Job search and screening of university graduates

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ABSTRACT

This paper analyzes the school-to-work transition of graduates using survival analysis. Using the REFLEX data, we show for a sample of Spanish graduates form the year 2000, that only the explicitly observable characteristics of graduates serve to potential employers as screening devices, rendering the process of job search easier. All the implicit characteristics, though potentially productive, do not offer any help in the school-to-work transition. The argument is in line with the widely accepted theory of screening by Kenneth Arrow (Arrow 1973).

Keywords: job search, school-to-work transitions, screening, signaling

JEL codes: J23, J24, J64

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1. Introduction

The youth unemployment has occupied for long a central stage in economic research on labor markets (Freeman and Wise 1982). The recent economic crisis has brought it back to attention with a doubled force. Most of the European governments strive to address it either through labor market reforms or through promotion of entrepreneurship and self-employment (European Commission 2009). Even though the unemployment rates for the most skilled and educated workers in Europe (18% for EU-17) are far from those for their lowest skilled peers (over 30% in EU-17), it remains a primary issue in the public debate. In these picture the southern European countries are particularly badly situated.

The pre-crisis figures collected in 2004 present a preoccupying picture. Using OECD official statistics Quintini and Martin (2006) show that a share of unemployed youth with higher education was the highest in the southern Europe with combined inactivity and unemployment rates reaching 55% in Greece, over 45% in Italy and 35% in Spain.

One of the key features of labor market related to the youth unemployment is the school-to-work transition (van der Klaauw and van Vuuren 2010). The transition from education to work is troublesome, because workers' real productivity is not observable to the potential employers. The rapid educational expansion in the industrialized societies adds, yet more, to this opacity (Hanushek and Woessmann 2008). Therefore, it seems chiefly important to investigate the mechanisms of transition from education to work, which would help mitigate the difficulties for the youth. This paper brings new evidence on school-to-work transition through estimation of a duration model for Spain using the pre-crisis, nationally representative, data collected among university graduates in 2005. We show, that only the explicitly observable individual ascribed attributes are productive in the job search. Whatever ascribed characteristic of the worker that the potential employers cannot see through the screening process, does not affect the job search time of potential workers. This observation, however, does not refer to the effort that individuals exert, which can only partially be observed to the employers. Our results corroborate empirically the well known facts for information asymmetry in the labor market (van der Klaauw and van Vuuren 2010).

The economic theory posits that workers aiming to find a job need to demonstrate their future productivity to potential employers (Stigler 1962). The asymmetry in the information between the worker and the potential employer causes that the job search process is costly in time and effort (McCall

1970). Workers have to exert effort not only to search for offers but also to signalize their potential productivity to employers (Spence 1973). According to Spence, workers signalize their future productivity through their educational credentials. Arrow (1973), takes Spence's discussion further claiming that higher education credentials need not be homogeneous causing that workers may be chosen among, not only by their ordinal credentials, but also by more subtle signals related to college selectivity and prestige. Arrow's analysis opens further a way to job competition model by Thurow (1974). In Thurow's model, workers may be ordered in a queue through a statistical observation of the quality of their credentials and then assigned jobs from most demanding and best remunerated to least demanding and worst paid. These research commonly underlined the negative, thus involuntary, nature of youth unemployment and associates it with low education and, thus, low skill. However, developments in the matching models show that workers perceive job search through the prism of their reservation wages and exert effort accordingly (Pissarides 2000). Furthermore, workers may be assigned to jobs not only due to their educational credentials but also because of the proper nature of the job which may require some special skills difficult to observe in the unemployed population (Sattinger 1993).

Our approach builds on the findings the aforementioned research and adds controls for explicit and implicit signals of workers' productivity. This way we try to bridge the gap in the literature of school-to-work transitions regarding the statistical signaling and screening between workers and employers respectively (Arrow 1973; Spence 1973). Firstly, we introduce a set of standard educational credentials readily observable to employers such as fields of study and grade point average. While fields of study embody different human capital types (Arcidiacono et al. 2010; Freeman and Hirsch 2007; Robst 2007), the GPA surrogates the individual cognitive ability (Heckman et al. 2006). It is clear from this literature that some fields such as engineering or health lead typically to quick and good matches in the labor market (Biggeri et al. 2001; Brunello and Cappellari 2008; Salas-Velasco 2007). On the other hand, fields like humanities, education or services experience usually a difficult education-to-work transitions. We confirm that engineering and health as compared to social science speed up the transitions, while the opposite holds for education. All these results hold and are robust to our control of ability through the average grade at secondary education. Our findings corroborate earlier evidence on school-to-work transitions (Salas-Velasco 2007).

In the next step, we introduce the controls for the program types. Different program types, even within the same field, equip individuals with different sets of skills. For example, an entrepreneurial program type is aimed at enhancing individual soft skills such as creativity, extraversion, alertness and assertiveness (Kirzner 1999; Martin et al. 2013; Tang et al. 2012). On the other hand a demanding and, therefore, usually also academically prestigious, program will aim at shaping highly skilled professional with demonstrably high level of directly productive skills (Hanushek and Zhang 2009; Heckman and Kautz 2012).

In the following step, we introduce more subtle controls for modes of teaching at the university. These characteristics are assumed to be non-observable to employers and thus demonstrate the implicit nature of skills possessed by the graduates (Borghans et al. 2001). Results suggest that what is not observable to potential employers does not affect the speed of job search. None of the characteristics included in our models prove to, neither enhance, nor diminish the time of finding a job after graduation. In a recent paper, Lerman (2013) reviews the literature on skills formation through different learning types and, suggests that the evolution of demand for skills shifts the emphasis from typically academic, to more occupationally oriented skills. However, we hypothesize that due to information asymmetry (Stigler 1962) employers cannot directly observe these skills and may not take them into account while extending the job offers to unemployed individuals. Thus, the modes of teaching even though potentially productive in desired skills, remain not recognized by the demand side of the labor market.

