WORKING PAPER 08-10

WP

Paolo Buonanno and Dario Pozzoli

Early Labour Market Returns to College Subjects

Department of Economics

ISBN 9788778823274 (print)
ISBN 9788778823281 (online)

Early Labour Market Returns to College Subjects

Paolo Buonanno[*]

University of Bergamo

Dario Pozzoli[†]

University of Aarhus

Abstract

This paper aims at estimating early labour market outcomes of Italian university graduates across college subjects. We devote great attention to endogenous selection issues using alternative methods to control for potential self-selection associated with the choice of the degree subject in order to unravel the causal link between college major and subsequent outcomes in the labour market. Our results suggest that "quantitative" fields (i.e. Sciences, Engineering and Economics) increase not only the speed of transition into the first job and employment probability but also early earnings, conditional on employment.

JEL classification: C34; J24; I21

Keywords: University to work transition; College subject; Self-selection; Returns to education.

[*] *Corresponding Author*. Address: Dipartimento di Scienze Economiche, Università degli Studi di Bergamo, Via dei Caniana 2, 24127 Bergamo, Italy. *Email*: paolo.buonanno@unibg.it. Usual disclaimers apply.

[†] Address: Aarhus School of Business, Department of Economics, Prismet, Silkeborgvej 2, DK 8000 Aarhus C, Denmark. Email: dpozzoli@asb.dk

1. Introduction

"…While sending your child to Harvard appears to be a good investment, sending him to your local state university to major in Engineering, to take lots of math, and preferably to attain a high GPA, is even a better private investment" (James et al., 1989, p. 252).

Over the last 40 years, a large body of research has focussed on the economic returns to higher education. However, the vast majority of these studies estimate the average return to education without controlling for the degree subject.

A number of previous works both for the US and for the UK (Daymont and Andrisani, 1984; Berger, 1988; James et al., 1989; Grogger and Eide, 1995; Loury and Garman, 1995; Loury, 1997; Blundell et al., 2000) document the large differences in earnings across fields of study, but none of these papers model the choice of college subject taking into account the issue of self-selection.

Recently, Arcidiacono (2004), developing a dynamic model of college and major choice that allows to control for selection shows that large earnings differences exist across majors. Similarly, Bratti and Mancini (2003) focus on the early occupational earnings of young UK graduates by adopting different methodological approaches and estimate the wage *premia* across different college subjects.

The aim of this paper is to investigate the differences in early labour market outcomes (i.e. the time to get the first job, employment probability and log hourly earnings three years after graduation) between Italian university graduates across college major using alternative methods to control for potential self-selection associated with the choice of the degree subject.

We consider a multiple treatment model, which distinguishes the impact of the different university groups, thus allowing the attainment of different educational qualifications to have separate effects.

We devote great attention to endogenous selection issues in order to unravel the casual link between field of study and subsequent outcomes in the labour market, using both matching methods (Rosenbaum and Rubin, 1983; Abadie and Imbens, 2006a) and the polychotomous selectivity model (Lee, 1983) to account for the existence of unobserved heterogeneity.

For our empirical analysis, we use two waves (2001 and 2004) of the Graduates' Employment Survey (GES) conducted by the Italian National Statistical Institute (ISTAT) three years after graduation.

The economic returns for Italian university graduates have been extensively investigated in Italian empirical works (Biggeri et al., 2000; Boero et al., 2004; Makovec, 2005; Brunello and Cappellari, 2007). However, none of the previous studies have explicitly modelled the choice of college subject taking into account the issue of self-selection.[3]

Our results suggest that "quantitative" fields (i.e. Sciences, Engineering and Economics) increase not only the speed of transition into the first job and employment probability but also early earnings, conditional on employment. Graduates in Humanities and Social Sciences are always the most disadvantaged in terms of employment probability and they generally have a negative earning *premium* with respect to graduates from the other subjects.

The rest of the paper proceeds as follows. Section 2 describes the empirical methodology. Data as well as model specification are presented in Section 3. Section 4 provides the empirical results and estimates the *premia* for different college subjects. Section 5 concludes.

[3] Ballarino and Bratti (2006) represent a notable exception, even if they focus on the effect of different fields of study in the university to work transition.

2. Empirical Methodology

In this section, we present the econometric methodology used to estimate the labour market returns to university degree across college subjects. We consider the effect of a multiple treatment, namely college major, on log of time to the first job, employment probability and log hourly wages.

We estimate labour market *premia* comparing labour market outcomes for individuals who graduated in one subject with "matched" individuals who graduated in a different major. This approach considers the college major as the treatment that the individual receives and aims at assessing the effect of this treatment on the outcome variables.

The general matching method is a non-parametric approach to the problem of identifying the treatment impact on outcomes. To recover the average treatment effect on the treated (ATT), the matching method tries to mimic *ex-post* an experiment by choosing a comparison group between the non-treated such that the selected group is as similar as possible to the treatment group in terms of their observable characteristics. Under the matching assumption, all the outcome-relevant differences between treated and non-treated individuals are captured in their observable attributes, the only remaining difference between the two groups being their treatment status. The central issue in the matching method is the choice of the appropriate matching variables.

Following Lechner (2001), the multiple evaluation problem can be presented as follows.[4]

Consider participation in (M+1) mutually exclusive treatments, denoted by an assignment indicator $D \in (1,\ldots,M)$. In our case, we assume that an individual can choose among five different alternatives $D \in (1,\ldots,5)$, which are: (1) Sciences, (2) Engineering,

[4] For a complete description of the methodology used in our paper, we refer to Lechner (2001).

(3) Economics, (4) Social Sciences and (5) Humanities.[5] X denotes the set of variables unaffected by treatments, while the outcome variables are denoted by ($Y^0,\dots,Y^M$). Each individual receives exactly one of the treatments, therefore for any participants only one component of ($Y^0,\dots,Y^M$) can be observed in the data. The remaining M outcomes represent counterfactuals. The number of observations in the population is N, such that $N = \sum_{m=0}^{M} N^m$, where N^m is the number of participants in treatment m. The focus is on a pair-wise comparison of the effects of treatment m and l, for all combinations of m, l $\in$ (0,1,…,M), m≠l. More formally, the outcome of interest in this study is presented by the following equation:

$$\theta_0^{ml} = E(Y^m - Y^l \mid D = m) = E(Y^m \mid D = m) - E(Y^l \mid D = m) \qquad (2.1)$$

θ_0^{ml} in equation (2.1) denotes the expected average treatment effect of treatment m relative to treatment l for participants in treatment m (sample size N^m).

The evaluation problem is a problem of missing data: one cannot observe the counterfactual $E(Y^l|D=m)$ for m≠l since it is impossible to observe the same individual in several states at the same time. Thus, the true causal effect of a treatment m relative to treatment l can never be identified. However, the average causal effect described by equation (2.1) can be identified under the conditional independence assumption (CIA).[6]

Moreover, for the average treatment effect to be identified, the probability of treatment m has to be strictly between zero and one,[7] i.e.

$$0<P^m(X)<1, \text{ where } P^m(x)=E[P(D=m \mid X=x)],\ \forall\ m=0,1,\dots,M \ (2.2)$$

[5] We present the composition of each university group in the following section.
[6] CIA states that all differences affecting the selection between the groups of participants in treatment m and treatment l are captured by observable characteristics X. In the multiple case as presented in this paper, the CIA is formalised as follows $(Y^0,\dots\dots, Y^M) \perp D \mid X=x,\ \forall\, x \in X$.
[7] This is also known as the common or overlap condition. Depending on the sample in use, this can be quite a strong requirement and the estimated treatment effect has then to be redefined as the mean treatment effect for those treated falling within the common support.

which prevents X from being perfect predictors of treatment status, guaranteeing that all treated individuals have a counterpart in the non-treated population for the set of X values over which we seek to make a comparison.

As discussed in Lechner (2001), the balancing score property, suggested by Rosenbaum and Rubin (1983) for the binary case, holds for multiple case as well:

$$(Y^0,\dots,Y^M) \perp D \mid X=x,\ \forall x \in X \text{ if } (Y^0,\dots,Y^M) \perp D \mid b(X)=b(x),\ \forall x \in X \qquad (2.3)$$

The main advantage of the balancing score property is the decrease in dimensionality: instead of conditioning on all the observable covariates, it is sufficient to condition on some function of the covariates. In the case of multiple treatments, a potential and quite intuitive balancing score is the M-dimensional vector of propensity scores $[P^0(x), P^1(x),\dots,P^M(x)]$.

To identify and estimate θ_0^{ml}, first of all we identify and estimate $E(Y^m|D=m)$ by the sample mean. The conditional independence assumption implies that the latter part of equation (2.3), $E(Y^l|D=m)$, is identified in large enough samples as:

$$E[\, E(Y^l \mid b(X), D=m) \mid D=m] = E(Y^l \mid D=m) \qquad (2.4)$$

To estimate (2.4), Imbens (2000) and Lechner (2001) show that instead of M-dimensional balancing score, the dimension of the conditioning set can be reduced to $[P^m(x), P^l(x)]$. Thus,

$$E(Y^l \mid D=m) = E[\, E(Y^l \mid P^m(X), P^l(X), D=l) \mid D=m] \qquad (2.5)$$

We decide to model this choice using a multinomial logit model. The probability that an individual i, with the set of characteristics X_i, chooses the subject m is given by the following expression:

$$\Pr(D_i = m) = \frac{\exp(X_i\eta_m)}{\sum_{l=0}^{4}\exp(X_i\eta_l)} \qquad (2.6)$$

where X_i includes pre-treatment variables: family background characteristics (parents' education, father's occupation), high school final mark, high school type, age, region of residence, survey year, compulsory military service before university and whether the individual transfers into another region to attend university.

3. Data Description and Model Specification

Our data originate from the 2001 and 2004 waves of the Graduates' Employment Survey (GES) conducted by the Italian National Statistical Institute. The sample, consisting of approximately 5 percent of the population of Italian university graduates, is representative of students who got their college degree in 1998 and 2001.[8] The surveys collect a wide range of information on academic curriculum, post-graduate labour market experiences, personal characteristics and family background for a representative sample of 46,850 Italian university graduates. The data allows in particular tracking the whole educational history of each individual and provides a full description of academic and labour market performance during the three years after their graduation.[9]

The list and the definition of the variables, together with summary statistics, are presented in Table 1. The university groups have been classified into 5 main categories: Sciences (Chemistry, Physics, Geology, Biology, Pharmacy, IT and Mathematics); Engineering (including Architecture); Economics (including Statistics and Business);

[8] Response rate in both surveys is around 60%.
[9] For the present analysis, the sample of 46,850 records has been reduced by eliminating those: i) who were employed and started their job while at university, since their post-graduation experiences might not be comparable with those of the rest of the sample; ii) for whom information on earnings is missing; iii) who graduated from Medicine and physical training. The resulting sample size is 34,089 high school leavers, of whom 26,442 participate to the labour market and 20,602 are full-time employed three years after graduation.

Social Sciences (Sociology, Political Sciences, and Law) and Humanities (Philosophy, Literature, Languages, Education, Psychology).[10]

As far as model specification is concerned, we present the set of socio-demographic and education variables used in our analysis. It is important to note that all the matching variables included in the selection equation (2.6) are variables that are unaffected by college choice enrolment, because fixed over time or measured before enrolment at university.

In our empirical analysis, we exploit the following information contained in the surveys. Individual characteristics include sex, age, region of university,[11] if the individual transfers into another region to attend university and whether the individual did the compulsory military service before college. Indicators of past educational choices and performance are the high school type (with the breakdown in Scientific general high school, Humanities general high school, Vocational high school, Other high schools[12]), the high school final mark and the interaction of high school type with high school final mark. Family background variables include both parents' education[13] (with a breakdown in university, high school and primary school) and fathers' occupation (with a breakdown in entrepreneur, professional, manager, high skilled and low skilled white collar, blue collar, other independent and no qualifications).

