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Becoming Economically Independent: Weakening or Strengthening Parental Ties?

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Abstract

This paper analyses patterns of behaviours of about three thousand graduates in some northern and central Italian universities. Different approaches to the job market and/or to further qualifications are followed up during the year after graduation and are related both to some choices adopted previously at university and to family traits, by means of longitudinal methods of Event History Analysis (EHA). Apparent behavioural inertia from college to the postgraduate period reveals a commonly shared underlying attitude. Also, family influence seems well conveyed by parents' educational levels, which emphasize the mothers' role in improving graduates qualifications and the fathers' function in involving their children in self employment.

1 Introduction

Surveys on social mobility generally compare the socio-economic level of young adults directly to the corresponding socio-economic level of their families of origin, expressing the latter mainly, but not exclusively, with reference to the fathers' economic condition. Traditionally computed measures of personal socio-economic level are based both on educational level and on professional activity, in a static representation.

However, the underlying process is quite complex and it spreads through the first decades of the life cycle. In this dynamics, the transition from University to work appears as an unambiguous step in the definition of an individual's social and economic status in adulthood. Therefore, we focus both on personal and family determinants of early occupational experiences, searching for specific patterns in the life course.

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2 Data and object

Our data is a section of an archive called STELLA (an acronym of Statistiche sul Tema Laureati e Lavoro in Archivio on line, Statistics on the Theme of Graduates and Work in Archive on line). The Stella archive involves data from 163,836 graduates in the three-years degree course in 2002-2004 from 12 Italian Universities that ratified the project. The survey, with a stratified probabilistic sampling design, was carried out via a questionnaire sent by electronic mail or, where a graduate did not have an e-mail address, via a CATI record. The questionnaire was completed in the month of May 2005, therefore within 15/18 months after graduation. The sample under examination is composed of 3,481 graduates from eight universities in northern and central Italy, both under the academic regimen existing prior to 2001 (with a legal duration from 4 to 6 years depending on the Faculty statement) and under the new ordinance (a B. Sc. of three-year duration) graduating in the academic sessions from September-October 2003 to January-February 2004.

Our analysis focuses on the transition from university to the labour market with respect to family and personal characteristics. Educational choices, living conditions, work, statuses customarily analysed one by one, cannot, in fact, be adequately understood without considering them as a unified whole. Moreover, events experienced by parents in a family may influence the course of events and outcomes experienced by their children, their lives being ‘linked’ (Wu, 2003). We therefore aim at explaining the effect on job search duration of both individual and family characteristics by means of a casual model, where covariates can be measured with regard to two domains. The first domain pertains to competencies gained by the graduate her/himself and specified as trajectories in the University curriculum. Indeed, the distinction between a bachelor of sciences and a masters degree -the first one corresponding to a three-year university course, the second one to a five year course and therefore to a higher qualification level- is fairly recent in the Italian education system, since it was introduced in 2001 by means of the so called “3+2 reform”. The second domain consists of the educational and economic level of the young adults’ parents. Its impact on the transition to the labour market, in terms of professional success of the graduate, is analysed differentially between parental roles, with emphasis on the maternal role.

Table 1: Descriptive statistics on characteristics of graduates and their parents.

Personal characteristics		Parental characteristics	
Sex		*father's education*	
Female	59.47	primary/middle school	42.04
Male	40.53	high school	39.86
		degree	*18.10*
working condition		*Mother's education*	
looking for a job	9.15	primary/middle school	46.22
working only	51.59	high school	39.48
studying while working	8.24	degree	14.30
studying only	25.68		
working while looking for another job	3.18		
not looking for a job	2.16		
coherence of job with course of studies		*father's sector of activity*	
very coherent	49.53	public	25.97
rather coherent	28.63	private	73.33
not very coherent	14.06	none	0.70
not at all coherent	7.77		
job search channel		*Mother's sector of activity*	
reply to job offer	16.52	public	31.31
active search	32.40	private	39.27
family/friends help	30.65	non labour force	29.42
employer direct call	11.21		
stage	9.22		
work experience while at University			
occasional	34.95		
part time	17.08		
full time	7.17		
none	40.80		

3 Methods

As aforementioned, our analysis deals with duration, namely with time spent in the transition from having graduated to the job market. Statistical methods for analysing the length of time until the occurrence of some event are grouped under the denomination of Event History Analysis (EHA). Generally speaking, the purpose of EHA is the detection of times patterns and the explanation of why some individuals are at a higher risk of experiencing that particular event rather than others.

