i with mean zero and variance σ_t^2. Let for simplicity $\alpha_L(\gamma)$ = L_h- z_i'γ ; with h=1, 2, 3, 4.

According to Heckman (1979)[12] and Maddala (1983) [15] we assume that u_i and ε_{ti} are correlated and because γ is estimated up to a scalar factor, we shall assume that $\sigma_u^2 = 1$. Therefore, least squares regression of wages in a specific task segment using only data observed in the sub sample produces inconsistent estimates of β_t. Applying a two stage switching regression model we obtain four new wage equations corrected by the selection bias to be estimated as follows:

$$\begin{aligned}
&\text{Regime1:} \quad \ln w_i = x'_{1i}\beta_1 + \sigma_{1u}\lambda_{1i} + \nu_{1i} \\
&\text{Regime2:} \quad \ln w_i = x'_{2i}\beta_2 + \sigma_{2u}\lambda_{2i} + \nu_{2i} \\
&\text{Regime3:} \quad \ln w_i = x'_{3i}\beta_3 + \sigma_{3u}\lambda_{3i} + \nu_{3i} \\
&\text{Regime4:} \quad \ln w_i = x'_{4i}\beta_4 + \sigma_{4u}\lambda_{4i} + \nu_{4i}
\end{aligned} \qquad (13)$$

σ_{tu} are the covariance between u_i and ε_{ti} to be estimated, λ_{ti} are the inverse Mill's ratios[5] that correct the wage functions associated with the task segment t.

υ_{ti} are the new residuals, with zero conditional means defined as $\upsilon_{ti} = \varepsilon_{ti} + \sigma_{tu}\lambda_{ti}$ with t = 1, 2, 3, 4.

Therefore, the two stage switching regression consists first in the estimation of the coefficients γ of the selection rule function, call it $\hat{\gamma}$, and the limits L_1, L_2 and L_3 using an ordered probit procedure. For each observation the respective λ_{ti} are computed substituting $\hat{\gamma}$ into γ. At the second stage we estimate equations (13) by OLS obtaining consistent estimates of β_t, where the inverse Mill's ratio is, as explained in Heckman (1979) [12], "… a monotone decreasing function of the probability that an observation is selected into the sample".

[5] In our equations (13) the correction for selection bias are $\lambda_{1i} = -\sigma_{1u}\dfrac{\phi(\alpha_1(\gamma))}{\Phi(\alpha_1(\gamma))}$; $\lambda_{2i} = \sigma_{2u}\dfrac{\phi(\alpha_1(\gamma)) - \phi(\alpha_2(\gamma))}{\Phi(\alpha_2(\gamma)) - \Phi(\alpha_1(\gamma))}$; $\lambda_{3i} = \sigma_{3u}\dfrac{\phi(\alpha_2(\gamma)) - \phi(\alpha_3(\gamma))}{\Phi(\alpha_3(\gamma)) - \Phi(\alpha_2(\gamma))}$; $\lambda_{4i} = \sigma_{4u}\dfrac{\phi(\alpha_3(\gamma))}{1 - \Phi(\alpha_3(\gamma))}$, $\phi(.)$ is the density function and $\Phi(.)$ is the cumulative distribution function. For more details see appendix B.

4 Estimation and results

The data at disposal for the estimation of our model consist of 48’472 individual observations of occupied jobs in Ticino in 2000. The information stems from the Federal Statistics on the Structure of Salaries (LSE) survey among a representative sample of 5’675 firms reporting salaries, job characteristics and individual attributes. Descriptive statistics of the variables included in our model can be found in the appendix C.

In the first step ordered probit model the choice variable has four levels according to the four task segments. The probability of an observation to belong to one of the four levels depends on the industry, the size of the firm, the hierarchical level of the job, the degree of occupation and the profession. The type of industry and the size of the firm serve as indicators for the production technology. The hierarchical level, the degree of occupation and the profession describe the job in the organizational context.

Table 1 presents the estimation results. Given that our interest in this first step lies mainly in the estimation of the limits between segments and the coefficient vector γ to compute the inverse Mill’s ratio to be included in the wage estimation, we limit our comments to the interpretation of signs[6].