[10] Due to the complexity of the model and the number of parameters to be estimated, we were not able to consider a finer definition of college majors. A similar level of aggregation is used in most of the studies reviewed in the previous section (Berger, 1988; Rochat and Demeulemeester, 2001; Bratti and Mancini, 2003; Arcidiacono, 2004).

[11] Makovec (2005) and Brunello and Cappellari (2007) document that the percentage of individuals who do not move to attend university is close to three quarters of the population of graduates. For instance, 71% of our sample did not move to attend college. Hence we can consider the region of university as a good proxy for the region of residence before enrolling at university.

[12] The classification of high schools used in the analysis is in particular the following: scientific general high school (liceo scientifico); humanities general high school (liceo classico); vocational high school (istituti tecnici e professionali); other high schools (istituti magistrali, liceo artistico, istituto d'arte; altra maturità.

[13] We decide to model in this way the parental education to capture the main interaction effects due to the assortative mating behaviour (Behrman and Rosenzweig, 2002).

Table 2 presents graduates distribution according to college major and shows that the (weighted) sample provides a very good representation of the population. Graduates from Sciences and Engineering represent 15% and 18% of the whole sample respectively, while graduates from Humanities and Social Sciences constitute approximately 23%. Finally, Economics graduates represent 20%.

Table 3 reports the distribution of graduates by high school final mark (an indicator of students' performance and ability). Nearly 30% and 25%, respectively, of students with high grades (above 56/60) in high school got a degree in Engineering and in Economics; while those students who performed low grades (below 40) instead are less likely to graduate from this field of study (only 9%). Table 4 presents the distribution of graduates by high school type: 50% and 37% of Economics and Engineering graduates got scientific general high school degree; while most of the students from Humanities and Social Sciences come from humanities general high school (30%).

We conduct our empirical analysis for three different labour market outcome variables. For those who declare to participate to the labour market at the date of the survey, we analyse the time to get the first job and the full-time employment probability. [14] For those who are full-time employed at the date of the survey, we look at the net hourly earnings. [15]

Wages are available for approximately 23,000 individuals and their distribution is presented in Figure 1.[16] From Table 5, that shows the average wage by university groups, it clearly emerges that the average outcome measure is highest for graduates in Engineering and Economics. Table 5 also reports the distribution of the time to get the first job and employment rates by college major. On the one hand, most of graduates from Engineering

[14] The latter is grouped in quarters, because the survey indicates only the quarter of graduation and not its precise month.
[15] It is important to note that in the 2001 survey the earnings are available only in a interval-censored form. We obtain the continuous variable through the interval regression model (see Stewart, 1983; Bryson, 2002).
[16] We dropped from the original sample the extreme observations of the monthly earnings and of the hours worked per week (those lower than 1th percentile of the earnings/hours distributions and those higher than 99th percentile). The log hourly earnings are available for 20,600 individuals.

and Economics find their first job after 7 or 8 quarters and 80% of them are full-time employed by the date of the survey. On the other hand, it is interesting to see that graduates from Humanities find their first job after almost 10 quarters and only 60% of them are full-time employed three years after graduation.

4. Empirical Results

This section provides the results from estimating the labour market *premia* by college majors. In the first subsection, we discuss balancing score property, the average treatment effect on the treated is shown in subsection 4.2, while subsection 4.3 presents the robustness of our findings to different methodologies.

4.1 Matching

In the pair-wise matching, each individual in the treated sub-sample *m* is matched with a comparison in the sub-sample *l*, and the criteria for finding the nearest possible match is to minimise the Mahalanobis distance of $[P^m(X), P^l(X)]$ between the two units. Matching is done with replacement, i.e. each comparison unit may be used more than once given that it is the nearest match for several treated units. The covariance matrix for the estimates of the average effects, suggested and presented by Lechner (2002), pays regard to the risk of over-using some of the comparison unit: the more times each comparison is used, the larger the standard error of the estimated average effect. For the estimated ATT the following formula applies:

$$Var(ATT) = \frac{1}{\overline{N}_m} Var\left(Y^m \mid D = m\right) + \frac{\left(\sum_{j \in I_0} \left(w_j\right)^2\right)}{\left(\overline{N}_m\right)^2} Var\left(Y^l \mid D = l\right)$$

where $\overline{N}_m$ is the number of matched treated individuals, w_j is the number of times individual j, from the control group and falling in the common support I_0, has been used. This takes into account that matching is performed with replacement. If no unit is matched more than once, the formula coincides with the "usual" variance formula. By using this formula to estimate the variance of the treatment effect at time t, we assume independent and fixed weights. We assume homoscedasticity of the variance of the outcome variables within treatment and control groups and the outcome variances do not depend on the estimated propensity score.[17]

Furthermore, covariates in the matched samples ought to be balanced according to the condition $X \perp D \mid b(X)$. Following Lechner (2001), the match quality is judged by the mean absolute standardized biases of covariates. The results reported in Table 6 show that, in general, a satisfactory matching is achieved for the reported model specifications and for the different sub-samples, and thus the condition $X \perp D \mid b(X)$ is fulfilled.

4.2 Is It Plausible to Assume Conditional Independence?

In the literature of economics of education a lot of studies on educational choices pointed out that family background, individual academic ability and gender are key elements in determining which college major an individual will enrol at. These factors are also likely to influence the future labour market performance, and thus, in order to conditional independence to be plausible, they should be included in the estimation of the propensities.

The importance of parental background for the children's educational choices and attainments is emphasized in various studies, starting with Haveman and Wolfe (1995). Examples of more recent studies that all point to parents' education as one of the most

[17] We choose to report the analytical standard errors and not the bootstrapped ones, given that a recent paper by Abadie and Imbens (2006b) proves that bootstrapping is not consistent with the one-to-one matching procedure. In our case, however, the bootstrapped standard errors are not very dissimilar to the analytical ones (results are available on request from the authors).

essential factors to be controlled for in measuring the effect of education on early labour market outcomes are Blundell et al (2003), Dustmann (2004), Checchi and Flabbi (2007).

Both parents' education, father's occupation when the child was 14 years old and academic performance prior to college (high school score and high school type) are all included in the data available for this study. Moreover, the data set provides detailed information on the other personal characteristics, such as age, gender and region of residence. Information is missing on some specific indicators of student's cognitive ability (test scores) and other important family characteristics (such as household income). However, as we have already seen in section 3, we can consider on one hand the final high school score and its interaction with high school type as a good proxy for unobserved student's ability and on the other hand parents' education and occupation as good indicator of family social class and wealth.

4.3 Average Treatment on the Treated Effects

In this section, we firstly estimate, on the sample of graduates who declare to participate to the labour market at the date of the survey, the time to get the first job and the probability of full-time employment. Finally, after dropping out from the sample those individuals who are unemployed, we estimate the average matching treatment on the treated effects on earnings conditional on employment.

We seek to ensure the quality of matches by setting different tolerance levels when comparing propensity scores (i.e. we impose two different calipers: 0.01 and 0.001). Imposing a caliper work in the same direction as allowing for replacement: bad matches are avoided and hence the matching quality raises. Furthermore, by setting different calipers we can check the robustness of our results to different common support definitions.

Each estimated effect is reported in relative terms expressed in percentage in Table 7. Our findings show better labour market outcomes both for Economics and Engineering graduates. In particular, the wage *premia* of Economics and Engineering relative to Humanities (Social sciences) are nearly 7% (13-15%). Economics and Engineering increase not only earnings but also the speed of transition into the first job and employment probability. For instance, graduates from Engineering present an employment rate and a time to get the first job that is respectively 27% (10%) higher and 25% (15%) lower relative to Humanities (Social Science). Very similar results are obtained comparing graduates from Economics with those from Humanities and Social Sciences. Graduates in Sciences have better labour market outcomes than Humanities and Social Sciences, but they show lower employment probability and higher time to get the first job with respect to graduates from Economics and Engineering. [18]

Overall, "quantitative" fields (Engineering, Economics and Sciences) ease the transition into the first job, increase employment probability and early earnings, conditional on employment.

In order to examine whether there is some heterogeneity in the treatment effects between women and men, the sample is divided by gender, and the matching procedure is applied to analyse the average treatment effects conditional on gender. The results are presented in tables 8 and 9. In brief, there is not considerable heterogeneity between the sexes, which is discovered by comparing the relative treatment effects expressed in percentage. The effects of Humanities on early labour market outcomes are more negative for men than for women.

[18] It is important to note, however, that all the treatment effects presented above are estimated only for those individuals that fall inside the region of common support because for the individuals that fall outside this region, the treatment effects cannot be estimated. Bryson et al (2002) note that when the proportion of lost individuals is large like in our case especially when treatment effects on earnings are considered, this poses some concerns about whether the estimated effect on the remaining individuals can be viewed as representative. However if we assume that the impact of the treatment is homogeneous, at least within the treated group, no additional problems arises besides this loss of information.

This is also the case for Social Sciences. Consequently “qualitative” education appears as significantly worse in terms of early labour market outcomes for men. Concerning quantitative fields, the opposite holds: Engineering for example seems to be more favourable for men than for women. Hence quantitative education seems to have been a better choice for men aiming at employment after graduation.

4.4 Sensitivity Analysis

This section reports the robustness checks of the results for the average treatment effects presented in the previous section.

Firstly, we calculate the average treatment effects implementing the matching estimator developed by Abadie and Imbens (2006a). The main advantage of the Abadie and Imbens estimator compared to the propensity score one is that it does not require to estimate the multinomial logit model in the first step as a consequence it does not imposes the Independence of Irrelavant Alternatives assumption. As discussed in the previous section, this assumption is convenient for estimation but not appealing from an economic or behavioural point of view.

Secondly, the sensitivity of the results to the methodology used to estimate the treatment effect on earnings is investigated. Even though matching is a relatively flexible and above all intuitive method to compare the effects of various treatments and to explore the extent of heterogeneity in the treatment effect among the individuals, it has some drawbacks. On the one hand, the assumption of conditional independence is not only very strong but also impossible to test. On the other hand, even though we do not need to specify the outcome model, we need to be careful about the specification of the discrete choice model, the criterion of matching, and the definition of common support. Hence, in this section we introduce a different approach to determine the average treatment effect on earnings and relate it to the propensity score matching method and results. In particular, we utilize the polychotomous selectivity model introduced by Lee (1983) to investigate the existence of unobserved heterogeneity.

4.4.1 Matching Estimates

In order to analyse the sensitivity of our propensity score matching results, we employ the non-parametric matching procedure proposed by Abadie and Imbens (2006a). This matching estimator imputes the missing potential outcome by using average outcomes for individuals with similar values for the covariates. As in the main analysis, we are assuming that selection is on observable characteristics but instead of conditioning on the propensity scores we are now conditioning on all the observable covariates. In general, the advantage of this estimator is that it does not require to estimate the propensity score in the first step and consequently it does not impose any parametric assumption. The standard errors are therefore more precisely estimated and in this case we do not need to impose the Independence of Irrelavant Alternatives assumption. Nevertheless, there are two shortcomings regarding this approach. First, there is a problem of dimensionality when the number of matching variables increases[19] and in general the simple matching estimator will be biased in finite sample when the matching is not exact. In practice, however, Abadie and Imbens (2006a) provide the possibility to remove some of this bias term that remains after the matching. They, in particular, propose to combine the matching process with a regression adjustment in order to adjust the differences within the matches for the differences in their covariate values (see Abadie and Imbens 2006a for more details). Another important drawback of the non-parametric estimator is that in each comparison

[19] Conditioning on all relevant covariates is limited in case of high dimensional vector X. For instance, if X contains s covariates which are all dichotomous, the number of possible matches will be 2^s.

only two options at a time are considered and consequently the choice is conditional on being in one of the two selected groups.