Since Cox's contribution in 1972, models for lifetime data have met increasing acceptance especially in the case of continuous-time data in several disciplines, from medicine to engineering, from sociology to economics (Singer and Willett, 1993). Nevertheless, in many applications and particularly in the case of retrospective data collection, continuous-time models do not adapt to contexts, because events are measured in discrete-time units, such as years or months. Besides, ties, also known as coinciding event times, can lead to bias in parameters estimates when using Cox's method (Yamaguchi, 1991). Hence, discrete-time survival analysis has been adopted as a straightforward approach that prevents possibly inaccurate statistical adjustments of continuous-time methods to discrete-time data (Allison, 1982, Singer and Willet, 1993). It has also been shown that the discrete-time model, developed for intrinsically discrete data, provides estimates that are a close approximation to a model for interval-censored data. This model assumes that the continuous hazard is constant within intervals (Allison, 1992).

We consider graduates in the years 2003-2004 at some universities in northern Italy, at risk of experiencing the target event of finding a job. Event occurrence is recorded in discrete intervals from the common origin of graduation. Let the letter j index months, the jth month of work search beginning immediately after time t_{j-1} and ending at time t_j; continuous time is then divided into an infinite sequence of contiguous time periods: $(0, t_1]$, $(t_1, t_2]$,…, $(t_{j-1}, t_j]$, … and so forth. Interest centres on whether and, if so, on when and how first employment takes place. By 'how' is here meant whether graduates decide to work exclusively or instead whether to work and to look for another job at the same time. EHA is therefore declined in the form of a series of independent multinomial trials, with first employment as a nonrepeatable event, with three specifications: i) as the exclusive activity, ii) as co- occurrent with additional investments in education or iii) with further job search. We thus adopt a competing risk model, competing risks being different events that may occur within the same risk period. The event occurrence is inherently conditional, since first employment after graduation can be experienced in month j only if never experienced before; each event is nonrepeatable, since it can occur only one time and, once it has occurred, neither itself nor others may occur again. Considering different strategies to first employment allows one to overtake a potential aggregation bias that arises with a single event (Yamaguchi, 1991).

Let T represent the discrete random variable (r.v.) that indicates the duration, i.e. time distance from origin to month j_i when a randomly selected graduate i from our population finds her/his first employment; then j_i denotes the month j when subject i experiments the event under study. In truth, j_i is observed only if the ith graduate finds a job before the end of the survey–the so-called truncation date t^*, otherwise her/his participation time is said to be right censored. To each graduate i it then corresponds a vector $\boldsymbol{c}$ specifying whether subject i is not right-censored:

$$c_{ii} = \begin{cases} 0 & j_i \le t^* \\ 1 & j_i > t^* \end{cases}$$

The censoring index c_{ij}, when unitary, indicates that the ith subject experienced no events, while it is null if any of the competing risks occurred before the last observation date t^*. With reference to the latter case, we can record the chronology of event occurrence, by means of dummy variables Y_{ij}, whose values y_{ij} are defined as:

$$y_{ij} = \begin{cases} 1 & j = j_i \\ 0 & j \neq j_i \end{cases}$$

The indicator y_{ij}, when unitary, means that subject i experienced the event in month j; therefore it is always equal to zero for a right-censored subject. For a non-censored subject, y_{ij} is null for all intervals prior to j_i and equal to one in j_i, when the event occurs for individual i. The two notations c_i and y_{ij} synthesise personal event histories.