Finally, the literature on school-to-work transition typically stresses the importance of effort exerted with the job search: the higher the effort the quicker the transition (Van der Klaauw et al. 2004). In order to control for effort exerted on job search we introduce controls for major job search methods (Addison and Portugal 2002). We do not observe directly the effort that individuals exert on job search. However, one could claim that direct methods of contacting the potential employer or referring to job advertisements require a much higher effort than do university placements, or friends and family referrals. Thus, while observing that direct methods of job search prove more productive than university placements or family referrals, we conclude from our results (though not without a word of caution), that more effort exerted by graduates shortens their time of unemployment after graduation significantly. At the same time DellaVigna and Paserman (2005) show that individuals, who are less patient, exert less effort in job search. Our results with respect to job search methods may then be understood, not only as a surrogate of job search effort, but also as a proxy of impatience in the process of job search. More patient individuals put more work into job search and, opt for direct methods of finding work, while their more impatient peers refer more to their social and institutional networks, and show less determination in their searches.

The remaining of the paper is organized as follows. The next section presents data and econometric methods applied in our analysis. The present paper is based on a REFLEX data collected in 2005 for university graduates from the year 2000 (Allen and Van der Velden 2009). Section 3 presents and discusses results in detail. Finally, the last section concludes the paper and provides policy implications.

2. Data and methods

We use the Research into Employment and professional FLEXibility (REFLEX) data. The REFLEX data is a cross-section survey of graduates interviewed in 2005 with information on their first jobs after graduation in 2000. The data contains contextually rich information on graduates' university education and their first jobs. Remarkably, there is information on the time elapsed between graduation and the first job for all graduates. This permits us to develop a duration model of job search presented in this paper. Furthermore, the data contains information on the method through which the first job after graduation was achieved. Another important factor is the richness of information about the studies. Not only do we know the field of study and average grade at the university, but also the teaching modes that dominated the studies. We can distinguish between conservative (lecture based) and vocational (practical) as well as problem based and expression based learning. Furthermore, we dispose of information about the internships and voluntary activities of graduates that took place during their studies. This information is very valuable for job search because it can be directly demonstrated to potential employers through the candidates' curriculum vitae.

We select for our analysis all graduates from Spain, who were not more than 34 years of age and, for whom we had information on all the variables of interest. The final sample consists of 1567 individuals.

[Insert Table 1 about here]

Table 1 presents variable definitions. We divide them into five major blocks. Firstly, there are basic individual characteristics with two implicit measures of effort. We distinguish between students who put extra effort for exams (either because they needed to or because they wanted to) and also we separate those who strived for the highest possible grades. These two variables are not observed by the potential employer but they demonstrate individual inert effort levels. In the next group, we present job search methods through which the job was achieved. We establish the "Public agency" as the reference category as we claim that it requires the least effort among all the methods. In the next step, we introduce fields of study with the Social science as the reference category, as it is the largest field in terms of numbers of graduates. Further, there are descriptions of teaching modes at the university and finally the program attributes. While the teaching modes are thought to be non-observable to potential employers, as they would require too much effort to learn about them, the university program attributes are a more diverse category. We believe that program attributes may be known to employers to some degree. It has been shown that such attributes play an important role in placements of college graduates (Brunello and Cappellari 2008).

[Insert Table 2 about here]

Table 2 presents the descriptive statistics for our sample. It is readily observable that the mean search time is 6.42 months. This figure coincides with earlier findings for Spain (Lassibille et al. 2001; Salas-Velasco 2007). The mean age of our graduates is 29 years of age and there are more women than men in our sample. Further, we can observe that the mean GPA from high school is 2.9 out of 5, with 0.915 standard deviation indicating an important variation of ability among the studied population.

Our dependent variable is *time of job search*. This means that we will use the duration models for our analysis. The duration analysis comes originally from biostatistics but has been expanding in economics during last decades. Duration models can now be found in birth studies (Newman and McCulloch 1984), child mortality studies (Wolpin 1984), strikes durations (Kennan 1985) among others. Apart from population economics, duration models have found a fertile ground in labor economics measuring the time of unemployment spells, job search behavior etc. Devine and Kiefer (1991) provide an extensive overview of the empirical literature on job search. A newer, but also more technical review of the relevant duration literature can be found in (Eckstein and van den Berg 2007). In view of this vast literature it is somewhat surprising that only few papers have looked at the school-to-work transition using survival analysis (Betts et al. 2000; Biggeri et al. 2001; Bradley and Nguyen 2004; Chuang 1999; Salas-Velasco 2007). Our model extends this literature introducing explicit and implicit controls relevant for the job search.

Let T denote time that elapses until an event occurs. The event in our case is finding a job and thus following the survival tradition it is considered a *failure*. We can define a *hazard function* $\lambda(t)$, which denotes the instantaneous probability of finding a job at time *t*, conditional on not having found a job before this time.

(1) $$\lambda(t) = \lim_{\Delta t \to \infty} \left\{ \frac{\Pr[t \le T < t + \Delta t \mid T \ge t}{\Delta t} \right\}$$

This hazard function does not depend on any parameters and is frequently described in the literature as a baseline hazard. The hazard function $\lambda(t)$ can be further extended to be conditional on other than just time *t* characteristics. In our case these are all the independent variables described above. These variables may, or may not have influence on the hazard function itself. If they do not influence we speak of proportional hazard models (PH). In the opposite case we have to estimate the accelerated failure-time models (AFT). The proportional hazard is much simpler than the accelerated failure time models as it can be factored into the baseline hazard (which is a function of time *t*, as before) and a function of parameters for other variables describing the individual characteristics.