The matching variables used in the non-parametric approach are identical to the ones described in the previous section. The matching procedure is based on one-dimensional nearest-match criterion, i.e. each individual in sample *m* is matched with a comparison in sample *l* with similar values for the covariates. Table 10 presents results for the average treatment effects on the treated on early labour market outcomes.

Results obtained using the Abadie and Imbens matching estimator do not qualitatively differ from our previous findings presented in Table 7. In other words, the bias corrected matching estimator produces very similar estimates to those obtained using the propensity score matching method. However, in this case the standard errors of the average treatment effects more precisely estimated.

4.4.2 Polychotomous Selectivity Model

The model presented by Lee (1983) is designed for dealing with selectivity bias in the polychotomous case when the dependent variable is continuous. The idea of this approach is largely the same as in the approach introduced by Dubin and McFadden (1984), which in turn is a multinomial generalisation of Heckman's two-stage method.[20] Like all these selectivity models, the Lee model is designed to adjust for both observed and unobserved selection bias. Thus, it does not require the conditional independence assumption to be valid.[21] Consider the following model:

$$y_1 = x\beta_1 + u_1$$

$$y_m^* = z\gamma_m + \eta_m \text{, m=0,.....,M (4.1)}$$

[20] The main shortcoming of the Lee approach compared to the one presented by Dubin and McFadden (1984) is that it contains relatively restrictive assumptions on the covariance between the error term ε and μ.
[21] However, it rests on other strong assumptions, among them linearity in the outcome variable and joint normality in the error terms.

where the disturbance u_1 is not parametrically specified and verifies $E(u_1 \mid x, z) = 0$ and $V(u_1 \mid x,z) = \sigma^2$; y_m is a categorical variable that describes the choice of an economic agent among M alternatives based on "utilities" y_m^*.[22] The vector x contains all determinants of the variable of interest and z contains the same variables plus some excluded instruments. Hence, this approach attempts to control for selection on unobservables by exploiting some exogenous variation in schooling through some excluded instruments. Our data set contains information on the number of siblings that often has been considered a potential instrument in the related literature (see Haveman and Wolfe, 1995). Hence this variable, may determine assignment to college major but conditional on the x_s could be excluded from the earnings equation.

Without loss of generality, the outcome variable y_1 is observed if and only if category 1 is chosen, which happens when:

$$y_1^* > \max_{\neq 1}(y_j^*) \quad (4.2)$$

Define

$$\varepsilon_1 = \max_{m\neq 1}(y_m^* - y_1^*) = \max_{m\neq 1}(z\gamma_m^* + \eta_m - z\gamma_1 - \eta_1) \quad (4.3)$$

Under definition (4.3), condition (4.2) is equivalent to $\varepsilon_1<0$. Assume that the (η_m)'s are independent and identically Gumbel distributed (the so-called IIA hypothesis). As shown by McFadden (1974), this specification leads to the multinomial logit model. Based on this assumption, consistent maximum likelihood estimates of (γ_m)'s can easily be obtained. The estimation of the parameter vector β_1 could be biased due to the possible correlation of the disturbance term u_1 with all (η_j)'s. This would introduce some correlation between the explanatory variables and the disturbance term in the outcome equation model (4.1). Because of this, least squares estimates of β_1 would not be consistent. Lee (1983) proposed

[22] The choice alternatives are: sciences (m=1), engineering (m=2), economics (m=3), social sciences (m=4) and humanities (m=5).

a generalisation of the two-step selection bias correction method introduced by Heckman (1979) that allows for any parameterised error distribution. His method could be extended to the case where selectivity is modelled as a multinomial logit. This approach is simple and requires the estimation of only one parameter in the correction term. This is, however, achieved at the cost of fairly restrictive assumptions (Lee, 1983).[23]

Under these assumptions, a consistent estimator of β_1 is obtained by estimating least squares of the following equation:

$$y_1 = x_1\beta_1 - \sigma\rho_1 \frac{\varphi(J_{\varepsilon 1}(0 \mid \Gamma)}{F_{\varepsilon 1}(0 \mid \Gamma)} + w_1 \quad (4.4)$$

A two-step estimation of (4.4) is thus implemented by first estimating the (γ_j)'s in order to obtain the selection adjustment terms $\frac{\varphi(J_{\varepsilon 1}(0 \mid \Gamma))}{F_{\varepsilon 1}(0 \mid \Gamma)}$ and then by including them into equation (4.4) to consistently estimate β_1 and $\sigma\rho_1$ by least squares.

The results in Table 11 show that including the selection adjustment terms in the equation for earnings produces somewhat different estimates in absolute value of the ATTs compared to the matching ones.[24] This is not surprising since identification is based on a different assumption, i.e. the individuals are allowed to select into college major on the basis of their idiosyncratic gains. Moreover these differences are presumably explained by the parametric restrictions underlying the control function approach. However, as in the matching framework the results indicate that Humanities and Social Sciences graduates show a negative earning *premium* with respect to graduates from the "quantitative" fields. Our results are robust to accounting for unobserved heterogeneity through the

[23] Call $F_{\varepsilon 1}(.|\Gamma)$ the cumulative distribution function of ε_1. The cumulative $J_{\varepsilon 1}(.|\Gamma)$, defined by the following transform: $J_{\varepsilon 1}(.|\Gamma) = \Phi^{-1}(F_{\varepsilon 1}(.|\Gamma))$, where Φ is the standard normal cumulative, has a standard normal distribution. Assume that u_1 and $J_{\varepsilon 1}(.|\Gamma)$ are linearly related with correlation ρ_1 (this holds in particular if they are bivariate normal). Then, the expected value of the disturbance term u_1, conditional on category 1 being chosen, is given by: $E(u_1|\varepsilon_1<0, \Gamma = \sigma\rho_1[\varphi\ J_{\varepsilon 1}(.|\Gamma)/\ F_{\varepsilon 1}(.|\Gamma)]$.

[24] Due to the presence of estimated coefficients in the creation of the counterfactual conditional means, we cannot easily surmise the correct standard deviations.

polychotomous selectivity model. Furthermore, as suggested by our estimates, the parameters for selection adjustment terms are never statistically significant[25]. Hence, we find evidence suggesting that the matching approach with the available set of Xs (i.e. observables) is not subject to selection bias. [26]

5. Concluding Remarks

The aim of this paper is to investigate the differences in early labour market outcomes (time to get the first job, employment probability and log hourly earnings three years after graduation) between Italian university graduates across college major. The analysis could be considered an advance in the literature because it does not limit itself to recognize that fields of study choice may be endogenous to the determination of early labour market outcomes, but attempts to correct directly for student self-selection into college major. To this end, we employ both matching techniques which corrects for selectivity through observable characteristics (Rosenbaum and Rubin, 1983; Abadie and Imbens, 2006a) and a simultaneous equation model of earnings determination and subject choice, which account for selectivity through unobservables (Lee, 1983).

Using two waves (2001 and 2004) of the Graduates' Employment Survey conducted by the Italian National Statistical Institute (ISTAT) three years after graduation, we find that "quantitative" fields (i.e. Sciences, Engineering and Economics) ease the transition into the first job, increase employment probability and early earnings, conditional on employment. Graduates in Humanities and Social Sciences are always the most disadvantaged in terms of early labour market outcomes. Our results suggest that for those graduates proceeding to

[25] Results are available on request from the authors.
[26] It is interesting to note that under the structure imposed on the model, the estimated coefficients of the control functions are informative on the presence and direction of the selection process. Specifically, if an exclusion restriction can be found and the joint normality of the unobservables, then the null hypothesis of no selection on the unobservables can be tested directly.

the labour market after leaving university, quantitative fields offer better early labour market opportunities.

The last annual report of the Bank of Italy (2007) indicates that even if there exist huge differences in the employment returns of graduates by fields of study, the labour supply does not seem to adequate rapidly to the labour demand. Indeed, over the last 50 years the distribution of university graduates by fields of study has been almost stable with more than 60% of graduates from Humanities and Social Sciences and only one fourth from the "quantitative" subjects.

Our findings may be reconciled with the shortage in the supply of graduates in the quantitative field more than with skill biased technical change hypothesis, since both R&D expenditure are very low in Italy and graduates' employment opportunities have not changed during the two last decades (e.g. the structure of the Italian industry does not seem to favour the job market for high qualified technicians). This may be due to the fact that high school students decide not to enrol in the quantitative fields because they consider them a difficult and risky investment.

References

Abadie A. and Imbens G. (2006a) "Large Sample Properties of Matching Estimators for Average Treatment Effects", *Econometrica*, 74: 235-267.

Abadie A. and Imbens G. (2006b) "On the Failure of the Bootstrap for Matching Estimators", NBER Working Paper No. 325.

Arcidiacono P. (2004) "Ability Sorting and the Returns to College Major", *Journal of Econometrics*, 121: 343-375.

Ballarino G. and Bratti M. (2006) "Fields of study and graduates' occupational outcomes in Italy during the 90s. Who won and who lost?" DEAS Working Paper n. 17, University of Milan.

Bank of Italy (2007) "Relazione Annuale" Roma: Banca d'Italia.

Behrman J.R. and Rosenzweig M.R. (2002) "Does Increasing Women's Schooling Raise the Schooling of the Next Generation?", *American Economic Review*, 92: 323-334.

Berger M.C. (1988) "Predicted future earnings and choice of college major", *Industrial and Labor Relations Review*, 41: 418-429.

Biggeri L., Bini M. and Grilli L. (2000) "The Transition from University to Work: A Multilevel Approach to the Analysis of the Time to Obtain the First Job", *Journal of the Royal Statistical Society Series A*, 164: 293-305.

Blundell R., Dearden L., Goodman A. and Reed H. (2000) "The Returns to Higher Education in Britain: Evidence from a British Cohort", *Economic Journal*, 110: 82-99.

Blundell R., Dearden L. and Sianesi B. (2003) "Evaluating the impact of education on earnings in the UK: Models, methods and results from the NCDS", IFS Working Papers n. 20.

Boero G., McKnight A., Naylor R.A. and Smith J. (2004) "Graduates and the graduate labour market: evidence from the UK and Italy'" in Checchi D. and Lucifora C. (eds.) *Education, Training and Labour Market Outcomes in Europe* New York: Palgrave Macmillan.

Bratti M. and Mancini L. (2003) "Differences in Early Occupational Earnings of UK Male Graduates by Degree Subject: Evidence from the 1980-1993 USR", IZA Discussion Paper No. 890.

Brunello G. and Cappellari L. (2007) "The Labour Market Effects of Alma Mater. Evidence from Italy", *Economics of Education Review*, forthcoming.

Bryson A., Dorsett R. and Purdon S. (2002) "The use of propensity score matching in the evaluation of active labour market policies", Department for Work and Pensions Working Paper No. 4.

Bryson A. (2002) "The Union Membership Wage Premium: An Analysis Using Propensity Score Matching", CEP Discussion Paper No. 530.

Checchi D. and Flabbi L. (2007) "Intergenerational Mobility and Schooling decisions", IZA Discussion Paper No. 2879.

Daymont T.N. and Andrisani P.J. (1984) "Job Preferences, College Major and the Gender Gap in Earnings", *Journal of Human Resources*, 19: 408-428.

Dubin J.A. and McFadden D.L. (1984) "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption", *Econometrica*, 52: 345-362.

Dustmann C. (2004) "Primary to Secondary School Transitions, Parental Characteristics, and Career Patterns", *Oxford Economic Papers*, 56, 209-230.

Grogger J. and Eide E. (1995) "Changes in College Skills and the Rise in the College Wage Premium", *Journal of Human Resources*, 30: 280-310.

Haveman R. and Wolfe B. (1995) "The Determinants of Children's Attainments: A Review of Methods and Findings", *Journal of Economic Literature*, 33: 1829-1878.

Heckman J.J. (1979) “Sample Selection Bias as a Specification Error”, *Econometrica*, 47: 153-161.

Imbens G. (2000) “The Role of the Propensity Score in Estimating Dose-Response Functions”, *Biometrika*, 87: 706-710.