[6] For interpretation, the coefficients from an ordered probit model would have to be transformed into marginal effects. This is of limited interest in our case given that the independent variables are dummies variables. The sign of the coefficients can in any case be interpreted in a straightforward way: a negative sign indicates an increasing probability of belonging to segment 1, and decreasing probability of belonging to segment 4, etc.

Table 1: Ordered probit estimates of the skill levels

variable	coefficient	z value
firm_XL	-0.1178574	-2.18
firm_L	-0.0715064	-3.63
firm_M	-0.0327703	-2.29
parttime	-0.2120388	-8.59
topmanager	2.9750870	67.60
middelmanager	1.9758190	59.84
lowmanager	1.1801460	45.89
prof_11	0.4644473	16.08
prof_12	0.7387156	23.65
prof_13	0.7217282	4.20
prof_20	1.4606560	23.86
prof_21	0.9686300	26.48
prof_22	0.5123573	15.10
prof_23	0.7007836	18.01
prof_24	0.7072660	9.44
prof_25	1.0326250	24.49
prof_26	1.0418870	10.91
prof_27	0.5441798	14.15
prof_28	1.3191060	13.75
prof_29	1.0653580	17.68
prof_30	1.1344790	24.43
prof_31	-0.0642756	-1.35
prof_32	-0.0405977	-0.22
prof_33	0.7349425	17.51
prof_34	0.2890783	3.96
prof_35	-0.9071762	-9.76
prof_36	1.1389460	16.84
prof_37	-0.1369302	-4.34
prof_38	1.1205680	13.78
prof_40	0.0873115	0.81
L1	0.2418482	0.022611
L2	2.0414150	0.026451
L3	3.6323640	0.039610
N. obs.	46125	
Log-likelihood	0.2883	

The dependent variable is the level of skill required by firms (task level).
The reference profession is the n. 10 (see appendix D): production, agriculture and sylviculture.

We note the following results. The large firms the more they present low skills workers. Firms offering jobs to part time workers have a significant bias towards low skill jobs. The fact that the probability to end up in the highest skill segment increases with hierarchical level confirms intuition.

Four log-linear hedonic regressions have been performed for the respective segments[7]. The dependent variable is the natural logarithm of the monthly wage, the explanatory variables can be seen from table 2. They measure the impact of human capital indicators (schooling, experience, tenure), martial status and gender, job descriptor (degree of occupation, profession), firm activity and finally the type of permit for the immigrant workers (the reference category being the Swiss labor force). Table 2 presents the estimation results for the four segments (we omitted the results for activities and professions see appendix E).

Table 2: Estimation of the wage function for four skill segments

	Skill Low		Skill Medium-Low		Skill Medium-High		Skill High	
variable	coefficient	t-statistic	coefficient	t-statistic	coefficient	t-statistic	coefficient	t-statistic
constant	7.795545	279.51	7.80072	280.66	7.923995	159.82	7.996492	72.17
education	0.021876	11.94	0.03317	17.05	0.036761	13.09	0.040012	7.72
experience	0.010629	14.41	0.01821	24.52	0.021966	13.45	0.019707	4.93
experiencesq	-0.017187	-11.49	-0.02950	-19.11	-0.031791	-9.44	-0.017551	-2.33
tenure	0.008743	11.44	0.00669	9.04	0.002942	2.17	0.002275	0.77
tenuresq	-0.012766	-4.94	-0.01047	-4.08	-0.003243	-0.79	-0.010142	-1.28
female	-0.203284	-34.82	-0.13249	-21.35	-0.166987	-14.56	-0.138271	-5.03
married	0.018928	4.26	0.01951	4.33	0.025437	2.79	0.043265	1.95
parttime	0.066201	10.88	0.05290	8.29	0.035586	2.41	0.089248	1.61
union	0.006353	1.24	-0.00516	-0.94	-0.065904	-5.21	-0.081190	-2.83
firm_XL	0.030519	2.2	0.01681	1.33	0.027761	1.28	0.290291	4.93
firm_L	0.044602	7.75	0.09902	16.97	0.164295	12.48	0.381208	10.21
firm_M	0.021504	5.24	0.06930	18.21	0.111530	12.61	0.255106	13.07
seasonal	-0.035002	-2.6	-0.02279	-1.37	0.045382	0.8	-0.075550	-0.69
annual	-0.023574	-2.99	0.02082	1.92	0.079304	2.67	0.157128	3.81
resident	-0.011489	-2.07	-0.01371	-2.55	-0.002431	-0.23	0.060609	2.45
transborder	-0.049474	-8.21	-0.05467	-10.64	-0.062870	-5.47	-0.046257	-1.15
othervisa	-0.013797	-0.61	-0.01509	-0.49	-0.072381	-1.52	0.012050	0.16
mill's ratio	-0.080106	-5.41	-0.11166	-23.56	-0.099951	-17.76	-0.122346	-7.99
N. obs.	16'339		18'725		6'119		2'693	
R square	0.5802		0.5003		0.5839		0.5032	

Dependent variable natural logarithm of wage.