Discrete-time hazard h^r_{ij} is defined as the conditional probability of the competing risk r of first employment in month j for a randomly selected graduate i, given that the event did not take place prior to month j. The hazard function models graduates' transitions out the state of looking for a job into the rth employment state above-mentioned, as a function of time j, j=1,2,.., J , being J the last period observed:

$$h^r_{ij} = P(T_i = j | T_i \geq j) \qquad r = 1,2,..R \tag{3.1}$$

The survivor function is then defined as the individual probability of experiencing the event after time j, given she/he experienced no events before j and it is equal to:

$$S_i(t) = \Pr(T \geq t) = \prod_{r=1}^{R} S_i^r(t) = \prod_{r=1}^{R}\left(\prod_{j;\, j<t}\left[1 - h^r_{ij}(j)\right]\right) \tag{3.2}$$

where:

$$S_i^r(t) = \Pr{}^r(T \geq t) = \prod_{j;\, j<t}\left[1 - h^r_{ij}(j)\right] \qquad r = 1,2,...,R \tag{3.3}$$

Hazard and survivor functions allow one to describe the time trend of specific risks. Their determination for discrete-time data refers to the so called actuarial or life table method. Let $y^r_{.j} = \Sigma_i y^r_{ij}$ be the number of subjects experiencing a target event in each interval and $c_j = \Sigma_i c_{ij}$ the number of censored subjects in the same interval. The rth risk rate in each interval j is then estimated by:

$$\hat{h}^r_j = \frac{y^r_{.j}}{n_{j-1} - \dfrac{y^r_{.j} + e_j}{2}} \qquad r = 1,2,...,R \tag{3.4}$$

where n_{j-1} is the number of individuals at risk[2] at the beginning of interval , e_j are losses to follow up in j and risk r is assumed constant within the interval. The

[2] From the assumption of uniform distribution of risk in each unitary interval, it follows that $y^r_{.j}$ are exposed to that risk on average only for one half of the interval. From a similar assumption of uniform distribution of losses to follow-up, drop-outs take place on average at the midpoint of each interval. Therefore, the quantity $(y^r_{.j}+e_j)/2$ is to be subtracted at the denominator of the risk rate from the number n_{j-1} of subjects at the beginning of the interval, because the exposure of subjects $(y^r_{.j}+e_j)$ is just half of each interval.

non parametric estimation of the risk and the survivor functions represent the traditional descriptive method in EHA, with established procedures for comparing survivor functions[3] (Blossfeld and Rohwer, 2002, Lawless, 2003).

After examining the general risk profile, covariates are commonly introduced. Their inclusion permits us to both estimate the effect of one covariate, holding the effect of all other covariates constant, and to make explicit systematic differences between people, in order to know what constitutes low-risk from high-risk individuals (Singer and Willett 1993, Yamaguchi 1991). This means assessing whether different types of individuals, distinguished by their values on specific predictors, correspond to different hazard functions (Crippa, 2004). Observed heterogeneity is therefore introduced by P predictors X_p (p=1,2,…,P), whose values may be constant or vary over time. Individual i's values for each of the P predictors in month j are denoted as vectors x_{ij}=[x_{1ij}, x_{21ij},…, x_{pij}]. Thus, equation (3.1) becomes:

$$h_{ij}^{r} = P\left(T_i = j \middle| T_i \geq j,\ X_{1ij} = x_{1ij}, X_{2ij} = x_{2ij}, ..., X_{Pij} = x_{Pij}\right) \qquad r = 1,2,..R \tag{3.5}$$

The functional form of the population hazard dependence, upon covariates and time periods in (3.5), can be hypothesized as logistic (Cox, 1972, Brown, 1975). Such a model has the advantage of factorizing into a baseline profile, when covariates are null (see (3.1)) and into shift parameters, expressing the effect of covariates on the baseline:

$$\ln\left(\frac{h_{ij}^{r}}{1-h_{ij}^{r}}\right) = \alpha' D_j + \beta_p' X_p \tag{3.6}$$

where:

α=[α_1 , α_2 ,.., α_J] is a vector of intercept parameters that capture the baseline level in each time period;

D_j=[D_{1ij} , D_{2ij} ,.., D_{Jij}] is a vector of dummy variables, J being the last period observed, with values [d_{1ij}, d_{2ij},.., d_{Jij}] indexing time periods, identically defined for everyone: d_{1ij}=1 for j=1 and d_{1ij}=0 otherwise, d_{2ij}=1 for j=2 and d_{2ij}=0 otherwise and so on;

β=[β_1 , β_2 ,.., β_J] is a vector of slope parameters expressing, on a logistic scale, the variation of the baseline function due to a unitary variation of the covariates;

X_p is a vector of covariates, accounting for all heterogeneity between individuals.