James E., Alsalam N., Conaty J.C. and To D.L. (1989) “College Quality and Future Earnings: Where Should You Send Your Child to College?”, *American Economic Review*, 79: 247-252.

Lechner M. (2001) “Identification and estimation of causal effects of multiple treatments under the conditional independence assumption” in Michael Lechner M. and Pfeiffer F. (eds) *Econometric Evaluation of Labour Market Policies* Heidelberg: Physica-Verlag.

Lechner M. (2002) “Some practical issues in the evaluation of heterogenous labour market programmes by matching methods”, *Journal of the Royal Statistical Society A*, 127: 59-82.

Lee, L.F. (1983) “Generalized Economic Methods with Selectivity Bias”, *Econometrica*, 51: 507-512.

Loury L.D. (1997) “The gender gap among college-educated workers”, *Industrial and Labor Relations Review*, 50: 580-593.

Loury L.D. and Garman D. (1995) “College Selectivity and Earnings”, *Journal of Labor Economics*, 13: 289-308.

Makovec M. (2005) “Does it pay to study far from home? Explaining the returns to geographic mobility of Italian college graduates”, Bocconi University, *mimeo*.

McFadden D.L. (1974) “Conditional Logit Analysis of Qualitative Choice Behavior” in Frontiers in Econometrics, edited by Zarembka P. New York: Academic Press.

Rochat D. and Demeulemeester J.L. (2001) “Rational choice under unequal constraints: the example of Belgian higher education”, *Economics of Education Review*, 20: 15-26.

Rosenbaum P.R., and Rubin D.B. (1983) “The Central Role of the Propensity Score in Observational Studies for Causal Effects”, *Biometrika*, 70: 41-55.

Sianesi B. (2004) “An Evaluation of the Swedish System of Active Labor Market Programs in the 1990s”, *Review of Economics and Statistics*, 86: 133-155

Stewart M.B. (1983) “On least squares estimation when the dependent variable is grouped”, *Review of Economic Studies*, 50: 737-753.

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Time to first job (in quarters)	19936	8.397	4.441	0	24
Full-time employment	34089	0.604	0.489	0	1
Hourly net earnings	22735	7.729	2.704	1.666	37.5
	College major				
Scientific	34089	0.231	0.421	0	1
Engineering	34089	0.215	0.411	0	1
Economics	34089	0.169	0.375	0	1
Social Sciences	34089	0.177	0.382	0	1
Humanities	34089	0.208	0.406	0	1
	High school type				
Scientific general high school (*liceo scientifico*)	34089	0.415	0.493	0	1
Humanities general high school (*liceo classico*)	34089	0.172	0.377	0	1
Vocational high school	34089	0.306	0.461	0	1
Other high schools	34089	0.107	0.309	0	1
	Parents' education				
Both parents: elementary school	34089	0.119	0.324	0	1
At least one parent: junior high school	34089	0.098	0.297	0	1
Both parents: junior high school	34089	0.140	0.347	0	1
At least one parent: high school	34089	0.189	0.391	0	1
Both parents: high school	34089	0.197	0.398	0	1
At least one parent: university	34089	0.164	0.370	0	1
Both parents: university	34089	0.094	0.291	0	1
	Father's occupation				
Entrepreneur	34089	0.053	0.225	0	1
Professional	34089	0.073	0.261	0	1
Independent	34089	0.140	0.347	0	1
Other independent	34089	0.052	0.223	0	1
Manager	34089	0.102	0.302	0	1
White collar high level	34089	0.112	0.315	0	1
White collar low level	34089	0.194	0.395	0	1
Office worker	34089	0.104	0.306	0	1
Blue collar	34089	0.159	0.366	0	1
Other dependent	34089	0.021	0.143	0	1
	University Region				
Centre	34089	0.267	0.442	0	1
South	34089	0.264	0.441	0	1
North-west	34089	0.250	0.433	0	1
North-east	34089	0.219	0.413	0	1
	Age at the date of interview				
no more than 24	34089	0.053	0.224	0	1
25-26	34089	0.246	0.431	0	1
27-29	34089	0.459	0.498	0	1
more than 30	34089	0.242	0.428	0	1
Female	34089	0.537	0.499	0	1
High school score	34089	49.167	7.151	36	60
Military done before university	34089	0.032	0.175	0	1
Mobility (Transfer into another region)	34089	0.298	0.457	0	1

Table 2: Evolution of graduates' composition by university groups

University Groups	2001	2004
Scientific	15.13	14.3
Engineering	18.3	18.96
Economics	20.38	19.41
Social Sciences	23.82	25.11
Humanities	22.37	22.21
Number of obs	16,266	17,823

Table 3: Distribution of high school grades by university groups (%)

University Groups	High school final marks				
	36-40	41-45	46-50	51-55	56-60
Scientific	15.4	19.49	25.91	16.78	22.42
Engineering	9.68	15.53	24.95	18.44	31.4
Economics	11.65	18.5	26.8	18.19	24.86
Social Sciences	16.32	20.94	26.76	15.56	20.42
Humanities	16.85	21.21	26.7	15.29	19.95
Total	14.14	19.29	26.29	16.74	24

Table 4: Distribution of high school types by university groups (%)

University Groups	High school types			
	scientific ghs	humanities ghs	vocational hs	other hs
Scientific	54.42	13.43	26.33	5.82
Engineering	51.85	9.53	32.24	6.39
Economics	37.86	8.32	51	2.41
Social Sciences	29.89	32.91	27	10.08
Humanities	25.73	28.82	17	28.75
Total	38.24	19.89	30.46	11.4

Table 5: Labour market outcomes by university groups

University Groups	Hourly net earnings (mean)	Time to first job (mean)	Employment rate (%)
Scientific	7.38	8.17	79.07
Engineering	7.76	7.40	88.17
Economics	7.39	8.18	87.32
Social Sciences	6.55	8.87	72.57
Humanities	6.68	9.57	59.37
Total	7.23	8.40	77.17

Table 6: Covariate balancing indicators before and after matching

		Time to first job					Employment probability					Hourly net earnings				
Treatment	Comparison	N_1 before	N_0 before	Median Bias before	Median Bias After	N_1 off support	N_1 before	N_0 before	Median Bias before	Median Bias after	N_1 off support	N_1 before	N_0 before	Median Bias before	Median Bias after	N_1 off support
Scientific	Engineering	2,740	3,821	4.29	4.20	50	3,578	4,725	4.30	3.36	30	2,836	4,147	4.09	3.60	38
	Economics		3,178	4.98	2.55	102		3,919	5.27	3.35	95		3,410	5.28	3.00	124
	Soc.Sciences		2,425	7.40	3.00	186		3,324	7.26	3.15	182		2,415	8.51	4.79	172
	Humanities		2,560	3.67	3.21	73		3,696	3.30	2.16	42		2,770	2.94	3.81	66
Engineering	Scientific	3,821	2,740	4.29	3.19	209	4,725	3,578	4.30	2.46	160	4,147	2,836	4.09	3.35	179
	Economics		3,178	5.69	2.01	238		3,919	6.01	1.35	228		3,410	5.64	2.32	226
	Soc.Sciences		2,425	7.74	4.72	306		3,324	7.55	3.79	295		2,415	7.14	3.97	304
	Humanities		2,560	3.96	4.19	171		3,696	3.89	3.35	103		2,770	5.77	3.64	122
Economics	Scientific	3,178	2,740	4.93	2.05	139	3,919	3,578	5.27	3.24	142	3,410	2,836	5.28	4.11	151
	Engineering		3,821	5.69	4.81	138		4,725	6.01	5.45	137		4,147	5.64	4.39	134
	Soc.Sciences		2,425	8.06	2.56	242		3,324	8.78	3.04	252		2,415	8.45	3.04	235
	Humanities		2,560	6.99	3.70	239		3,696	6.26	2.38	184		2,770	6.33	1.96	171
Soc.Sciences	Scientific	2,425	2,740	7.40	2.99	222	3,324	3,578	7.26	3.50	248	2,415	2,836	8.51	4.01	197
	Engineering		3,821	7.74	3.33	189		4,725	7.55	3.51	174		4,147	7.14	3.74	170
	Economics		3,178	8.06	3.10	216		3,919	8.78	2.56	224		3,410	8.45	3.49	183
	Humanities		2,560	5.83	3.19	66		3,696	5.47	2.78	46		2,770	7.90	3.11	74
Humanities	Scientific	2,560	2,740	3.67	4.23	156	3,696	3,578	3.30	3.26	161	2,770	2,836	2.94	4.12	178
	Engineering		3,821	3.96	3.44	146		4,725	3.89	3.21	125		4,147	5.77	5.91	165
	Economics		3,178	6.99	3.32	197		3,919	5.47	1.76	94		3,410	7.90	2.45	133
	Soc.Sciences		2,425	5.83	3.39	94		3,324	6.26	2.08	244		2,415	6.33	2.52	202
Caliper = 0.01																

Notes: N_1 indicates treated sample, while N_0 the non-treated one. N_1 off support indicates the number of observations not in the common support. Median absolute standardized bias before and after matching median taking all the regressors is calculated as follows: $B_{before}(X) = 100\frac{X_1 - X_0}{\sqrt{(V(X_1) + V(X_0)/2}}$ $B_{after}(X) = 100\frac{X_{1M} - X_{0M}}{\sqrt{(V(X_1) + V(X_0)/2}}$.

Table 7: Average treatment on the treated effects on early labour market outcomes

Treatment	Comparison	Time to first job		Employment probability		Hourly net earnings	
Scientific	Engineering	5.54	4.73	-3.60	-3.63	0.84	0.59
		(2.04)	*(2.27)*	*(1.22)*	*(1.32)*	*(1.20)*	*(1.33)*
	Economics	-5.03	-4.06	-7.43	-7.11	-0.65	-0.66
		(1.95)	*(2.20)*	*(1.15)*	*(1.29)*	*(1.07)*	*(1.25)*
	Social sciences	-12.86	-11.33	5.79	5.16	12.65	10.95
		(2.08)	*(2.53)*	*(1.44)*	*(1.65)*	*(1.47)*	*(1.79)*
	Humanities	-20.41	-20.40	20.42	20.55	8.19	8.45
		(2.31)	*(2.67)*	*(1.76)*	*(1.94)*	*(1.66)*	*(2.00)*
Engineering	Scientific	-6.83	-4.81	5.99	5.82	1.81	0.45
		(2.04)	*(2.35)*	*(1.26)*	*(1.36)*	*(1.12)*	*(1.28)*
	Economics	-11.41	-11.21	-2.41	-1.89	0.43	1.36
		(1.97)	*(2.20)*	*(1.11)*	*(1.19)*	*(1.15)*	*(1.24)*
	Social sciences	-15.19	-11.02	10.17	10.04	15.37	14.89
		(2.56)	*(2.56)*	*(1.76)*	*(1.67)*	*(1.94)*	*(1.83)*
	Humanities	-25.29	-30.04	26.95	26.90	7.11	7.10
		(3.37)	*(3.04)*	*(2.54)*	*(2.37)*	*(2.75)*	*(2.43)*
Economics	Scientific	2.20	2.35	6.24	5.64	-0.29	-1.17
		(1.99)	*(2.24)*	*(1.24)*	*(1.37)*	*(1.08)*	*(1.26)*
	Engineering	4.39	6.33	1	0.34	-1.73	-0.17
		(2.12)	*(2.25)*	*(1.21)*	*(1.23)*	*(1.25)*	*(1.28)*
	Social sciences	-5.12	-4.04	13.18	13.82	13.69	12.65
		(2.02)	*(2.30)*	*(1.40)*	*(1.56)*	*(1.46)*	*(1.70)*
	Humanities	-17.59	-16.46	24.58	24.80	7.07	6.88
		(2.33)	*(2.59)*	*(1.83)*	*(1.86)*	*(1.81)*	*(1.86)*
Social Sciences	Scientific	9.47	13.65	-4.76	-3.77	-12.12	-10.97
		(2.13)	*(2.58)*	*(1.42)*	*(1.62)*	*(1.37)*	*(1.71)*
	Engineering	12.43	12.47	-9.60	-9.21	-12.54	-12.92
		(2.25)	*(2.46)*	*(1.49)*	*(1.59)*	*(1.52)*	*(1.67)*
	Economics	4.04	3.49	-14.57	-12.90	-11.09	-12.03
		(2.06)	*(2.33)*	*(1.31)*	*(1.47)*	*(1.30)*	*(1.55)*
	Humanities	-8.57	-12.71	10.60	10.27	-6.30	-6.00
		(2.07)	*(2.33)*	*(1.58)*	*(1.73)*	*(1.63)*	*(1.92)*
Humanities	Scientific	21.33	21.67	-15.49	-16.41	-4.15	-6.36
		(2.31)	*(2.57)*	*(1.56)*	*(1.71)*	*(1.45)*	*(1.70)*
	Engineering	19.71	21.27	-16.20	-19.10	-2.95	-5.71
		(2.83)	*(2.72)*	*(1.83)*	*(1.76)*	*(1.80)*	*(1.85)*
	Economics	15.19	10.80	-26.09	-26.24	-3.14	-6.29
		(2.77)	*(2.40)*	*(1.70)*	*(1.70)*	*(1.60)*	*(1.65)*
	Social sciences	6.93	10.80	-9.05	-9.63	5.67	4.81
		(2.09)	*(2.40)*	*(1.54)*	*(1.69)*	*(1.66)*	*(1.94)*
Caliper		*0.01*	*0.001*	*0.01*	*0.001*	*0.01*	*0.001*