In accordance with our expectations, the coefficients of the selected variables are significant, confirming a selection process with respect to the skill levels. The signs of the human capital indicators are also according to expectations. The wage differential for an additional

[7] For a systematic discussion of the functional form in hedonic regression see Cadlini 2001 [3].

schooling year shows significant increasing differences among segments, is 2.2% for low skills (mean of "schooling" in this segment: 10.5 years), 3.4% in the medium-low skill segment (mean of "schooling" in this segment: 12 years), 3.7% in the middle-high skill segment (mean of "schooling" in this segment: 13.2 years) and 4.1% in the high skill segment (mean of "schooling" in this segment: 14.5 years). Segmentation by skills seems to result in slightly lower returns to schooling than those reported (for earlier years) from wage functions on the whole sample (see [5]). "Experience" shows significant slightly difference among segments. An additional year in the same profession in the low segment returns a 0.3% increase of wage at the average experience of 22.5 years[8], a 0.6% increase in the medium-low skill segment at an average experience of 20.5 years, and a 0.8% increase in the medium-high skill at average experience of 21.6 years, In contrast, the marginal wage increase in the high skill segment amounts to 1.1% at an average of 26.1 years. Experience seems to pay above all in the high skill segment. The impacts of an additional year are very similar for tenure, i.e. 0.3% and 0.6% for the low and medium-low skill segments, respectively, but differ for the medium-high skill segment, where 0.3% is found and no significant decreasing returns. In contrast in the high skill segment tenure is not significant. Given the high average tenure in this segment (26 years), this provides a first evidence for a labor market with low job turnover, and hence with a positive differential for newcomers. A second evidence in the same direction is provided by the dummy for workers with annual permits. This variable returns a negative sign in the low skill segment, but a positive one in the other three segments. First, it is instructive that the results found when segmenting by skills contradict the intuition that wage discrimination against foreigners prevails, independently from the type of permit. Second, the drastic positive wage differential in the medium-high and high skill segments (respectively 8.3% and 17%)[9] indicates that scarce top positions are selectively being occupied by mobile immigrant workforce[10]. Further

[8] "Experience" and "tenure" appear in the wage functions in a quadratic formulation to capture the decreasing rate of return. Therefore, the marginal effect on wage has to be calculated from two coefficients.

[9] For the right computation on the marginal impact on the wage for a variable that appears in the wage function as a dummy see Halvrsen R., Palmquist R. (1980).

[10] Note that discrimination against Swiss labor force implies a shortage also on the labor market at the immigrants' origin. In this case the contingent regulation

results on immigrant workers show that foreign residents take more or less the same salary as Swiss in the first three segments but a positive wage differential of 6.2% is observed in the high skill segment. Trans-border commuters are discriminated to an increasing extent with rising skill levels. In their case, the Swiss regulation clearly works in favor of the resident work force, exploiting a very elastic labor supply from neighboring Lombardy provinces with lower cost of living.

Important variation among skill levels is to be observed with respect to the effect of firm size. Large size firms have significant positive impact on wages only in the lower and in the highest skill segment (respectively 3.1% and 33.7%). Across all skill levels wages increase c.p. with firm size. A further result is that the labor market pays a premium for part time work in all first three segments, but not significant premium is paid in the higher skill segment. Finally it is worth noting that wage discrimination by gender is slightly higher in the low skill segment than in the other three, but in general lower than what has been found without segmentation [9].

The coefficient of the inverse Mill's ratio is significant in all four equations, indicating a relevant selection bias stemming from firm's identification of skill segments. The negative sign however has different interpretation with respect to the skill segment. In the low skill segment the inverse Mill's ratio is always negative, given the negative sign of the coefficient the total effect of the correction for the selection bias is positive as expected. This indicates that for low skill workers wages are corrected upward. In contrast in the high skill segment the inverse Mill's ratio is always positive, thus wages are downward corrected.