Expression (3.4) is the logit of the probability of experiencing the target event, given it has never been experienced before, for a given covariate vector. It postulates that a predictor has a linear effect on the hazard profile and that there is

[3] In particular, it is possible to compare two or more subgroups, defined by values of a covariate as measured on population such as gender, education level and alike, relying on specific test statistics, such as log-rank test, Wicoxon test, generalized Wilcoxon test, Wilconxon-Gehan test and alike.

no unobserved heterogeneity as above-mentioned. Besides, it assumes that the odds ratio of the occurrence of a target event over time is constant among groups with different covariates[4]. Equivalently, it implies that, for every individual in the population, at each time j the odds of experiencing the event are proportional to the odds of some individuals who represent the covariates baseline values. It therefore implies both that every covariate is time-independent[5] and that all possible logit-hazard profiles, generated by different values of covariates, share a common shape and are mutually parallel. This proportional-odd characteristics is referred to as the 'proportionality assumption' (Yamaguchi, 1991, Singer and Willet, 1993).

Maximum likelihood estimates[6] of the discrete-time hazard model (3.6) can be obtained using standard logit regression techniques; in the case of competing risks, a multinomial logistic regression model with covariates can be fitted, where multinomial responses are different risks of first employment as opposed to non employment or another given reference status (Allison, 1982, Yamaguchi, 1991).

4 Results

4.1 Postgraduate crossroads

Descriptive life table analysis highlights time patterns in the transition to the labour market[7]. Apart from cases of exclusive attendance to postgraduates studies and the like, a graduate's first job takes place mostly within the first year of search. In fact, less then 10% of health sciences majors are still looking for a job after twelve months, almost 20% in the case of engineering, economics or statistics majors and about 30% of humanities (Figure 1.a). These differences prove significant in tests for life tables comparisons, namely to Wilcoxon-Gehan statistics.

When they are determined to study further after graduation, subjects mostly opt to postpone their entry onto the job market instead of working while studying. The latter option, in effect, involves only 19,4% out of all postgraduate students

[4] As the width of time intervals diminishes, the ratio of two odds approaches the ratio of the corresponding rates and the model becomes a continuous-time proportional hazard model.

[5] Time varying covariates can be introduced by extending the model to a non proportional odds model.

[6] The likelihood function for the discrete-time hazard process is $L = \prod_i \prod_j \left(h_{ij}^r\right)^{c_i} \left(1 - h_{ij}^r\right)^{(1-c_i)}$

[7] Out of 3481 subjects, 394 found a job long before graduation, having some students enrolled at University while working. As a cut-off rule in determining this group, when joined more than twelve months prior to graduation, a job was regarded as extraneous to the University educational process. Therefore 394 subjects were excluded from the analyses of post graduate employment strategies.

and it varies according not only to subjects' majors, as above, but also to the parental level of education. Actually, family cultural background seems well synthesized by the mothers' educational level only. Firstly, homogamy - homogeneity of education levels- is prevalent, since it involves 66.8% of parental couples, being Spearman's Rho equal to 0.634, p<0.0001. Secondly, when schooling is heterogeneous across parents, life tables comparisons tend to be clearer with reference to mothers. The higher their education, the more young adults devote solely to their postgraduate studies and conversely, the lower their educational level, the more graduates' work at the same time as improving their educational qualifications (Figure 1.b).