Notes: The propensity score matching-average treatment on the treated effects are in relative terms expressed in percentage. The outcome variables are: 1) log of time to first job measured in quarters; 2) full-time employment probability; 3) log of net hourly earnings. The matching variables are the following: family background characteristics (parents' education, father's occupation), high school final mark, high school type, age, region of residence, survey year, compulsory military service before university and whether the individual transfers into another region to attend university. Mahalanobis matching is done with replacement. The figures reported in parentheses are the approximate standard errors on the treatment effects assuming independent observations, fixed weights, homoskedasticity of the outcome variable within the treated and within the control groups and that the variance of the outcome does not depend on the propensity-score.

Table 8: Average treatment on the treated effects on early labour market outcomes: sub-sample of women

Treatment	Comparison	Time to first job		Employment probability		Hourly net earnings	
Scientific	Engineering	5.86	3.51	-5.83	-7.72	1.52	1.56
		(3.23)	*(4.41)*	*(2.05)*	*(2.55)*	*(1.86)*	*(2.58)*
	Economics	-4.36	-3.24	-8.92	-6.91	0.54	0.64
		(2.96)	*(3.54)*	*(1.87)*	*(2.16)*	*(1.62)*	*(1.96)*
	Social sciences	-13.07	-16.37	4.18	4.13	11.42	12.91
		(2.88)	*(3.78)*	*(2.07)*	*(2.53)*	*(2.02)*	*(2.61)*
	Humanities	-16.75	-23.94	15.23	16.03	6.90	6.28
		(2.72)	*(3.30)*	*(2.10)*	*(2.39)*	*(1.85)*	*(2.18)*
Engineering	Scientific	-2.07	-0.97	4.47	5.48	-2.44	-0.09
		(3.23)	*(4.34)*	*(2.17)*	*(2.66)*	*(1.89)*	*(2.51)*
	Economics	-10.30	-11.06	-4.21	-2.28	-1.35	0.75
		(3.39)	*(4.81)*	*(2.16)*	*(2.75)*	*(1.97)*	*(2.72)*
	Social sciences	-16.24	-12.63	7.23	7.85	7.44	9.47
		(3.28)	*(4.62)*	*(2.39)*	*(3.00)*	*(2.35)*	*(3.21)*
	Humanities	-18.09	-20.28	17.86	16.54	6.01	5.01
		(3.25)	*(4.40)*	*(2.39)*	*(2.99)*	*(2.32)*	*(2.94)*
Economics	Scientific	0.89	2.65	5.47	7.63	-1.90	-2.27
		(3.21)	*(3.69)*	*(2.13)*	*(2.27)*	*(1.57)*	*(1.86)*
	Engineering	2.50	5.61	1.79	0.71	-0.42	-1.02
		(3.80)	*(4.87)*	*(2.39)*	*(2.79)*	*(2.25)*	*(2.85)*
	Social sciences	-6.05	-10.37	15.89	16.58	12.67	14.68
		(2.75)	*(3.72)*	*(2.02)*	*(2.47)*	*(1.93)*	*(2.58)*
	Humanities	-16.06	-13.98	26.01	26.59	5.93	7.55
		(2.81)	*(3.44)*	*(2.18)*	*(2.46)*	*(1.93)*	*(2.38)*
Social Sciences	Scientific	13.93	14.44	-6.31	-6.30	-13.24	-14.33
		(3.01)	*(3.83)*	*(2.00)*	*(2.48)*	*(1.76)*	*(2.46)*
	Engineering	10.50	7.37	-11.26	-9.21	-8.86	-7.21
		(3.44)	*(4.67)*	*(2.35)*	*(2.90)*	*(2.27)*	*(3.10)*
	Economics	5.87	10.55	-17.32	-17.46	-12.07	-12.97
		(2.85)	*(3.68)*	*(1.84)*	*(2.27)*	*(1.71)*	*(2.34)*
	Humanities	-7.28	-9.21	10.77	10.31	-8.80	-10.52
		(2.48)	*(3.27)*	*(1.89)*	*(2.25)*	*(1.85)*	*(2.51)*
Humanities	Scientific	24.13	23.30	-15.38	-15.84	-5.54	-6.01
		(2.86)	*(3.41)*	*(1.95)*	*(2.26)*	*(1.69)*	*(2.12)*
	Engineering	20.59	18.45	-17.49	-16.12	-6.60	-6.97
		(3.34)	*(4.36)*	*(2.32)*	*(2.87)*	*(2.16)*	*(2.70)*
	Economics	13.20	13.32	-25.13	-26.66	-4.51	-5.10
		(3.15)	*(3.45)*	*(2.11)*	*(2.23)*	*(1.90)*	*(2.33)*
	Social sciences	4.44	7.45	-9.09	-8.72	8.95	9.88
		(2.39)	*(3.15)*	*(1.81)*	*(2.20)*	*(1.90)*	*(2.57)*
Caliper		*0.01*	*0.001*	*0.01*	*0.001*	*0.01*	*0.001*

Note: see Note to Table 7.

Table 9: Average treatment on the treated effects on early labour market outcomes: sub-sample of men

Treatment	Comparison	Time to first job		Employment probability		Hourly net earnings	
Scientific	Engineering	6.24	5.51	-6.80	-6.29	-4.08	-5.28
		(2.59)	*(3.34)*	*(1.39)*	*(1.70)*	*(1.56)*	*(1.90)*
	Economics	-3.60	-5.52	-6.25	-5.96	-1.11	-1.63
		(2.72)	*(3.91)*	*(1.51)*	*(2.06)*	*(1.58)*	*(2.47)*
	Social sciences	-11.38	-10.68	4.73	3.35	14.66	12.86
		(3.23)	*(4.70)*	*(2.05)*	*(2.79)*	*(2.31)*	*(3.31)*
	Humanities	-14.14	-8.12	18.59	16.85	5.35	7.63
		(3.91)	*(5.89)*	*(3.04)*	*(3.83)*	*(2.97)*	*(3.90)*
Engineering	Scientific	-3.13	-5.38	6.05	5.89	1.07	1.78
		(2.52)	*(3.29)*	*(1.46)*	*(1.75)*	*(1.41)*	*(1.94)*
	Economics	-13.26	-14.08	1.03	0.50	1.26	2.62
		(2.55)	*(2.99)*	*(1.27)*	*(1.47)*	*(1.44)*	*(1.85)*
	Social sciences	-17.46	-21.27	13.72	15.69	12.20	13.06
		(3.20)	*(3.73)*	*(2.17)*	*(2.47)*	*(2.62)*	*(3.01)*
	Humanities	-27.78	-37.17	29.15	27.87	8.19	7.06
		(3.86)	*(5.25)*	*(3.14)*	*(3.60)*	*(3.18)*	*(3.90)*
Economics	Scientific	6.91	8.84	5.25	6.94	1.60	1.16
		(2.75)	*(3.98)*	*(1.62)*	*(2.13)*	*(1.63)*	*(2.50)*
	Engineering	13.79	14.79	0.23	-0.87	-1.73	-2.34
		(2.54)	*(3.04)*	*(1.22)*	*(1.44)*	*(1.46)*	*(1.81)*
	Social sciences	-1.87	-2.04	9.82	12.5	12.76	14.18
		(2.98)	*(4.17)*	*(1.92)*	*(2.58)*	*(2.28)*	*(3.16)*
	Humanities	-17.51	-22.14	28.29	31.31	7.79	9.66
		(3.60)	*(5.36)*	*(3.01)*	*(3.76)*	*(3.16)*	*(4.41)*
Social Sciences	Scientific	7.66	11.28	-3.59	-4.31	-12.86	-10.65
		(3.37)	*(4.79)*	*(2.06)*	*(2.83)*	*(2.20)*	*(3.28)*
	Engineering	12.12	13.94	-11.94	-15.02	-14.60	-15.29
		(2.99)	*(3.79)*	*(1.71)*	*(2.09)*	*(2.24)*	*(2.92)*
	Economics	-0.26	-2.35	-12.36	-13.55	-14.70	-15.90
		(3.12)	*(4.11)*	*(1.77)*	*(2.35)*	*(2.18)*	*(2.95)*
	Humanities	-11.20	-15.17	16.78	17.77	-2.87	-3.68
		(3.90)	*(5.24)*	*(3.09)*	*(4.20)*	*(3.25)*	*(5.12)*
Humanities	Scientific	17.60	15.61	-23.07	-20.27	-5.15	-10.48
		(4.19)	*(5.96)*	*(2.81)*	*(3.68)*	*(3.15)*	*(3.75)*
	Engineering	31.22	34.10	-27.74	-29.84	-11.56	-7.06
		(4.12)	*(5.51)*	*(2.44)*	*(3.18)*	*(2.82)*	*(3.76)*
	Economics	18.01	20.94	-28.39	-32.51	-8.55	-8.76
		(4.09)	*(5.56)*	*(2.53)*	*(3.41)*	*(2.91)*	*(4.35)*
	Social sciences	9.95	17.76	-19.07	-24.65	1.97	0.33
		(4.23)	*(5.58)*	*(2.97)*	*(4.05)*	*(3.41)*	*(5.07)*
Caliper		*0.01*	*0.001*	*0.01*	*0.001*	*0.01*	*0.001*

Note: see Note to Table 7.