5 Conclusions

The main aim of this paper was to disentangle segmentation by skills from wage discrimination against immigrant workers in the case of the Ticino labor market. The leading hypothesis was that in the proposed analytical perspective of implicit markets for skills, wage differentials with respect to work permits will reflect screening. This expectation is by and large confirmed by the empirical findings. The

plays a bad trick to residents filling up the jobs first, when thereafter the firms have to pay premiums to attract internationally mobile labor force to the local market.

most striking result is a positive wage differential in the segment for highly skilled labor in favor of holders of a yearly permit that contrasts with a negative differential for trans-border commuters in this, as well as in the lower skill segments. Finally, foreign residents do not seem to suffer from wage discrimination as compared to residents of Swiss nationality. The contingents on yearly permits seem to play against the Swiss top managers with a rather high tenure and in favor of internationally sourced but expensive managers and specialists. On the other hand, priority obligation for Swiss workers allow for a significant discrimination of trans-border commuters.

Speculating about the impact of the liberalization to be brought about by the bilateral treaty on free mobility with the European Union our results imply the following: in the market segment for high skills, the opening of the market will reduce scarcity and increase competition among foreigners for jobs on the Ticino labor market. The impact on salaries depends on the real wages in the country of origin and on mobility cost. In the medium skills level from annual permits the liberalization will tend to shift salaries upward. On the enlarged trans-border labor market in this segment the salaries can be expected to fall. For the lower skill segment, given the highly elastic supply and the important share of immigrant workers in the low skill labor market, the liberalization will not have a relevant impact on salaries of Swiss residents.

Appendix A: variable specification

Variable	Description
Task	Skill level required by employer
High skill	Job that implies the most demanding activities and most difficult tasks
Medium-high skill	Job that implies independent tasks and high skills.
Medium-low skill	Job that implies specific competences.
Low skill	Job that implies repetitive tasks.
Ln Wage	Natural logarithm of 2000 October's monthly standardized wage.
Noga	List of activities (see apendix E)
Profession	List of individual professions (see appendix E)
Firm size:	Number of employees in the firm at 31 October 2000
Extra large (XL)	Dummy variable: 1= firm with > 500 employees, 0= otherwise.
Large (L)	Dummy variable: 1= firm with > 50 and £ 500 employees, 0= otherwise.
Medium (M)	Dummy variable: 1= firm with > 10 and £ 50 employees, 0= otherwise.
Little (S)	Dummy variable: 1= firm with <= 10 employees, 0= otherwise. Reference category.
Hierarchical level:	
Top manager	Dummy variable: 1= top management, 0 = otherwise.
Middle manager	Dummy variable: 1= middle management, 0 = otherwise.
Lower manager	Dummy variable: 1= lower management, 0 = otherwise.
Employees	Dummy variable: 1= employee with limited responsibility, 0 = otherwise. Reference category.
Gender	Dummy variable: 1= female, 0 = man.
Part time	Dummy variable: 1= if the degree of occupation is <90%; 0 = otherwise.
Schooling	Years of schooling
Experience	Years of experience in the labor market.
Tenure	Years spent in the current employment.
Martial status	Dummy variable: 1= married; 0 = otherwise.
Union	Dummy variable: 1= unionized worker; 0= otherwise.
Permits:	
Seasonal	Dummy variable: 1= seasonal (A) work permit; 0 = otherwise.
Annual	Dummy variable: 1= annual (B) work permit; 0 = otherwise.
Resident	Dummy variable: 1= resident (C) work permit; 0 = otherwise.
Cross border	Dummy variable: 1= cross border (G) work permit; 0 = otherwise.
Other permits	Dummy variable: 1= other permits (< 1 year); 0 = otherwise.
Swiss	Dummy variable: 1= Swiss worker; 0 = otherwise. Reference category.