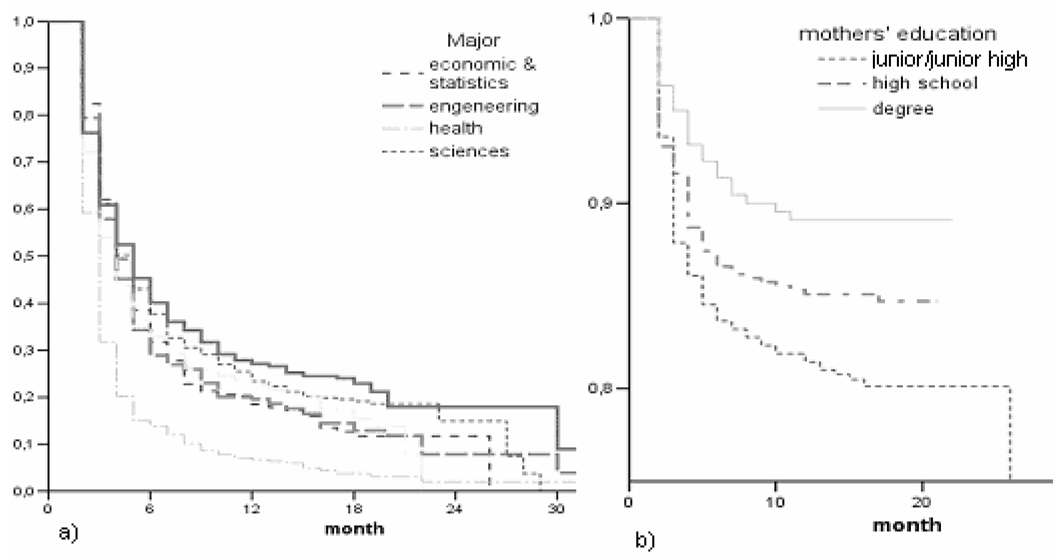

Figure 1: Survivor cumulative functions of entries in the labour market according respectively to a) majors b) mothers' level of education.

4.2 The long adolescence of the young adult: outdoor as indoor?

Although quite powerful for time trends identification, methods so far adopted become awkward when searching for explanations. Considering covariates in Wilcoxon-Gehan comparisons one by one, or even two by two, turns out no less than unproductive. As described in paragraph 2, EHA is to be considered a Generalized Linear Models (GLM), as it introduces time dimension in binary and multinomial logit regression (Allison, 1984; Yamagouchi, 1991). Discrete-time model regression in equation (3.6) is estimated via multinomial logit procedures as incorporated in current statistical software, such as SAS or SPSS (used both in our analysis), provided data are stored in the format required.. As a matter of fact, in typical person-oriented formats, each person in the sample has a single record of data. Prior to a multinomial logistic regression analyses, such a data set must be converted into a new one, where each record represents the person-'time unit', in our case, person-month, in order that each person has as many records as her/his months of observation (Allison, 1984; Yamagouchi, 1991; Singer and Willet, 1993). Henceforth, the dynamics of entries in the labour market is modelled as the dependent variable in a corresponding multinomial logit model, where covariates are time-invariant and separable in two sets. The first set includes personal traits and educational path: gender, months spent in looking for the present job, years spent at University for graduating, possible work experiences during studies. The second set consists of parental characteristics, such as level of education and professional activity. Just one variable, channels for job search, merges personal and family action, the latter being parents' acquaintances helpful in finding their children a job,.

Firstly, graduates' strategies of improving their qualifications, either at academic institutions or at other training sites, are taken into account, as a function of personal and parental human capital. Results of the multinomial model estimation show gender and previous work experiences as significant on the subjective side, mother's education on the familiar side (Table 2).

Table 2: Analysis of variance table and model fitting information for multinomial logit model on time patterns of qualifications improvement.

Effect[(a)]	-2 log likelihood for reduced model	Chi-square	df	Sig.
Intercept	1740.397	.000	0	.
month	2422.210	681.813	2	.000
gender	1843.833	103.436	2	.000
work as undergraduates	1789.282	48.885	2	.000
mother's education	1801.939	61.542	4	.000
Model	**-2 log likelihood**	**Chi-square**	**df**	**Sig.**
Final[(b)]	2285.394	821.974	14	.000

(a) Results refer to subjects, namely 1150 out of the 3481, that attend some kind of courses after graduation, for any working condition.
(b) Final model is tested against the one with the intercept only

Table 3: Parameters estimates for multinomial logit model on time patterns of qualifications improvement.