(2) $$\lambda(t\,|\,\mathbf{X}) = \lambda_0(t)\phi(\mathbf{X},\boldsymbol{\beta})$$

If the hazard rates were proportional in our model we could specify the above functional form and estimate it through maximum likelihood to obtain the coefficients of the ***X*** covariates. The covariates included in the ***X*** vector, change the hazard rates of individuals proportionally to the baseline hazard. Let $S(t)$ denote the survival function. The survival function can be defined as a probability of time searching for a job be greater than *t*:

(3) $$S(t) = \mathrm{Pr}(T \geq t\,|\,\mathbf{X})$$

Figure 1 presents the survival time for the search of the first job in our sample. More than half of the sample finds their first job by fourth month. It can be observed that the survival probability by the fourth month declines to 50%. The descriptive statistics confirm that.
If our job search model followed the proportionality condition, then we should observe that survival estimates for the baseline hazard should be parallel for different levels of covariates in ***X***. It can be observed in Figures 2 and 3 that on average this is the case.

[Insert Figure 2 about here]

The survival rates by fields of study are in general proportional with small exceptions for field Services. Particularly, it can be observed that Social sciences, Health and welfare and Sciences keep parallel, thus reinforcing the proportionality assumption.

[Insert Figure 3 about here]

However, as the lines are not generally totally parallel and we need to test further the specification of the model for the proportionality assumption.
We use the Schoenfeld statistic of likelihood ratio in order to test the proportionality of hazards. The Schoenfeld test of proportionality of hazards proves however, that our preferred model type is from the family of proportional hazard models (Grambsch and Therneau 1994). The best model from this family in our case follows Weibull distribution: it has the lowest AIC statistic among the three proportional hazard models tested: Weibull, Gompertz and Exponential presented in Table 3.
Knowing that our model specification is a proportional hazard model, with Weibull baseline hazard, we can define the following hazard function:

$$\lambda(t\,|\,\mathbf{X}) = \gamma\alpha t^{\alpha-1} \quad (4)$$

And the survival function:

$$S(t\,|\,\mathbf{X}) = \exp\left(-\gamma t^{\alpha}\right) \quad (5)$$

Substituting $\gamma = \exp(\mathbf{X}'\boldsymbol{\beta})$ in (4) we obtain:

$$\lambda(t\,|\,\mathbf{X}) = \alpha t^{\alpha-1} \exp(\mathbf{X}'\boldsymbol{\beta}) \quad (6)$$

Which is the proportional hazard model with Weibull baseline hazard. It can be observed that the first component $\alpha t^{\alpha-1}$ in (6) is only time-dependent, while the second one $\exp(\mathbf{X}'\boldsymbol{\beta})$ depends entirely on covariates and not on time. This way for instance, one should expect as demonstrated in Figure 4, that individuals who attended university programs with different levels of entrepreneurial training should have different, but parallel, survival probability when it comes to job search.

[Insert Figure 4 about here]

It is clear from Figure 4 that individuals who attended programs with higher entrepreneurship component found their jobs significantly faster than their peers who attended non-entrepreneurial programs. Certainly, this is not a net effect of other variables included in the second component of (6). The next section presents results and discusses the precise effects of fields of study, university program attributes and modes of teaching on the time of search for the first job.

3. Results

Our modeling strategy follows the model building pattern, which allows us to check the net effects of explanatory variables on the dependent variable. Our dependent variable is the *time of search for the first job after graduation from university in the year 2000 in Spain*.

Table 3 contains comparisons of different types of models. Given that the Schoenfeld test does not reject the proportionality hypothesis we choose between the first three columns of the Table 3 according to the Akaike Information Criteria (AIC statistic). It is clear that the Weibull model has the lowest AIC statistic and is chosen as the preferred specification.

Next, we move to Table 4 where we test different model specifications with respect to the explanatory variables described at length in the previous section. All four models, depicted in Table 4 present a remarkably stable and coherent view.

Firstly, all models include basic individual statistics such as age, gender, GPA from the secondary education and methods of search for the first job. It is clear that being a woman and having studied *Licenciatura* decreases the likelihood (hazard) of finding a job quickly. High GPA at secondary education, which surrogates the unobserved ability (Arcidiacono 2004; Hanushek and Woessmann 2008) only weakly affects the likelihood of finding a job faster. On the other hand, having been a volunteer has a strong and positive effect on the speed of finding a first job. Among the search methods, the relatively effort-intensive direct contact and replying to advertisements show to speed up the school-to-work transition. In contrast to the earlier evidence (Ioannides and Loury 2004), social networks do not prove particularly productive and their impact, though positive is very limited in terms of search time.

In the following step we test different model specification in order to tackle possible correlation between the explanatory variable and test the model robustness to different specifications. In the first model, we include fields of study as further controls beyond the ones described until now. The second model excludes fields of study and includes the modes of teaching. The third model, test whether the university program attributes have a significant effect on the job search time. Finally, model 4 includes all the three groups of controls beyond the standard ones found in the job search literature.

Our results show that while Engineering proves to be the best field in terms of job search time, Education is the mirror reflection of it causing individuals significant hurdles when it comes to job search after graduation. Since fields of study are readily observable to employers, and their knowledge content is clearly defined they serve as a good screening device when searching for employees (Freeman and Hirsch 2007).