Appendix B: computation of the invers Mill's ratio

Starting from equations (12) we compute the expected value of each wage function conditional on task t and observable characteristics x obtaining:

$$\begin{array}{ll} \text{Regime1} & E(\ln w_i | t_i = 1, x) = x'_{1i}\beta_1 + E(\varepsilon_{1i} | u_i \le \alpha_1) \\ \text{Regime2} & E(\ln w_i | t_i = 2, x) = x'_{2i}\beta_2 + E(\varepsilon_{2i} | \alpha_1 < u_i \le \alpha_2) \\ \text{Regime3} & E(\ln w_i | t_i = 3, x) = x'_{3i}\beta_3 + E(\varepsilon_{3i} | \alpha_2 < u_i \le \alpha_3) \\ \text{Regime4} & E(\ln w_i | t_i = 4, x) = x'_{4i}\beta_4 + E(\varepsilon_{4i} | u_i > \alpha_3) \end{array}$$

given the assumption on the distribution of the error terms that ε_{1i}, ε_{2i}, ε_{3i}, ε_{4i} and u_{ti} are jointly normal with zero means and variance covariance matrix of type:

$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{1u} \\ & \sigma_2^2 & \sigma_{23} & \sigma_{24} & \sigma_{2u} \\ & & \sigma_3^2 & \sigma_{34} & \sigma_{3u} \\ & & & \sigma_4^2 & \sigma_{4u} \\ & & & & 1 \end{bmatrix}$$

we have to obtain the expectation of the error terms ε_{ti} conditional to u_{ti} and following Maddala (1983)

[15]:

$$\begin{aligned} E(\varepsilon_{1i} | u_i \le \alpha_1(\gamma)) &= \sigma_{1u}\left[-\frac{\phi(\alpha_1(\gamma))}{\Phi(\alpha_1(\gamma))}\right] = \sigma_{1u}\lambda_{1i} \\ E(\varepsilon_{2i} | \alpha_1 < u_i \le \alpha_2) &= \sigma_{2u}\frac{\phi(\alpha_1(\gamma)) - \phi(\alpha_2(\gamma))}{\Phi(\alpha_2(\gamma)) - \Phi(\alpha_1(\gamma))} = \sigma_{2u}\lambda_{2i} \\ E(\varepsilon_{3i} | \alpha_2 < u_i \le \alpha_3) &= \sigma_{3u}\frac{\phi(\alpha_2(\gamma)) - \phi(\alpha_3(\gamma))}{\Phi(\alpha_3(\gamma)) - \Phi(\alpha_2(\gamma))} = \sigma_{3u}\lambda_{3i} \\ E(\varepsilon_{4i} | u_i > \alpha_3) &= \sigma_{4u}\frac{\phi(\alpha_4(\gamma))}{1 - \Phi(\alpha_4(\gamma))} = \sigma_{4u}\lambda_{4i} \end{aligned}$$

where $\phi(.)$ is the normal density function and $\Phi(.)$ is the normal cumulative distribution function, and λ_{ti} are called the inverse Mill's ratio.

Appendix C: Descriptive statistics

variable	all sample	low skill	m-low skill	m-high skill	high skill
wage**	4'357	3'508	4'566	5'940	8'564
education*	11.7	10.5	12.0	13.2	14.5
experience*	21.7	22.5	20.5	21.6	26.1
tenure*	8.1	6.9	8.2	9.5	12.2
parttime*	0.96	0.88	0.93	0.92	0.96
female	18'632	8'996	7'255	2'018	363
married	28'388	10'948	11'411	3'934	2'095
union	6'413	2'982	2'666	580	185
firm_XL	3'689	1'318	1'468	782	121
firm_L	8'730	3'678	3'727	1'020	305
firm_M	17'383	6'922	7'321	2'177	963
firm_S	18'421	6'148	8'044	2'813	1'416
Swiss	23'288	2'027	4'494	10'920	5'847
seasonal	683	439	201	33	10
annual	2'517	1'403	728	247	139
resident	10'357	4'975	3'973	1'024	385
transborder	10'838	5'185	4'576	894	183
othervisa	498	190	148	101	59
prof_10	7'416	4'072	2'744	487	113
prof_11	5'449	2'012	2'851	477	109
prof_12	3'106	741	1'979	318	68
prof_13	39	12	14	12	1
prof_20	1'617	1	97	297	1'222
prof_21	2'398	182	1'001	917	298
prof_22	3'264	1'172	1'732	343	17
prof_23	2'435	625	1'134	571	105
prof_24	574	126	169	209	70
prof_25	1'835	179	768	668	220
prof_26	146	9	75	50	12
prof_27	4'753	2'288	2'049	358	58
prof_28	436	15	213	155	53
prof_29	642	52	340	211	39
prof_30	1'103	73	484	391	155
prof_31	1'854	1'101	657	82	14
prof_32	93	50	40	3	0
prof_33	2'225	559	1'202	336	128
prof_34	381	167	184	29	1
prof_35	741	686	47	7	1
prof_36	474	15	297	154	8
prof_37	5'798	3'743	1'689	310	56
prof_38	386	72	216	63	35
prof_40	276	63	176	33	4

Note: The table report the number of observation each variable. *average; **median.