Table 10: Robustness checks: Abadie-Imbens (2007) procedure

Treatment	Comparison	Time to first job	Employment probability	Hourly net earnings
Scientific	Engineering	6.58	-3.10	-2.16
		(1.83)	*(1.12)*	*(1)*
	Economics	-6.32	-7.14	0.96
		(1.81)	*(1.13)*	*(1.03)*
	Social sciences	-10.46	5.31	11.33
		(2.02)	*(1.36)*	*(1.34)*
	Humanities	-16.91	16.76	6.41
		(2.08)	*(1.48)*	*(1.33)*
Engineering	Scientific	-8.39	7.37	3.37
		(1.84)	*(1.04)*	*(1.03)*
	Economics	-14.09	-0.52	0.95
		(1.80)	*(0.96)*	*(1.02)*
	Social sciences	-15.13	12.09	15.52
		(2.08)	*(1.26)*	*(1.43)*
	Humanities	-22.65	26.15	9.73
		(2.14)	*(1.47)*	*(1.51)*
Economics	Scientific	2.91	7.53	-0.27
		(1.90)	*(1.16)*	*(1.05)*
	Engineering	10.30	0.81	-3.15
		(1.84)	*(0.99)*	*(0.97)*
	Social sciences	-7.98	11.47	12.56
		(1.93)	*(1.23)*	*(1.37)*
	Humanities	-11.89	24.28	8.50
		(2.04)	*(1.44)*	*(1.35)*
Social Sciences	Scientific	10.28	-6.51	-12.90
		(2.08)	*(1.40)*	*(1.38)*
	Engineering	18.08	-7.89	-11.33
		(2.01)	*(1.30)*	*(1.36)*
	Economics	6.57	-14.34	-12.60
		(2.05)	*(1.31)*	*(1.36)*
	Humanities	-7.20	11.21	-5.47
		(1.99)	*(1.42)*	*(1.55)*
Humanities	Scientific	17.58	-15.33	-2.89
		(2.05)	*(1.51)*	*(1.39)*
	Engineering	20.88	-16.37	-2.19
		(2.16)	*(1.53)*	*(1.43)*
	Economics	10.23	-24.46	-2.86
		(2.06)	*(1.51)*	*(1.35)*
	Social sciences	4.25	-11.88	6.67
		(1.99)	*(1.48)*	*(1.54)*

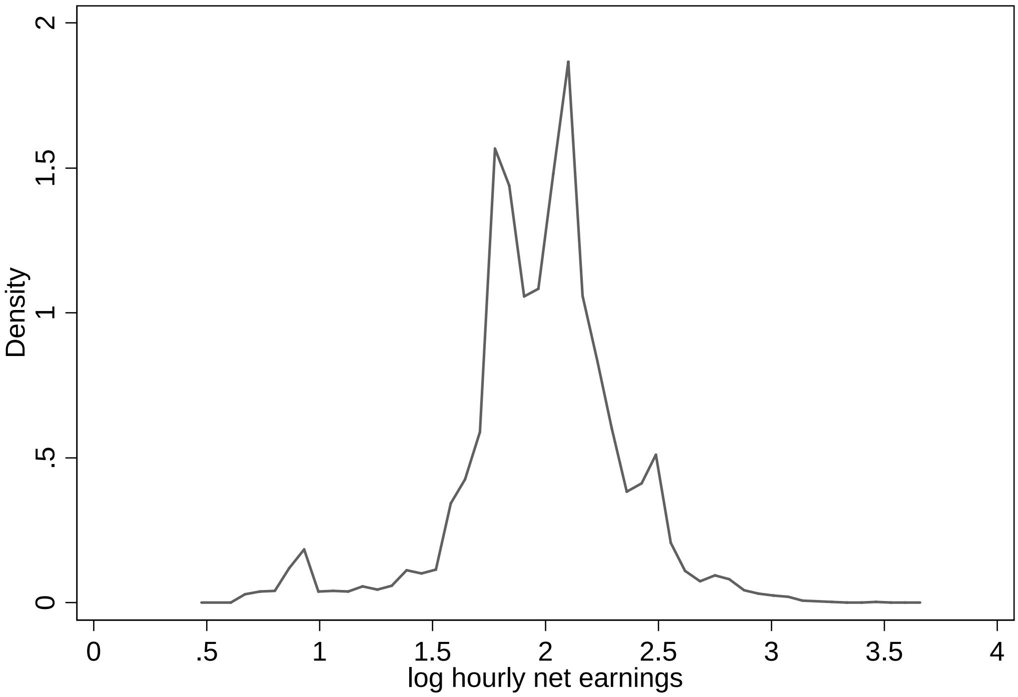
Notes: The matching-average treatment on the treated effects are in relative terms expressed in percentage. The matching estimator adjusts the difference within the matches for the differences in their covariate values. The outcome variables are: 1) log of time to first job measured in quarters; 2) full-time employment probability; 3) log of net hourly earnings. The matching variables are the following pre-treatment variables: family background characteristics (parents' education, father's occupation), high school final mark, high school type, age, region of residence, survey year, compulsory military service before university and whether the individual transfers into another region to attend university. The matching is based on one-dimensional nearest-match criterion. Standard errors are calculated assuming a constant treatment-effect and homoskedasticity.

Table 11: Robustness checks: Lee (1983) model

Treatment	Comparison	ATT(Lee)	(s.e.)
Scientific	Engineering	2.12	(5.97)
	Economics	1.50	(7.94)
	Social sciences	10.75	(12.07)
	Humanities	8.75	(14.38)
Engineering	Scientific	-2.65	(5.98)
	Economics	-1.90	(7.94)
	Social sciences	1.34	(16.94)
	Humanities	15.05	(20.50)
Economics	Scientific	-1.89	(8.18)
	Engineering	-1.09	(7.29)
	Social sciences	8.22	(11.04)
	Humanities	9.72	(14.52)
Social Sciences	Scientific	-14.55	(8.64)
	Engineering	-12.91	(11.81)
	Economics	-13.19	(9.43)
	Humanities	-8.77	(12.32)
Humanities	Scientific	-3.97	(8.51)
	Engineering	-0.02	(10.58)
	Economics	-3.85	(10.20)
	Social sciences	5.66	(13)

Note: Average treatment effects are in relative terms expressed in percentage. Standard errors do not take into account the estimated coefficients used to construct the conditional means and are therefore imprecise. Average treatment effects are in relative terms expressed in percentage.

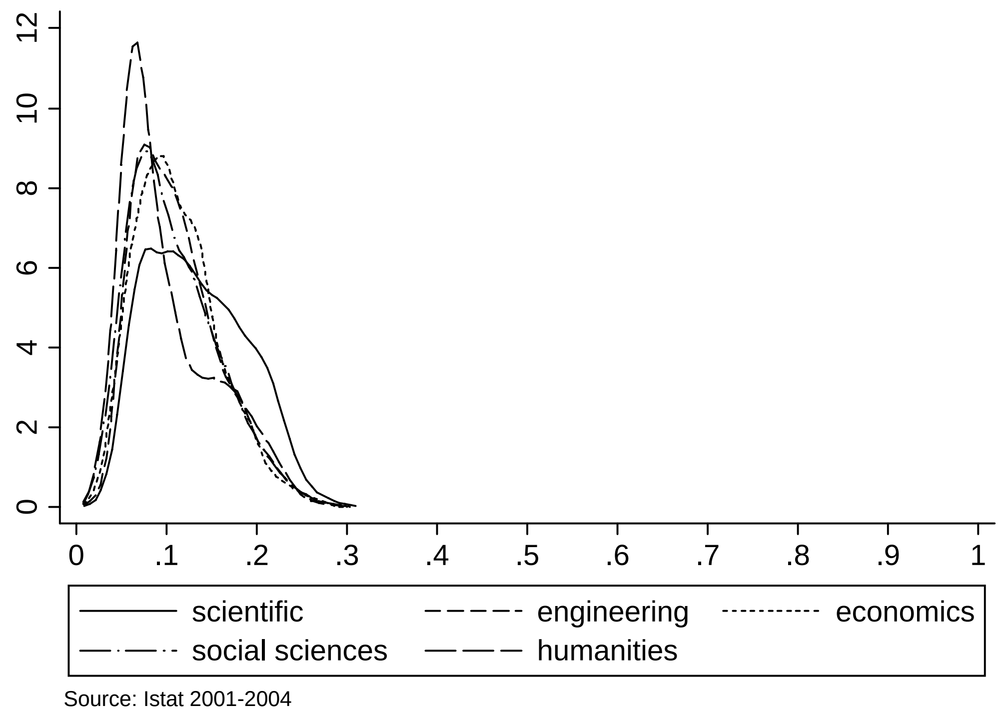
Figure 1: Log net hourly earnings



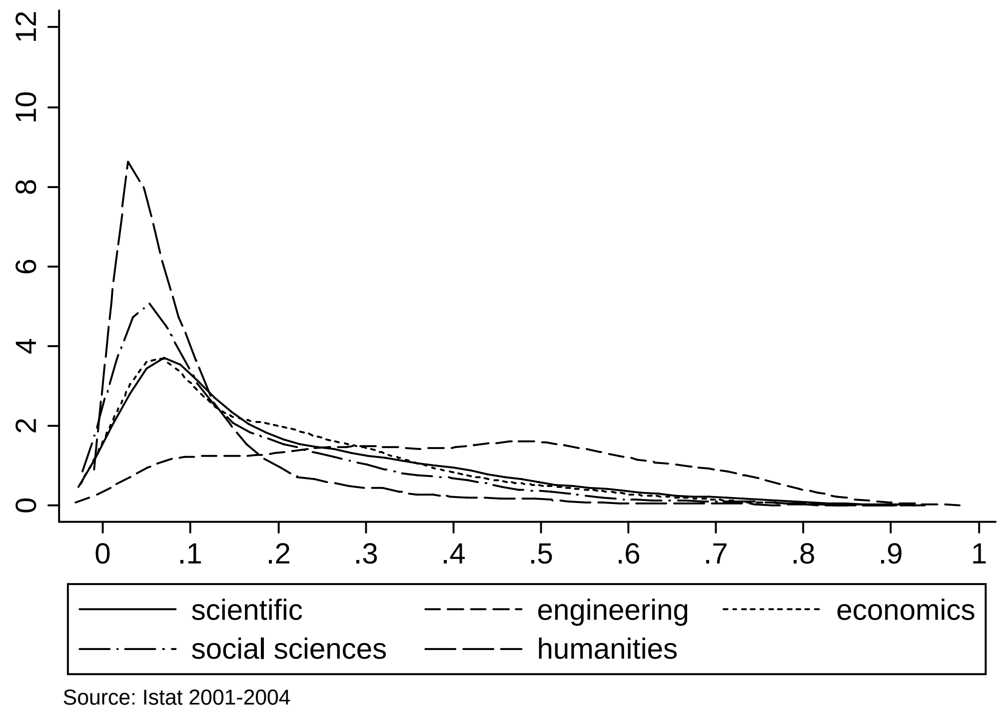
Source: Istat 2001-2004

Figure 2: Distributions of the estimated propensities to be assigned into the fields of study. Sample of university graduates who participate to the labour market

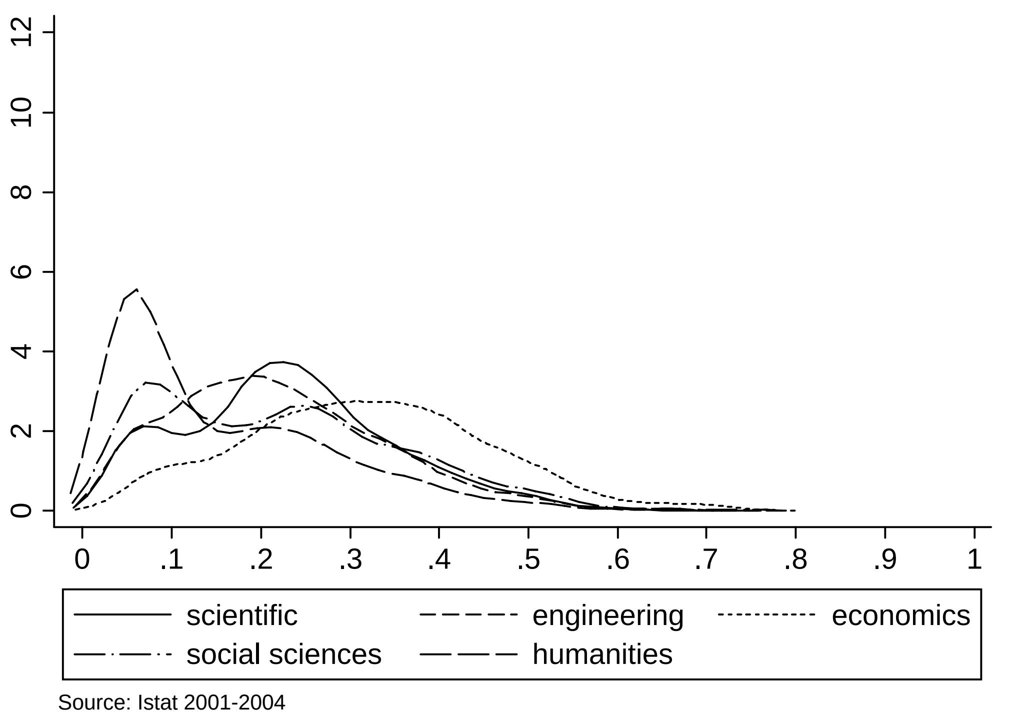
Estimates for propensity to enrol at the Scientific Field