Model 2 considers the modes of teaching instead of fields of study. We exclude fields and while introducing the modes of teaching because some fields may be more prone to some particular types of teaching. One could argue, for instance, that Humanities would require much more expression based learning than Engineering. On the other hand practical learning would be common among engineers but not among graduates of Sciences. Also, the project-based learning could be relatively easily implemented in Social sciences and Engineering but it would be difficult in Health or Sciences. Notwithstanding, we also claim that the modes of teaching are very difficult to be observed by employers rendering them useless as a screening device. Our results confirm this view. Virtually no mode of teaching has any impact on the time of job search by university graduates in our sample. This goes in line with our argument that only the easily observable characteristics of the job candidates will be taken into account by the employers. Anything that would be costly to learn about will be discarded.
In the third model we introduce university program attributes and check their impact on the time of job search. It turns out that an entrepreneurial program, a program known to employers and a demanding program are the key characteristics when it comes to school-to-work transition of graduates. All these three attributes reduce significantly the time of job search. Entrepreneurial education has been shown to have a positive impact on individuals' alertness levels (Martin et al. 2013) rendering them more market aware and more aware of their human capital and skills, and hence, more able to look for jobs. The familiarity of employers with the program as well as the academic level of them have been shown to have a significantly positive effect on job search as well (Brunello and Cappellari 2008). The mechanism here is through previous graduates' creating what Simon and Warner (1992) call "old boys network". Even though our results suggest that the private networks do not prove the best job search methods it may well be, that employers draw their knowledge about the potential productivity about graduates from their experiences with the previous cohorts as suggested by Arrow (1973).
Finally, in Model 4 we introduce all three blocks of controls, and the results do not change. Also, this model is the preferred one by the AIC statistic. This way we show that only the explicitly observed characteristics of individuals, such as fields of study, program name that was known to employers and job search effort exerted through different search methods influence the speed of school-to-work transition. The implicit characteristics, though probably equally productive in the job market do not serve as a screening device to employers and have no impact on finding the first job. This observation has important policy implications which we depict in the concluding section.

4. Conclusions

This paper analyzes the school-to-work transition of graduates using a survival analysis. With use of the REFLEX data for a sample of 1576 graduates we obtain clear insight into what speeds up and what slows down the already difficult transition of youth in Spain. Our results suggest that only the signals that are explicitly readable to potential employers matter for the speed of the transition between university and the first jobs.

There are very few studies on school-to-work transitions that use the survival analysis. This methodology permits us to estimate consistently the impact of particular explanatory variables on the timing of obtaining the first job. Using the CHEERS data for 1990s, Salas-Velasco (2007) obtained the estimates of school-to-work transition of Spanish university graduates. However, his analysis though parsimonious does not offer further evidence than the one already known from the theoretical literature. We go a step further in our analysis, as we are able to establish a clear distinction between observable and non-observable characteristics of individuals in the screening process by the employers. Drawing on the insights from the screening model (Arrow 1973) and on the asymmetry of information in the labor market (Stigler 1962) we present an argument which says that whatever the employers cannot directly observe is not considered as a screening device and thus is directly discarded by the potential employers. We are able to establish this distinction by comparing observable program attributes (demanding, known to employers) with non-observable directly teaching modes. While the first ones affect the job search positively (even after controlling for various other characteristics such as fields of study and job search methods), the latter ones are completely unproductive in the job search after graduation. Young university graduates lack demonstrable skills and their potential productivity is unknown to employers. This situation creates frictions in the process of matching the individuals to jobs producing suboptimal results. It is, thus, of chief importance to clarify which are the characteristics that universities should enhance in order to achieve good insertion rates of their graduates in jobs and which of them could be safely downplayed without any loss for the school-to-work transition of graduates. Policies aimed at demonstrating how students learn may prove costly and largely ineffective. On the other hand, higher selectivity, more academic rigor and tighter links with successful alumni may prove very useful for the academic management in the battle for better insertion rates of their graduates in the job markets.

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Tables and figures

Table 1. Variables definitions

Variable	Description
Time of search for 1st job	Dependent variable: time to find the first job in months
Age	Age of the individual
Female	Female gender (vs. Male)
Grade secondary education	Grade Point Average (GPA) from secondary education
Long program	*Licenciatura* (4-year) program (vs. 3-year *Diplomatura*) university program
Worked extra for exams	Dummy variable based on a self-reported 5-level Likert scale variable asking if the individual worked extra time for exams at the university (implicit measure of inert effort)
Strived for grades	Dummy variable based on a self-reported 5-level Likert scale variable asking if the individual strived to obtain highest possible grades at the university (implicit measure of inert effort)
Volunteer	Individual served as a volunteer during the university studies
Internship	Participation in the internships (either found by the individual or organized by the university)
	Job search methods
Advertisements	Contacted the employer through advertisements (either online or in printed press)
Direct contact	Contacted the employer directly without explicit advertisement
Public agency	Obtained the job through a public agency (*Reference category*)
University placements	University obtained the job placement for the individual
Friends and family	Used private social networks to obtain the job
Other	Other non-descript job search method
	Fields of study
Education	Education studies (primary, special etc.)
Humanities	Humanities and arts
Social sciences	Social sciences, business and law (*Reference category*)
Sciences and maths	Science, mathematics and computing
Engineering	Engineering, construction and manufacturing
Agriculture & vet	Agriculture and veterinary
Health	Health and welfare studies
Services	Services (e.g. tourism, sports)

Modes of teaching at the university (self-reported 5-level Likert scale)	
Practical learning	Learning based mostly on practical assignments
Conservative learning	Learning based on master lectures, and home assignments
Expression-based learning	Learning mostly through assignments with written and/or oral presentations
Project-based learning	Learning through projects and case-studies

University program attributes (self-reported 5-level Likert scale)	
Entrepreneurial	University program was good for developing entrepreneurial skills
Demanding	University program was academically demanding
Employers familiar with it	Employers were familiar or very familiar with the university program
Free to choose path	Program was composed of modules which students had to choose on their own and construct their own study path
Prestigious	Academically prestigious university program
Vocational	University program was regarded academically prestigious
Broad	University program had a broad scope (as opposed to specific in focus).