Descriptive statistics continued

variable	all sample	low skill	m-low skill	m-high skill	high skill
noga_1	97	33	48	16	0
noga_2	23	12	10	1	0
noga_10	155	87	54	10	4
noga_15	1'119	567	413	91	48
noga_16	15	15	0	0	0
noga_17	104	33	56	11	4
noga_18	453	320	85	36	12
noga_19	56	22	30	2	2
noga_20	401	80	224	62	35
noga_21	67	29	25	8	5
noga_22	543	159	258	91	35
noga_23	382	124	161	78	19
noga_25	264	119	96	32	17
noga_26	414	197	171	30	16
noga_27	1'925	909	737	198	81
noga_29	1'704	371	930	302	101
noga_30	1'120	483	400	177	60
noga_33	879	493	253	87	46
noga_36	553	297	170	70	16
noga_40	83	19	56	5	3
noga_45	6'598	2'168	3'383	767	280
noga_50	2'150	686	1'075	288	101
noga_51	3'354	1'055	1'382	581	336
noga_52	5'108	2'238	2'250	408	212
noga_55	5'439	3'348	1'646	348	97
noga_60	849	367	365	78	39
noga_61	41	3	37	1	0
noga_62	21	8	5	6	2
noga_63	669	263	266	86	54
noga_64	126	14	62	42	8
noga_65	3'233	695	1'381	933	224
noga_66	202	25	139	28	10
noga_67	182	35	55	52	40
noga_70	246	73	84	64	25
noga_72	4'672	981	1'962	1'083	646
noga_73	2	0	0	1	1
noga_75	4	0	2	1	1
noga_80	541	109	234	165	33
noga_85	2'967	1'048	1'446	362	111
noga_90	98	82	12	2	2
noga_91	202	52	93	40	17
noga_92	576	210	234	84	48
noga_93	585	237	264	70	14
observations	48222	18066	20554	6797	2805

Note: The table report the number of observation each variable.

Appendix D: Table of professions and activities

Table of professions

Code	Profession
prof_10	production, agriculture and sylviculture
prof_11	professions in the construction activities
prof_12	maintenance, reparations of machinery
prof_13	artistic craftsmanship
prof_20	definition of the firm strategies
prof_21	bookeeping, financial management, human resources management
prof_22	secretariat, backoffice
prof_23	other commercial and administrative professions
prof_24	logistic
prof_25	consulting in general , insurance, frontoffice,
prof_26	trade of basic products
prof_27	retail trade
prof_28	researche and development
prof_29	analysis, programming, operating
prof_30	planning, design
prof_31	transport
prof_32	security services
prof_33	professions in health and social services
prof_34	body treatements (hairdresser barber), cleanliness of clothing
prof_35	cleanliness and public hygiene
prof_36	education
prof_37	hotels and restaurants professions
prof_38	professions in culture, sport, leisures
prof_40	other professions