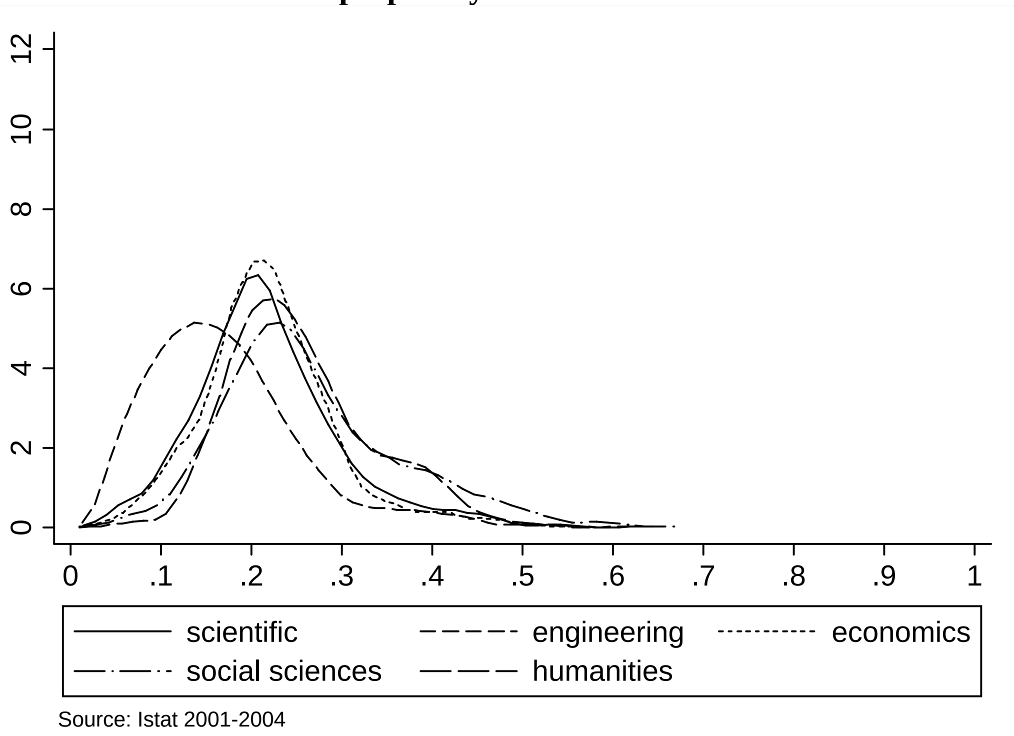
Estimates for propensity to enrol at Engineering



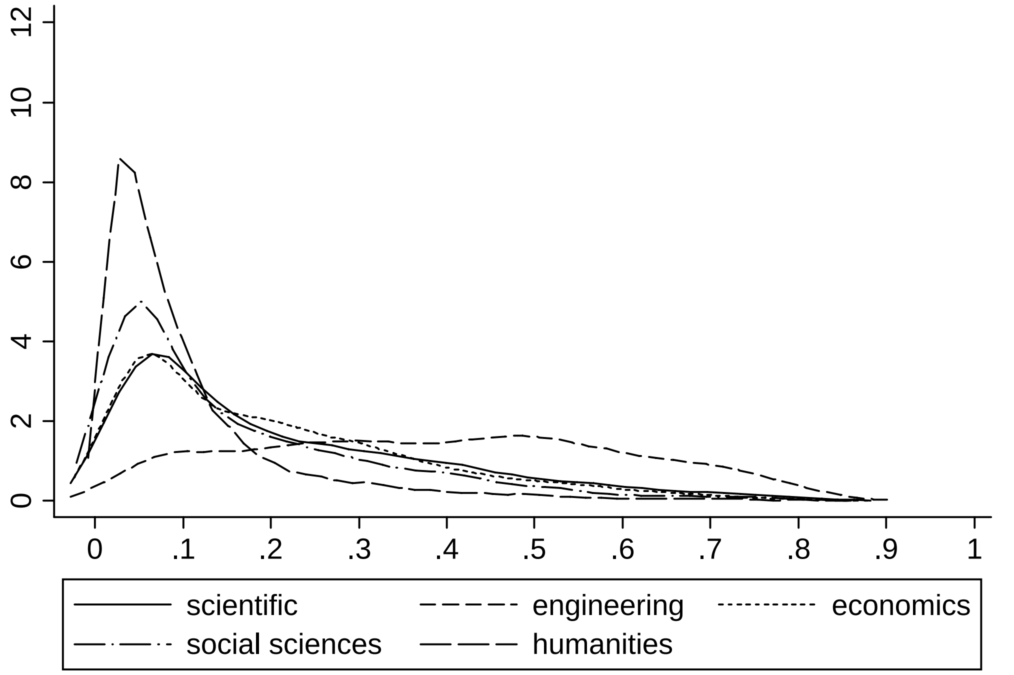
Estimates for propensity to enrol at Economics



Estimates for propensity to enrol at Social Sciences



Estimates for propensity to enrol at Humanities



Source: Istat 2001-2004

Department of Economics:

Skriftserie/Working Paper:

2003:

WP 03-1 Søren Harck: Er der nu en strukturelt bestemt langsigts-ledighed i SMEC?: Phillipskurven i SMEC 99 vis-à-vis SMEC 94. ISSN 1397-4831.

WP 03-2 Beatrice Schindler Rangvid: Evaluating Private School Quality in Denmark. ISSN 1397-4831.

WP 03-3 Tor Eriksson: Managerial Pay and Executive Turnover in the Czech and Slovak Republics. ISSN 1397-4831.

WP 03-4 Michael Svarer and Mette Verner: Do Children Stabilize Marriages? ISSN 1397-4831.

WP 03-5 Christian Bjørnskov and Gert Tinggaard Svendsen: Measuring social capital – Is there a single underlying explanation? ISSN 1397-4831.

WP 03-6 Vibeke Jakobsen and Nina Smith: The educational attainment of the children of the Danish 'guest worker' immigrants. ISSN 1397-4831.

WP 03-7 Anders Poulsen: The Survival and Welfare Implications of Altruism When Preferences are Endogenous. ISSN 1397-4831.

WP 03-8 Helena Skyt Nielsen and Mette Verner: Why are Well-educated Women not Full-timers? ISSN 1397-4831.

WP 03-9 Anders Poulsen: On Efficiency, Tie-Breaking Rules and Role Assignment Procedures in Evolutionary Bargaining. ISSN 1397-4831.

WP 03-10 Anders Poulsen and Gert Tinggaard Svendsen: Rise and Decline of Social Capital
– Excess Co-operation in the One-Shot Prisoner's Dilemma Game. ISSN 1397-4831.

WP 03-11 Nabanita Datta Gupta and Amaresh Dubey: Poverty and Fertility: An Instrumental Variables Analysis on Indian Micro Data. ISSN 1397-4831.

WP 03-12 Tor Eriksson: The Managerial Power Impact on Compensation – Some Further Evidence. ISSN 1397-4831.

WP 03-13 Christian Bjørnskov: Corruption and Social Capital. ISSN 1397-4831.

WP 03-14 Debashish Bhattacherjee: The Effects of Group Incentives in an Indian Firm
– Evidence from Payroll Data. ISSN 1397-4831.

WP 03-15 Tor Eriksson och Peter Jensen: Tidsbegränsade anställninger – danska erfarenheter. ISSN 1397-4831.

WP 03-16 Tom Coupé, Valérie Smeets and Frédéric Warzynski: Incentives, Sorting and Productivity along the Career: Evidence from a Sample of Top Economists. ISSN 1397-4831.

WP 03-17 Jozef Koning, Patrick Van Cayseele and Frédéric Warzynski: The Effects of Privatization and Competitive Pressure on Firms' Price-Cost Margins: Micro Evidence from Emerging Economies. ISSN 1397-4831.

WP 03-18 Urs Steiner Brandt and Gert Tinggaard Svendsen: The coalition of industrialists and environmentalists in the climate change issue. ISSN 1397-4831.

WP 03-19 Jan Bentzen: An empirical analysis of gasoline price convergence for 20 OECD countries. ISSN 1397-4831.

WP 03-20 Jan Bentzen and Valdemar Smith: Regional income convergence in the Scandinavian countries. ISSN 1397-4831.

WP 03-21 Gert Tinggaard Svendsen: Social Capital, Corruption and Economic Growth: Eastern and Western Europe. ISSN 1397-4831.

WP 03-22 Jan Bentzen and Valdemar Smith: A Comparative Study of Wine Auction Prices: Mouton Rothschild Premier Cru Classé. ISSN 1397-4831.

WP 03-23 Peter Guldager: Folkepensionisternes incitamenter til at arbejde. ISSN 1397-4831.

WP 03-24 Valérie Smeets and Frédéric Warzynski: Job Creation, Job Destruction and Voting Behavior in Poland. ISSN 1397-4831.

WP 03-25 Tom Coupé, Valérie Smeets and Frédéric Warzynski: Incentives in Economic Departments: Testing Tournaments? ISSN 1397-4831.

WP 03-26 Erik Strøjer Madsen, Valdemar Smith and Mogens Dilling-Hansen: Industrial clusters, firm location and productivity – Some empirical evidence for Danish firms. ISSN 1397-4831.

WP 03-27 Aycan Çelikaksoy, Helena Skyt Nielsen and Mette Verner: Marriage Migration: Just another case of positive assortative matching? ISSN 1397-4831.

2004:

WP 04-1 Elina Pylkkänen and Nina Smith: Career Interruptions due to Parental Leave – A Comparative Study of Denmark and Sweden. ISSN 1397-4831.

WP 04-2 Urs Steiner Brandt and Gert Tinggaard Svendsen: Switch Point and First-Mover Advantage: The Case of the Wind Turbine Industry. ISSN 1397-4831.

WP 04-3 Tor Eriksson and Jaime Ortega: The Adoption of Job Rotation: Testing the Theories. ISSN 1397-4831.

WP 04-4 Valérie Smeets: Are There Fast Tracks in Economic Departments? Evidence from a Sample of Top Economists. ISSN 1397-4831.

WP 04-5 Karsten Bjerring Olsen, Rikke Ibsen and Niels Westergaard-Nielsen: Does Outsourcing Create Unemployment? The Case of the Danish Textile and Clothing Industry. ISSN 1397-4831.

WP 04-6 Tor Eriksson and Johan Moritz Kuhn: Firm Spin-offs in Denmark 1981-2000 – Patterns of Entry and Exit. ISSN 1397-4831.

WP 04-7 Mona Larsen and Nabanita Datta Gupta: The Impact of Health on Individual Retirement Plans: a Panel Analysis comparing Self-reported versus Diagnostic Measures. ISSN 1397-4831.

WP 04-8 Christian Bjørnskov: Inequality, Tolerance, and Growth. ISSN 1397-4831.

WP 04-9 Christian Bjørnskov: Legal Quality, Inequality, and Tolerance. ISSN 1397-4831.

WP 04-10 Karsten Bjerring Olsen: Economic Cooperation and Social Identity: Towards a Model of Economic Cross-Cultural Integration. ISSN 1397-4831.

WP 04-11 Iben Bolvig: Within- and between-firm mobility in the low-wage labour market. ISSN 1397-4831.