Table 2. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Time of search for 1st job	1567	6,428	7,488	1	60
Age	1567	29,25	1,907	26	34
Female	1567	0,632	0,482	0	1
Grade secondary education	1567	2,922	0,915	1	5
Long program	1567	0,703	0,457	0	1
Worked extra for exams	1567	0,529	0,499	0	1
Strived for grades	1567	0,676	0,468	0	1
Volunteer	1567	0,093	0,290	0	1
Internship	1567	0,555	0,497	0	1
Advertisements	1567	0,272	0,445	0	1
Direct contact	1567	0,093	0,291	0	1
Public agency	1567	0,239	0,426	0	1
University placements	1567	0,105	0,306	0	1
Friends and family	1567	0,215	0,411	0	1
Other	1567	0,077	0,266	0	1
Education	1567	0,090	0,286	0	1
Humanities	1567	0,070	0,256	0	1
Social sciences	1567	0,340	0,474	0	1
Sciences and maths.	1567	0,147	0,355	0	1
Engineering	1567	0,169	0,375	0	1
Agriculture & vet	1567	0,044	0,205	0	1
Health	1567	0,133	0,340	0	1
Services	1567	0,006	0,076	0	1
Practical learning	1567	2,674	1,030	1	5
Conservative learning	1567	3,822	0,712	1	5
Expression-based learning	1567	2,696	0,967	1	5
Project-based learning	1567	2,491	0,809	1	5
Entrepreneurial	1567	2,736	1,201	1	5
Demanding	1567	0,598	0,490	0	1
Employers familiar with it	1567	0,412	0,492	0	1
Free to choose path	1567	0,302	0,459	0	1
Prestigious	1567	0,373	0,484	0	1
Vocational	1567	0,230	0,421	0	1
Broad	1567	0,530	0,499	0	1

Table 3. Proportional vs. non-proportional hazard model specifications

	Weibull	Gompertz	Exponent	Log-Normal	Log-Log	Gamma	Cox
Age of respondent	-0.015	-0.015	-0.015	0.024*	0.029*	0.025*	-0.013
	(0.016)	(0.014)	(0.015)	(0.014)	(0.016)	(0.014)	(0.013)
Female	-0.127*	-0.114**	-0.119*	0.106*	0.124**	0.094*	-0.113**
	(0.066)	(0.058)	(0.061)	(0.055)	(0.060)	(0.054)	(0.052)
Grade secondary education	0.061*	0.056*	0.057*	-0.053*	-0.066*	-0.047	0.051*
	(0.037)	(0.032)	(0.034)	(0.030)	(0.035)	(0.030)	(0.029)
Long program	-0.234***	-0.204***	-0.215***	0.152**	0.159**	0.126**	-0.179***
	(0.075)	(0.066)	(0.069)	(0.063)	(0.069)	(0.063)	(0.059)
Education	-0.551***	-0.480***	-0.507***	0.396***	0.451***	0.337***	-0.429***
	(0.117)	(0.103)	(0.108)	(0.113)	(0.125)	(0.120)	(0.093)
Humanities	-0.053	-0.026	-0.039	-0.074	-0.099	-0.098	-0.026
	(0.144)	(0.123)	(0.132)	(0.114)	(0.133)	(0.110)	(0.111)
Science & Maths	-0.164	-0.127	-0.143	0.009	-0.003	-0.027	-0.111
	(0.104)	(0.090)	(0.096)	(0.086)	(0.097)	(0.085)	(0.081)
Engineering	0.405***	0.359***	0.374***	-0.336***	-0.343***	-0.319***	0.317***
	(0.096)	(0.084)	(0.088)	(0.078)	(0.085)	(0.076)	(0.076)
Agriculture & Vet	0.027	0.019	0.023	-0.002	0.037	0.000	0.014
	(0.137)	(0.119)	(0.125)	(0.116)	(0.122)	(0.117)	(0.107)
Health	-0.157	-0.124	-0.135	-0.036	-0.080	-0.086	-0.101
	(0.112)	(0.100)	(0.104)	(0.097)	(0.108)	(0.095)	(0.090)
Services	0.185	0.181	0.180	-0.284	-0.353	-0.291	0.171
	(0.400)	(0.358)	(0.371)	(0.323)	(0.340)	(0.298)	(0.322)
Entrepreneurial program	0.094***	0.083***	0.087***	-0.081***	-0.089***	-0.076***	0.073***
	(0.026)	(0.023)	(0.024)	(0.022)	(0.025)	(0.021)	(0.020)
Demanding	0.230***	0.204***	0.211***	-0.134**	-0.148**	-0.103*	0.179***
	(0.069)	(0.060)	(0.063)	(0.058)	(0.067)	(0.059)	(0.054)
Employers familiar with it	0.147**	0.133**	0.138**	-0.148***	-0.173***	-0.144***	0.118**
	(0.062)	(0.054)	(0.057)	(0.051)	(0.058)	(0.050)	(0.048)
Free to choose path	0.060	0.049	0.054	-0.028	-0.032	-0.016	0.042
	(0.066)	(0.058)	(0.061)	(0.054)	(0.061)	(0.053)	(0.052)
Prestigious program	-0.037	-0.021	-0.030	-0.027	-0.042	-0.042	-0.018
	(0.073)	(0.063)	(0.067)	(0.060)	(0.067)	(0.058)	(0.057)
Vocationally oriented	-0.157*	-0.130*	-0.140*	0.064	0.055	0.045	-0.106*
	(0.081)	(0.070)	(0.074)	(0.064)	(0.071)	(0.062)	(0.063)
Broadly oriented	-0.007	-0.011	-0.008	-0.004	0.009	-0.017	-0.008
	(0.062)	(0.054)	(0.057)	(0.053)	(0.058)	(0.052)	(0.049)
Practical learning	0.015	0.008	0.011	0.019	0.035	0.023	0.006
	(0.039)	(0.034)	(0.036)	(0.034)	(0.039)	(0.033)	(0.031)
Conservative learning	-0.037	-0.029	-0.031	-0.004	-0.005	-0.013	-0.024
	(0.038)	(0.034)	(0.035)	(0.035)	(0.040)	(0.035)	(0.030)
Expression-based learning	0.002	0.005	0.003	-0.022	-0.027	-0.027	0.003
	(0.040)	(0.035)	(0.037)	(0.035)	(0.040)	(0.035)	(0.032)
Projects-based learning	0.034	0.024	0.028	0.016	0.018	0.030	0.021
	(0.051)	(0.044)	(0.047)	(0.043)	(0.048)	(0.043)	(0.040)
Worked extra for exams	0.002	0.004	0.003	-0.017	-0.011	-0.020	0.007
	(0.067)	(0.058)	(0.061)	(0.055)	(0.061)	(0.054)	(0.052)
Strived for grades	0.003	-0.003	-0.001	0.055	0.070	0.068	-0.000
	(0.068)	(0.060)	(0.063)	(0.060)	(0.066)	(0.059)	(0.054)