Note: professions defined by LSE 2000

Appendix E: continued results of table 2: activities and professions

	Skill Low		Skill Medium-Low		Skill Medium-High		Skill High	
variable	coefficient	t-statistic	coefficient	t-statistic	coefficient	t-statistic	coefficient	t-statistic
noga_1	-0.0875481	-2.91	-0.15525	-6.35	-0.226976	-4.45	(dropped)	
noga_2	0.0123387	0.70	0.05302	1.25	-0.187521	-7.37	(dropped)	
noga_10	0.1446160	8.93	0.08785	4.41	-0.155898	-3.16	-0.4039684	-2.99
noga_15	-0.1136313	-7.48	-0.09081	-5.20	-0.136608	-3.95	-0.1785090	-2.80
noga_16	-0.3441270	-11.14	(dropped)		(dropped)		(dropped)	
noga_17	-0.1612143	-5.00	-0.20053	-7.07	-0.184279	-4.45	-0.3891845	-2.14
noga_18	-0.3391373	-16.56	-0.34120	-9.58	-0.165948	-2.45	-0.0061590	-0.03
noga_19	-0.2931984	-6.19	-0.06686	-1.28	0.080494	2.28	-0.4026817	-3.26
noga_20	0.0650734	2.52	0.05248	3.30	-0.073283	-2.22	-0.2178678	-3.56
noga_21	-0.1188110	-3.33	-0.08528	-1.98	-0.049181	-1.14	-0.1843216	-1.44
noga_22	0.0009563	0.04	0.07870	4.47	-0.054854	-1.82	-0.1409108	-1.94
noga_23	0.0197328	0.95	0.03531	1.38	0.035576	0.90	-0.0358263	-0.47
noga_25	-0.0100333	-0.49	0.02560	1.17	0.045197	0.78	-0.1022888	-1.44
noga_26	0.0388651	2.11	0.05566	3.23	0.039726	0.93	-0.1758406	-2.47
noga_27	-0.0379060	-2.46	-0.04797	-3.58	-0.034948	-1.39	-0.1900974	-3.98
noga_29	-0.0288984	-1.45	0.01551	1.22	-0.000381	-0.01	-0.0760274	-1.54
noga_30	-0.1216650	-6.64	-0.03956	-2.21	-0.038472	-1.10	-0.1151758	-1.76
noga_33	-0.1922714	-10.41	-0.02170	-1.00	-0.021534	-0.68	0.0441084	0.43
noga_36	-0.0854706	-4.73	-0.00431	-0.24	-0.039735	-0.72	-0.2039432	-2.87
noga_40	0.1760048	9.74	0.10435	5.27	0.145104	4.24	0.1264958	1.56
noga_45	0.0170385	1.16	0.02501	2.10	-0.067213	-3.07	-0.2415863	-6.33
noga_50	-0.0491277	-3.75	-0.05386	-4.72	-0.100126	-4.36	-0.1824537	-3.01
noga_52	-0.0338463	-2.82	-0.07592	-6.49	-0.116360	-4.98	-0.1579567	-3.62
noga_55	-0.0941289	-5.87	-0.13730	-7.13	-0.156499	-5.20	-0.4165379	-5.08
noga_60	0.0272235	1.72	-0.01511	-0.82	-0.095577	-2.14	-0.0813936	-1.17
noga_61	0.0527893	1.06	0.13179	5.91	0.217024	8.45	(dropped)	
noga_62	-0.0262986	-0.63	-0.13829	-1.92	-0.030915	-0.18	-0.1712365	-1.34
noga_63	-0.0623724	-3.57	0.03185	1.23	-0.061563	-1.59	-0.3085163	-3.16
noga_64	0.1084959	1.84	0.12758	4.13	0.126700	3.27	-0.0066524	-0.07
noga_65	0.1314493	7.36	0.19058	13.26	0.360684	13.13	0.5667493	10.01
noga_66	0.1085560	1.89	0.03315	1.09	0.116136	2.28	0.1051981	0.76
noga_67	0.0888318	1.74	0.16776	3.44	0.079055	1.00	0.5983098	5.51
noga_70	-0.0516792	-1.63	-0.02080	-0.93	-0.127115	-3.97	-0.2416706	-3.18
noga_72	0.0283450	1.88	0.05579	4.32	0.059323	2.83	0.1498207	4.12
noga_73	(dropped)		(dropped)		0.131542	3.79	0.3157942	4.72
noga_75	(dropped)		0.34006	14.44	0.333306	15.33	0.4559037	6.94
noga_80	0.0366114	1.24	-0.00290	-0.11	-0.063157	-1.47	-0.2679027	-3.06
noga_85	0.1409080	7.91	0.05675	3.30	-0.075564	-2.71	-0.3110905	-5.09
noga_90	0.0003540	0.02	0.06019	0.99	-0.238121	-2.61	-0.2561332	-1.19
noga_91	-0.0199617	-0.46	-0.04688	-1.60	-0.082682	-1.84	-0.2711517	-2.49
noga_92	0.0327680	1.23	-0.11188	-4.47	-0.149586	-3.96	-0.2467935	-3.03
noga_93	-0.1490345	-6.89	-0.23468	-6.29	-0.284973	-5.43	-0.2618376	-2.19
prof_11	0.0715854	5.90	-0.00843	-0.80	-0.005925	-0.28	0.0482549	0.84
prof_12	-0.0082573	-0.63	-0.00623	-0.67	-0.041293	-2.00	0.0638761	1.08
prof_13	-0.0350367	-0.83	0.05787	1.00	-0.171089	-4.43	0.0620827	0.61
prof_20	-0.0009627	-0.03	0.02401	0.67	0.022675	0.88	0.1791938	3.13
prof_21	0.1032627	4.42	0.01509	0.95	0.037381	1.96	0.0737074	1.28
prof_22	0.0984545	7.32	0.01860	1.53	0.032457	1.42	0.1012285	1.21
prof_23	0.0667183	4.02	0.04506	3.54	0.085957	3.93	0.1891147	2.77
prof_24	0.0511982	2.26	0.09649	4.85	0.110457	3.33	0.1897147	2.87
prof_25	0.1417055	5.22	0.10270	6.57	0.132832	5.65	0.0870508	1.31
prof_26	0.0225949	0.23	0.08505	3.06	0.193843	3.46	0.2650976	1.74
prof_27	-0.0658413	-5.41	-0.03215	-2.55	0.038013	1.33	0.1133244	1.07
prof_28	0.0213459	0.40	0.03408	1.39	-0.015066	-0.47	0.0067652	0.11
prof_29	0.0746093	1.50	0.06639	3.68	0.106545	3.44	0.0291908	0.30
prof_30	0.0017656	0.06	-0.03546	-2.16	-0.045317	-2.07	-0.0768544	-1.24
prof_31	0.0042108	0.36	-0.05614	-3.49	0.028253	0.54	0.2498692	1.83
prof_32	-0.0888560	-3.54	-0.01052	-0.14	-0.067474	-1.17	(dropped)	
prof_33	0.0052664	0.26	0.08297	4.74	0.154058	5.61	0.2833025	4.08
prof_34	-0.0180298	-0.78	-0.01508	-0.41	-0.016103	-0.25	0.1299379	1.00
prof_35	-0.0966443	-4.76	-0.12774	-2.53	-0.034466	-0.66	(dropped)	
prof_36	0.0970255	1.67	0.07625	3.36	0.063472	1.31	-0.0254988	-0.10
prof_37	-0.0338449	-2.21	-0.00391	-0.21	0.005425	0.18	0.1870133	1.95
prof_38	0.0475310	0.68	-0.00240	-0.08	0.043893	0.56	0.0166173	0.12
prof_40	0.0755539	1.95	0.11543	5.65	0.111217	1.88	0.7202591	3.31