		β	Std error	Wald	df	Sig.	Odds ratio Exp(β)	95% confidence interval for Exp(β)	
								Lower limit	Upper limit
working while studying versus studying only	**Intercept**	-1.584	.140	127.101	1	.000			
	month	-.278	.013	444.143	1	.000	.757	.738	.777
	female	*.011*	*.087*	*.014*	*1*	*.904*	*1.011*	*.851*	*1.199*
	male	0	.	.	0	.	.	.	.
	not working while at college	-.607	.089	46.638	1	.000	.545	.458	.649
	working while at college	0	.	.	0	.	.	.	.
	mother: basic education	.685	.129	28.157	1	.000	1.983	1.540	2.554
	mother: high school	*.151*	*.135*	*1.248*	*1*	*.264*	*1.163*	*.892*	*1.516*
	mother: degree	0	.	.	0	.	.	.	.
looking for a job while studying versus studying only	**Intercept**	-2.303	.088	683.771	1	.000			
	month	*-.010*	*.005*	*3.337*	*1*	*.068*	*.990*	*.980*	*1.001*
	female	.579	.059	97.811	1	.000	1.784	1.591	2.001
	male	0	.	.	0	.	.	.	.
	not working while at college	*-.062*	*.054*	*1.290*	*1*	*.256*	*.940*	*.845*	*1.046*
	working while at college	0	.	.	0	.	.	.	.
	mother: basic education	-.248	.073	11.599	1	.001	.781	.677	.900
	mother: high school	-.197	.071	7.743	1	.005	.822	.715	.944
	mother: degree	0	.	.	0	.	.	.	.

(a) (.) implies that the antilog value is omitted because the corresponding parameter is non significant
(b) Results in italics are non significant

Focus is here on the probability of attending some kind of postgraduate courses respectively: a) as an exclusive activity, b) while working or c) while looking for a job. Assuming category a) as the reference, parameters estimation suggests an inertial attitude, since the option for working and studying at the same time after graduation tends to be related to the same behaviour before graduation. Former work experience at University doubles the propensity to work and study simultaneously with respect to subjects who never worked as undergraduate, as odds ratios[8] show (Table 3).

[8] In order to interpret parameters correctly in a logit model estimation, their antilog has to be computed. Then, the antilog of β parameters in Table 3 gives the odds ratio of the event under

Gender plays a decisive role in the option of looking for a job while improving one's qualifications, as young women have this propensity almost twice (precisely, 1.784) as much as their male colleagues. Parental background receives its share in this decisional process. When their mothers have a low education level, graduates have double the chance to work while studying than their colleagues whose mothers hold a degree, being the odds ratio equal to 1.984. Due to the homogamy phenomenon aforesaid, this implies that the more cultured are their parents, the greater the graduates' investment in further learning becomes, with driving forces on mothers' side.

Table 4: Analysis of variance table and model fitting information for multinomial logit model on job agreements**.**

Effect (a)	-2 log likelihood for the reduced model	Chi-square	df	Sig.
month	1470.554	247.960	2	.000
gender	1272.588	49.994	2	.000
father's education	1278.262	55.668	4	.000
work as undergraduates	1230.843	8.249	2	.016
Model	**-2 log likelihood**	**Chi-square**	**df**	**Sig.**
Final[(b)]	1343.885	443.420	7	.000

(a) Results refer to 1753 subjects in the labour force, while other 394 ones were discharge since they had already found a job more then a year before graduation

(b) Final model is tested against the one with the intercept only

Table 5: Parameters estimates table for multinomial logit model on time patterns of contractual job agreements in entering the labour market.

scrutiny for the specified covariate. In our case, Table 3 gives respectively the odds of working while studying, and the odds of looking for a job while studying, over the probability of studying exclusively.