Volunteer	0.319***	0.269***	0.287***	-0.175**	-0.166*	-0.145*	0.231***
	(0.087)	(0.078)	(0.081)	(0.078)	(0.086)	(0.077)	(0.071)
Internship	0.029	0.026	0.027	-0.027	-0.032	-0.025	0.022
	(0.069)	(0.060)	(0.064)	(0.057)	(0.062)	(0.056)	(0.054)
Constant	-1.899***	-1.640***	-1.711***	1.016**	0.891*	0.851*	
	(0.536)	(0.471)	(0.494)	(0.475)	(0.532)	(0.472)	
ln_p							
Constant	0.075***						
	(0.017)						
gamma							
Constant		-0.008**					
		(0.003)					
ln_sig							
Constant				-0.042***		-0.059***	
				(0.014)		(0.015)	
ln_gam							
Constant					-0.570***		
					(0.016)		
kappa							
Constant						-0.290***	
						(0.087)	
Observations	1567	1567	1567	1567	1567	1567	1567
AIC	4583.1	4593.7	4596.5	4364.6	4452.6	4355.6	20137.8
BIC	4733.1	4743.7	4741.2	4514.6	4602.6	4511.0	20277.1

Table 4. Proportional hazard models with Weibull distribution

	Model 1	Model 2	Model 3	Model 4
Age of respondent	-0.005	0.009	-0.004	-0.013
	(0.017)	(0.016)	(0.017)	(0.017)
Female	-0.172***	-0.234***	-0.231***	-0.175***
	(0.063)	(0.062)	(0.062)	(0.064)
Grade secondary education	0.074**	0.106***	0.114***	0.087**
	(0.036)	(0.037)	(0.038)	(0.037)
Long program	-0.157**	-0.184***	-0.225***	-0.172**
	(0.077)	(0.069)	(0.067)	(0.078)
Worked extra for exams	0.039	0.054	0.006	-0.008
	(0.064)	(0.063)	(0.066)	(0.066)
Strived for grades	0.026	0.004	-0.036	0.001
	(0.068)	(0.067)	(0.068)	(0.068)
Volunteer	0.222**	0.187*	0.160	0.207**
	(0.100)	(0.102)	(0.103)	(0.097)
Internship	0.063	0.010	0.042	0.059
	(0.068)	(0.070)	(0.064)	(0.069)
Advertisements	0.234**	0.296***	0.263***	0.225**
	(0.106)	(0.109)	(0.101)	(0.101)
Direct contact	0.298***	0.335***	0.295***	0.284***
	(0.103)	(0.104)	(0.101)	(0.098)
University placements	0.217*	0.276**	0.249**	0.182
	(0.117)	(0.124)	(0.114)	(0.112)
Friends & family	0.194*	0.227**	0.207*	0.183*
	(0.109)	(0.112)	(0.108)	(0.105)
Other	-0.738***	-0.736***	-0.821***	-0.793***
	(0.126)	(0.123)	(0.122)	(0.126)
Education	-0.346***			-0.338***
	(0.122)			(0.124)
Humanities	0.015			0.033
	(0.124)			(0.125)
Science & Maths	-0.156			-0.195*
	(0.105)			(0.106)
Engineering	0.409***			0.316***
	(0.093)			(0.099)
Agriculture & Vet	0.097			0.074
	(0.122)			(0.132)
Health	0.176			0.064
	(0.109)			(0.116)
Services	0.036			0.072
	(0.462)			(0.440)
Practical learning		0.034		0.009
		(0.038)		(0.040)
Conservative learning		-0.011		-0.029
		(0.038)		(0.039)
Expression-based learning		-0.061		-0.006
		(0.039)		(0.040)
Projects-based learning		0.083*		0.021
		(0.047)		(0.050)