Note: reference activity is noga_51, reference profession is prof_10, see appendix E for details.

Table of activities (NOGA):

Code	Activitiy
noga_1	agriculture, hunts
noga_2	sylviculture
noga_10	mining and quarrying
noga_15	food, beverage
noga_16	tobacco products
noga_17	textiles
noga_18	garments and furs
noga_19	manufacture of leather goods and shoes
noga_20	processing of wood
noga_21	paper- and boardmaking
noga_22	printing, publishing, reproduction of recorded media
noga_23	coke, refined petroleoum products, nuclear fuels
noga_25	rubber and plastics products
noga_26	other products from nonmetallic minerals
noga_27	metals and metals products
noga_29	mechanical engineering
noga_30	computers and office equipment
noga_33	precision equipment
noga_36	manufacturing no elsewhere cassified
noga_40	enery supply
noga_45	construction
noga_50	sale and repair of automobiles, filling stations
noga_51	wholesale trade and commission trade
noga_52	retail trade, repair of consumer durables
noga_55	hotels and restuaurants
noga_60	ground transports
noga_61	water transports
noga_62	air transports
noga_63	agency of transports
noga_64	postal services and telecommunications
noga_65	banking
noga_66	insurance
noga_67	activities related to banking and insurance
noga_70	real estate
noga_72	IT services
noga_73	research and development
noga_75	public administration, defense, social insurance
noga_80	education
noga_85	health and social services
noga_90	smaltimento
noga_91	religious organizations
noga_92	activities in sport and culture
noga_93	other services

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