		β	Std error	Wald	df	Sig.	Odds ratio Exp(β)	95% confidence interval for Exp(β) Lower limit	Upper limit
Fixed term vs open ended	**intercept**	1.039	0.106	96.624	1	0.000			
	month	0.079	0.008	106.021	1	0.000	1.082	1.066	1.098
	female	0.275	0.062	19.464	1	0.000	1.317	1.165	1.488
	male	0.000	.	.	0	.	.	.	.
	father: basic education	-0.610	0.103	35.241	1	0.000	0.543	0.444	0.664
	father: high school	-0.477	0.104	20.918	1	0.000	0.620	0.506	0.761
	father: degree	0.000	.	.	0	.	.	.	.
	not working while at college	-0.129	0.062	4.325	1	0.038	0.879	0.778	0.993
	working while at college	0.000	.	.	0	.	.	.	.
Self employed vs open ended	***intercept***	*0.150*	*0.142*	*1.122*	*1*	*0.289*			
	month	-0.049	0.015	11.213	1	0.001	0.952	0.925	0.980
	female	-0.253	0.092	7.564	1	0.006	0.776	0.648	0.930
	male	0.000	.	.	0	.	.	.	.
	father: basic education	-0.906	0.140	41.699	1	0.000	0.404	0.307	0.532
	father: high school	-0.545	0.139	15.421	1	0.000	0.580	0.442	0.761
	father: degree	0.000	.	.	0	.	.	.	.
	not working while at University	*0.070*	*0.093*	*0.575*	*1*	*0.448*	*1.073*	*0.895*	*1.286*
	working while at University	0.000	.	.	0	.	.	.	.

(a) (.) implies that the antilog value is omitted because the corresponding parameter is non significant

(b) Results in italics are non significant

Regardless of studies extension, when graduates resolve to enter the labour market, determinants in Table 1 can be appraised with respect to monthly probabilities of attaining respectively: a) open-ended contracts, b) fix-term contracts or instead of c) self-employment. Adopting category a) as the reference, estimation procedures once again establish as significant gender and undergraduate work experiences as personal resources, while fathers' education replaces mothers' one in familiar determinants (Table 4). Not surprisingly, this result reflects domestic course in self-employment as a family based phenomenon, with children joining family business or legal practice and the alike. When fathers' hold a degree, graduates opt for self-employment almost twice as much as graduates whose fathers are less educated (Table 5). The intersection of graduates' human capital with their family resources becomes visible in joining parents' professional activities, especially fathers' ones. Such intergenerational junctions are above all a male business, for women are less involved in self employment altogether. Instead, they are involved more often in fixed-term contracts rather than in open ended jobs, being the odds ratio equal to 1.37 with respect to men. Lack of employment stability should not necessarily be ascribed negative implications, though. The higher their fathers' education level, the more graduates accept contracts other than open ended ones. In particular, with a graduate father, employment instability is tolerated twice as much as in other cases (Table 5).

5 Conclusive remarks

As sketched by results above, suggestions are twofold. In the first place, the attitude of studying while working appears as constant in time, before and after graduation. Subjects who devote their efforts both to increase their qualifications and to keep their professional achievements in the job market, very often were working as undergraduates. In addition, far more often than their colleagues, they belong to the least cultured families. This behavioural inertia certainly reflects a cogent needs of self-sustainment and it appears as a strategy of upward mobility from one generation, less cultured, to the next, that rises in education at the cost of a more intense struggle. In the second place, the outcome of this mobility is not undifferentiated in terms of employment conditions, as it proves to be a function of parental background. Family influence, in fact, seems well synthesized by parents' education levels, with emphasis on the mothers' role in affecting the choice of postgraduate studies/training. The emphasis shifts to the fathers' role when comes to the options for job legal agreements. Higher levels of parents' education correspond, in effect, to more resolute investment in postgraduate qualifications and to specific forms of self employment.

Implications on intergenerational relations drawn so far could be understood further extending EHA to allow the inclusion of unobserved heterogeneity between graduates due to unobserved individual characteristics that are fixed in time, in a model also known as *shared frailty* model.

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