WP 04-12 Odile Poulsen and Gert Tinggaard Svendsen: Social Capital and Market Centralisation: A Two-Sector Model. ISSN 1397-4831.

WP 04-13 Aditya Goenka and Odile Poulsen: Factor Intensity Reversal and Ergodic Chaos. ISSN 1397-4831.

WP 04-14 Jan Bentzen and Valdemar Smith: Short-run and long-run relationships in the consumption of alcohol in the Scandinavian countries.
ISBN 87-7882-010-3 (print); ISBN 87-7882-011-1 (online).

WP 04-15 Jan Bentzen, Erik Strøjer Madsen, Valdemar Smith and Mogens Dilling-Hansen: Persistence in Corporate Performance? Empirical Evidence from Panel Unit Root Tests.
ISBN 87-7882-012-X (print); ISBN 87-7882-013-8 (online).

WP 04-16 Anders U. Poulsen and Jonathan H.W. Tan: Can Information Backfire? Experimental Evidence from the Ultimatum Game.
ISBN 87-7882-014-6 (print); ISBN 87-7882-015-4 (online).

WP 04-17 Werner Roeger and Frédéric Warzynski: A Joint Estimation of Price-Cost Margins and Sunk Capital: Theory and Evidence from the European Electricity Industry.
ISBN 87-7882-016-2 (print); ISBN 87-7882-017-0 (online).

WP 04-18 Nabanita Datta Gupta and Tor Eriksson: New workplace practices and the gender wage gap.
ISBN 87-7882-018-9 (print); ISBN 87-7882-019-7 (online).

WP 04-19 Tor Eriksson and Axel Werwatz: The Prevalence of Internal Labour Markets – New Evidence from Panel Data.
ISBN 87-7882-020-0 (print); ISBN 87-7882-021-9 (online).

WP 04-20 Anna Piil Damm and Michael Rosholm: Employment Effects of Dispersal Policies on Refugee Immigrants: Empirical Evidence.
ISBN 87-7882-022-7 (print); ISBN 87-7882-023-5 (online).

2005:

WP 05-1 Anna Piil Damm and Michael Rosholm: Employment Effects of Dispersal Policies on Refugee Immigrants: Theory.
ISBN 87-7882-024-3 (print); ISBN 87-7882-025-1 (online).

WP 05-2 Anna Piil Damm: Immigrants' Location Preferences: Exploiting a Natural Experiment.
ISBN 87-7882-036-7 (print); ISBN 87-7882-037-5 (online).

WP 05-3 Anna Piil Damm: The Danish Dispersal Policy on Refugee Immigrants 1986-1998: A Natural Experiment?
ISBN 87-7882-038-3 (print); ISBN 87-7882-039-1 (online).

WP 05-4 Rikke Ibsen and Niels Westergaard-Nielsen: Job Creation and Destruction over the Business Cycles and the Impact on Individual Job Flows in Denmark 1980-2001.
ISBN 87-7882-040-5 (print); ISBN 87-7882-041-3 (online).

WP 05-5 Anna Maria Kossowska, Nina Smith, Valdemar Smith and Mette Verner: Til gavn for bundlinjen – Forbedrer kvinder i topledelse og bestyrelse danske virksomheders bundlinje?
ISBN 87-7882-042-1 (print); ISBN 87-7882-043-X (online).

WP 05-6 Odile Poulsen and Gert Tinggaard Svendsen: The Long and Winding Road: Social Capital and Commuting.
ISBN 87-7882-044-8 (print); ISBN 87-7882-045-6 (online).

WP 05-7 Odile Poulsen and Gert Tinggaard Svendsen: Love Thy Neighbor: Bonding versus Bridging Trust.
ISBN 87-7882-062-6 (print); ISBN 87-7882-063-4 (online).

WP 05-8 Christian Bjørnskov: Political Ideology and Economic Freedom.
ISBN 87-7882-064-2 (print); ISBN 87-7882-065-0 (online).

WP 05-9 Sebastian Buhai and Coen Teulings: Tenure Profiles and Efficient Separation in a Stochastic Productivity Model.
ISBN 87-7882-066-9 (print); ISBN 87-7882-067-7 (online).

WP 05-10 Christian Grund and Niels Westergård-Nielsen: Age Structure of the Workforce and Firm Performance.
ISBN 87-7882-068-5 (print); ISBN 87-7882-069-3 (online).

WP 05-11 Søren Harck: AD-AS på dansk.
ISBN 87-7882-070-7 (print); ISBN 87-7882-071-5 (online).

WP 05-12 Søren Harck: Hviler Dansk Økonomi på en Cobb-Douglas teknologi?
ISBN 87-7882-092-8 (print); ISBN 87-7882-093-6 (online).

2006:

WP 06-1 Nicolai Kristensen and Edvard Johansson: New Evidence on Cross-Country Differences in Job Satisfaction Using Anchoring Vignettes.
ISBN 87-7882-094-4 (print); ISBN 87-7882-095-2 (online).

WP 06-2 Christian Bjørnskov: How Does Social Trust Affect Economic Growth?
ISBN 87-7882-096-0 (print); ISBN 87-7882-097-9 (online).

WP 06-3 Jan Bentzen, Erik Strøjer Madsen and Valdemar Smith: The Growth Opportunities for SMEs?
ISBN 87-7882-098-7 (print); ISBN 87-7882-099-5 (online).

WP 06-4 Anna Piil Damm: Ethnic Enclaves and Immigrant Labour Market Outcomes: Quasi-Experimental Evidence.
ISBN 87-7882-100-2 (print); ISBN 87-7882-101-0 (online).

WP 06-5 Svend Jespersen, Nicolai Kristensen og Lars Skipper: En kritik af VEU-udvalgets arbejde.
ISBN 87-7882-159-2 (print); ISBN 87-7882-160-6 (online).

WP 06-6 Kræn Blume and Mette Verner: Welfare Dependency among Danish Immigrants.
ISBN 87-7882-161-4 (print); ISBN 87-7882-162-2 (online).

WP 06-7 Jürgen Bitzer, Wolfram Schrettl and Philipp J.H. Schröder: Intrinsic Motivation versus Signaling in Open Source Software Development.
ISBN 87-7882-163-0 (print); ISBN 87-7882-164-9 (online).

WP 06-8 Valérie Smeets, Kathryn Ierulli and Michael Gibbs: Mergers of Equals & Unequals.
ISBN 87-7882-165-7 (print); ISBN 87-7882-166-5 (online).

WP 06-9 Valérie Smeets: Job Mobility and Wage Dynamics.
ISBN 87-7882-167-3 (print); ISBN 87-7882-168-1 (online).

WP 06-10 Valérie Smeets and Frédéric Warzynski: Testing Models of Hierarchy: Span of Control, Compensation and Career Dynamics.
ISBN 87-7882-187-8 (print); ISBN 87-7882-188-6 (online).

WP 06-11 Sebastian Buhai and Marco van der Leij: A Social Network Analysis of Occupational Segregation.
ISBN 87-7882-189-4 (print); ISBN 87-7882-190-8 (online).

2007:

WP 07-1 Christina Bjerg, Christian Bjørnskov and Anne Holm: Growth, Debt Burdens and Alleviating Effects of Foreign Aid in Least Developed Countries.
ISBN 87-7882-191-6 (print); ISBN 87-7882-192-4 (online).

WP 07-2 Jeremy T. Fox and Valérie Smeets: Do Input Quality and Structural Productivity Estimates Drive Measured Differences in Firm Productivity?
ISBN 87-7882-193-2 (print); ISBN 87-7882-194-0 (online).

WP 07-3 Elisabetta Trevisan: Job Security and New Restrictive Permanent Contracts. Are Spanish Workers More Worried of Losing Their Job?
ISBN 87-7882-195-9 (print); ISBN 87-7882-196-7 (online).

WP 07-4 Tor Eriksson and Jaime Ortega: Performance Pay and the "Time Squeeze".
ISBN 9788778822079 (print); ISBN 9788778822086 (online).

WP 07-5 Johan Moritz Kuhn: My Pay is Too Bad (I Quit). Your Pay is Too Good (You're Fired).
ISBN 9788778822093 (print); ISBN 9788778822109 (online).

WP 07-6 Christian Bjørnskov: Social trust and the growth of schooling.
ISBN 9788778822116 (print); ISBN 9788778822123 (online).

WP 07-7 Jan Bentzen and Valdemar Smith: Explaining champagne prices in Scandinavia – what is the best predictor?
ISBN 9788778822130 (print); ISBN 9788778822147 (online).

WP 07-8 Sandra Cavaco, Jean-Michel Etienne and Ali Skalli: Identifying causal paths between health and socio-economic status: Evidence from European older workforce surveys
ISBN 9788778822154 (print); ISBN 9788778822161 (online).

WP 07-9 Søren Harck: Long-run properties of some Danish macro-econometric models: an analytical approach.
ISBN 9788778822390 (print); ISBN 9788778822406 (online).

WP 07-10 Takao Kato and Hideo Owan: Market Characteristics, Intra-Firm Coordination, and the Choice of Human Resource Management Systems: Evidence from New Japanese Data.
ISBN 9788778822413 (print); ISBN 9788778822420 (online).

WP 07-11 Astrid Würtz: The Long-Term Effect on Children of Increasing the Length of Parents' Birth-Related Leave.
ISBN 9788778822437 (print); ISBN 9788778822444 (online).

WP 07-12 Tor Eriksson and Marie-Claire Villeval: Performance Pay, Sorting and Social Motivation.
ISBN 9788778822451 (print); ISBN 9788778822468 (online).

WP 07-13 Jane Greve: Obesity and Labor Market Outcomes: New Danish Evidence.
ISBN 9788778822475 (print); ISBN 9788778822482 (online).

2008:

WP 08-1 Sebastian Buhai, Miguel Portela, Coen Teulings and Aico van Vuuren: Returns to Tenure or Seniority
ISBN 9788778822826 (print); ISBN 9788778822833 (online).

WP 08-2 Flora Bellone, Patrick Musso, Lionel Nesta et Frédéric Warzynski: L'effet pro-concurrentiel de l'intégration européenne : une analyse de l'évolution des taux de marge dans les industries manufacturières françaises
ISBN 9788778822857 (print); ISBN 9788778822864 (online).

WP 08-3 Erdal Yalcin: The Proximity-Concentration Trade-Off under Goods Price and Exchange Rate Uncertainty
ISBN 9788778822871 (print); ISBN 9788778822888 (online)

WP 08-4 Elke J. Jahn and Herbert Brücker: Migration and the Wage Curve: A Structural Approach to Measure the Wage and Employment Effects of Migration
ISBN 9788778822895 (print); ISBN 9788778822901 (online)

WP 08-5 Søren Harck: A Phillips curve interpretation of error-correction models of the wage and price dynamics
ISBN 9788778822918 (print); ISBN 9788778822925 (online)

WP 08-6 Elke J. Jahn and Thomas Wagner: Job Security as an Endogenous Job Characteristic
ISBN 9788778823182 (print); ISBN 9788778823199 (online)

WP 08-7 Jørgen Drud Hansen, Virmantas Kvedaras and Jørgen Ulff-Møller Nielsen: Monopolistic Competition, International Trade and Firm Heterogeneity - a Life Cycle Perspective -
ISBN 9788778823212 (print); ISBN 9788778823229 (online)

WP 08-8 Dario Pozzoli: The Transition to Work for Italian University Graduates
ISBN 9788778823236 (print); ISBN 9788778823243 (online)

WP 08-9 Annalisa Cristini and Dario Pozzoli: New Workplace Practices and Firm Performance: a Comparative Study of Italy and Britain
ISBN 9788778823250 (print); ISBN 9788778823267 (online)

WP 08-10 Paolo Buonanno and Dario Pozzoli: Early Labour Market Returns to College Subjects
ISBN 9788778823274 (print); ISBN 9788778823281 (online)