Entrepreneurial program			0.106***	0.104***
			(0.026)	(0.026)
Demanding			0.217***	0.203***
			(0.065)	(0.067)
Employers familiar with it			0.184***	0.166***
			(0.061)	(0.061)
Free to choose path			0.085	0.057
			(0.062)	(0.064)
Prestigious program			0.095	0.037
			(0.075)	(0.074)
Vocationally oriented			-0.105	-0.118
			(0.074)	(0.076)
Broadly oriented			-0.048	-0.041
			(0.064)	(0.063)
Constant	-2.137***	-2.597***	-2.591***	-2.279***
	(0.530)	(0.549)	(0.512)	(0.553)
ln_p				
Constant	0.094***	0.075***	0.097***	0.116***
	(0.018)	(0.019)	(0.019)	(0.018)
Observations	1567	1567	1567	1567
AIC	4505.8	4551.6	4492.0	4468.8
BIC	4623.6	4653.4	4609.9	4645.6

Figure 1. Time to find the first job (survival time, KM estimates)

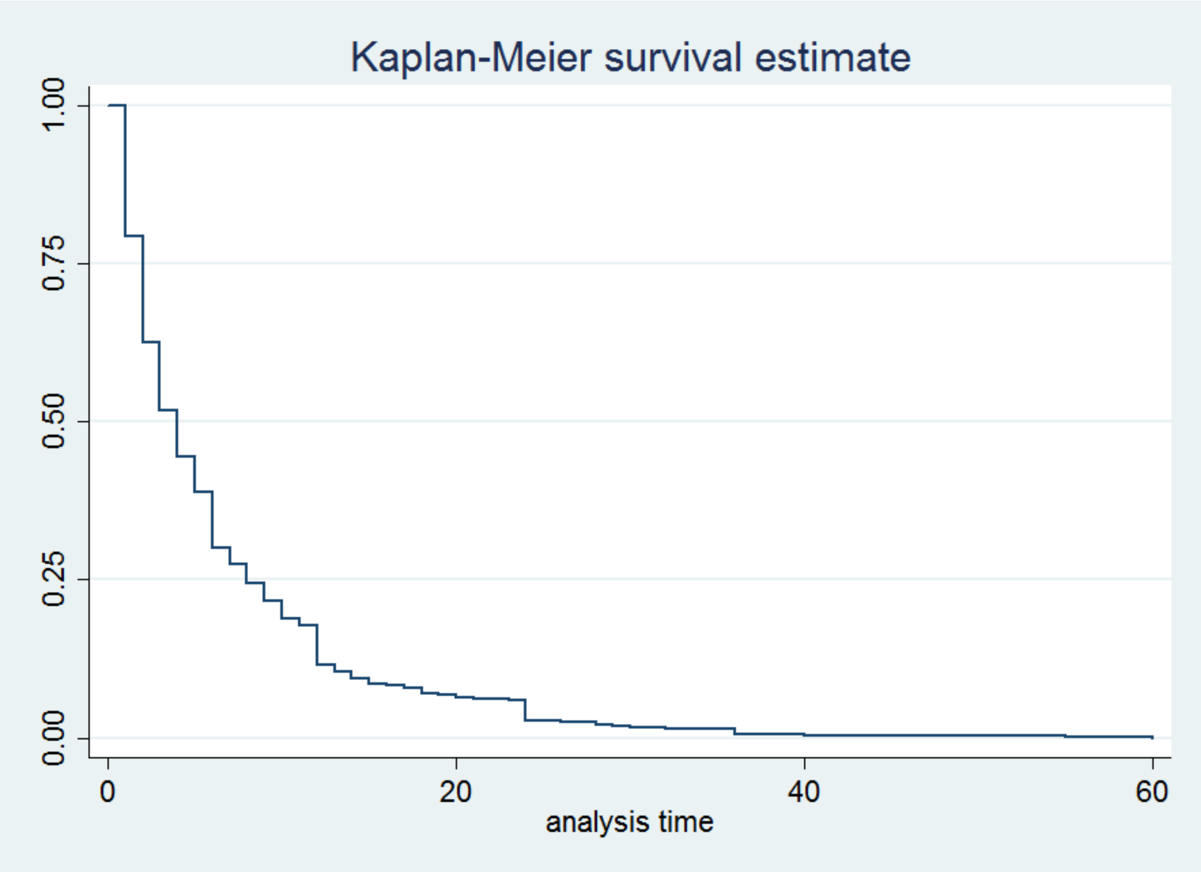

Figure 2. Time to find the first job by field of studies (survival time, KM estimates)

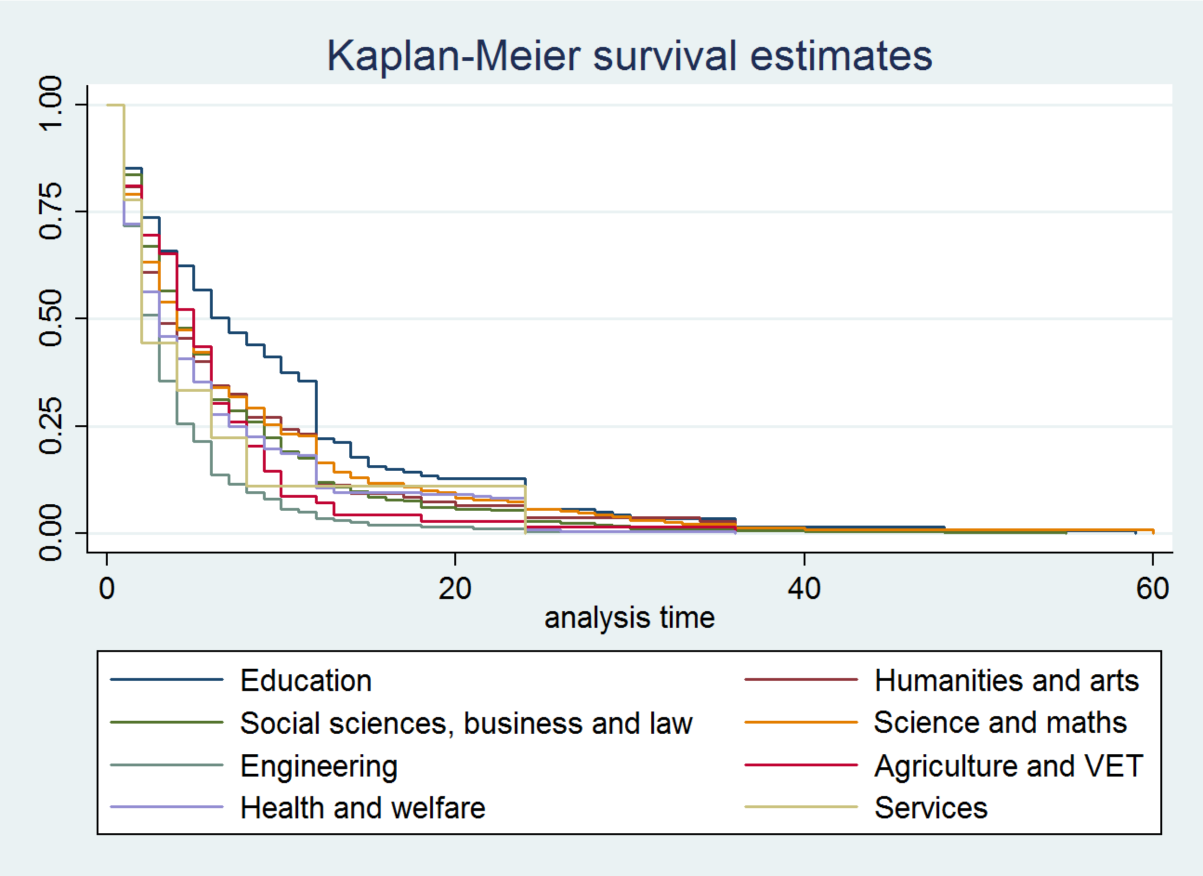

Figure 3. Time to find the first job by job search method (survival time, KM estimates)

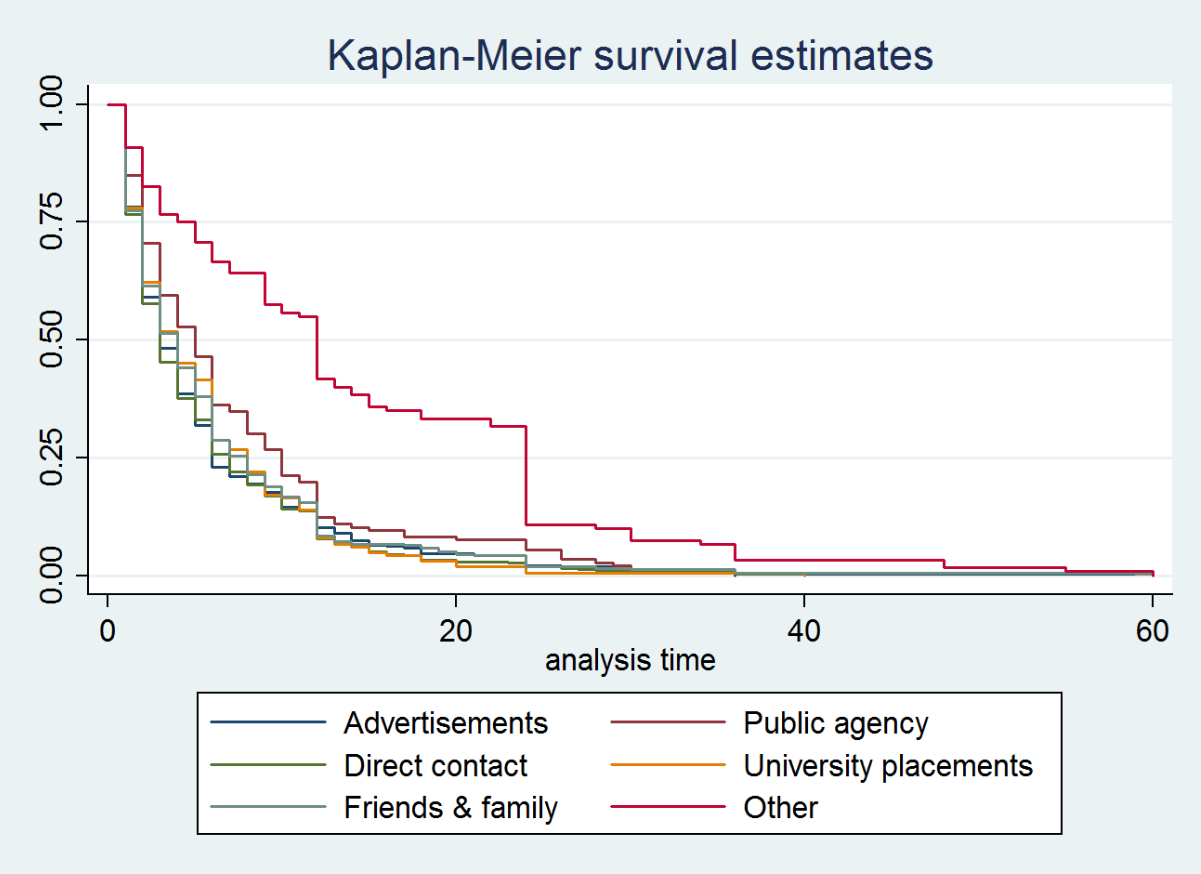

Figure 4. Time to find the first job by level of entrepreneurial university program (survival time, KM estimates)