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Adele Whelan
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Adele Whelan
ESRI and Trinity College Dublin

Seamus McGuinness
ESRI, Trinity College Dublin and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Does a Satisfied Student Make a Satisfied Worker?

We investigate the effect of satisfaction at higher education on job satisfaction using propensity score matching, the special regressor method and a unique European dataset for graduates. Acknowledging that perceptions of satisfaction at higher education are endogenous to job satisfaction, we present models available to the deal with this endogeneity. Our analysis confirms that a positive university experience is important for success in future employment and suggests that emphasis should be focused on the utility of participating in third-level education along with academic outcomes.

JEL Classification: J20, J28, I23, I31

Keywords: graduate labour market, job satisfaction, higher education

Corresponding author:
Adele Whelan
Economic and Social Research Institute
Whitaker Square
Sir John Rogerson's Quay
Dublin 2
Ireland
E-mail: adele.whelan@esri.ie

1. Introduction

The study of job satisfaction has been a consistent feature of the labour economic literature (Borjas, 1979; Krueger and Schkade, 2008; Oswald and Wu, 2010, Oswald et al., 2015). Job satisfaction has been found to be a highly significant determinant of key employee performance indicators such as productivity and quits (Hamermesh, 1977; Freeman, 1978; Akerlof et al. 1988; Clark et. al, 1998; Sousa-Poza and Sousa-Poza, 2000; Clark, 2001; Sousa-Poza and Sousa-Poza, 2007; Oswald et al., 2015). Furthermore, job satisfaction has been shown to be one of the most important predictors of overall well-being or happiness for working individuals (Argyle, 1989; Judge and Watanabe, 1993; Oswald, 1997). Measures of job satisfaction also provide information about the distribution of job quality across individuals and are a key component in identifying groups more likely to experience inferior labour market outcomes. In this context, job satisfaction is part of a more general 'economics of happiness' field of research that studies the factors affecting human well-being, in connection or apart from the usual economic variables such as income and wealth (Frey and Stutzer, 2002).

While the personal and job characteristics associated with job satisfaction have been extensively studied, virtually nothing is known with regard to the role of educational experiences on determining subsequent satisfaction at work. Arguably a positive schooling experience is associated with the development of key skills, such as the ability to learn, communicate and adapt, which are also likely to be important factors in determining success, and satisfaction, in the workplace. This key question is addressed in this paper by investigating the effect of satisfaction at higher education on job satisfaction five years after graduation using a large international dataset with a wide range of controls for worker and job characteristics. We use propensity score matching (PSM) to control for potential bias arising from individual unobserved heterogeneity and the special regressor model (SRM) to control for endogeneity bias. By comparing estimators that control for non-random selection, unobserved heterogeneity and endogeneity we are able to draw conclusions regarding the causal influence of a positive university experience on subsequent job satisfaction.

Our results show that graduates who have a positive higher education experience tend to be more satisfied in their work life five years after graduation. Our analysis confirms that a positive university experience is important for success in future employment and suggests that more emphasis should be focused on the utility of participating in third-level education along with academic outcomes.

1.1 Related Literature

In general, job satisfaction is measured subjectively (Clark and Oswald, 1996; Clark, 1997; Ritter and Anker, 2002; Gazioglu and Tansel, 2006; Sousa-Poza and Sousa-Poza, 2007).[1] Existing studies have shown that job satisfaction is typically driven by factors such as age (Clark, Oswald and Warr, 1995), gender (Clark, 1997; Clark and Oswald, 1996), job security (Blachflower and Oswald, 1999; Ritter and Anker, 2002), public sector employment (Ghinetti, 2007), firm size (Idson, 1990), hours of work and education levels (Clark and Oswald, 1996). In terms of outcomes, job satisfaction has been shown to impact on both individual wellbeing (Argyle, 1989; Judge and Watanabe, 1993; Oswald, 1997) and firm level performance due to its impact on worker productivity, as shown by survey and experimental studies (Clark et. al, 1998; Oswald et al., 2015). Freeman (1978), Akerlof et al. (1988) and Clark et al. (1998) indicate that job satisfaction is as good a predictor of quits as wages. Furthermore, the meta-analysis by Harter et al. (2002) shows that job satisfaction and employee engagement are related to firm performance across business-unit outcomes, such as, profitability, productivity, turnover and absenteeism.

Measurement approaches to educational satisfaction are typically also measured subjectively. Richardson (2005) reports that the bulk of research surrounding satisfaction with university experiences is motivated by theories outlining a strong relationship between satisfaction with the university experience and learning outcomes. While theoretical conceptualisations relating to students' satisfaction with higher education are expressed as more multi-dimensional in nature, with existing studies tending to focus on particular aspects of the educational experience involving the interaction of personal, sociological and contextual factors and the methods affecting their development (Benjamin & Hollings, 1995; Beltyukova & Fox, 2002; Elliott & Shin, 2002; Rautopuro & Vaisanen, 2000; Symanski & Henard, 2001; Wiers-Jenssen, Stensaker & Grogaard, 2002). Navarro et al. (2005) proposes to group such dimensions, based on the existing studies, into the following categories: facilities, teaching staff, teaching methods, environment, enrolment and support services. These aspects, managed by the universities, can each be considered determinants of a positive higher education experience.

There is a relatively limited empirical literature assessing the determinants of educational satisfaction, Garcia-Aracil (2009) when analysing students' satisfaction with their university experience found that graduates who were most satisfied scored course content and social aspects highest. Interestingly, the study found that student satisfaction levels across 11 different European countries were relatively stable, despite significant differences in

[1] In related literature, Oswald and Wu (2010), show that there is a close match between individual's subjective life-satisfaction scores and objectively estimated quality of life data in a sample of one million Americans across 50 states.

education systems. Other factors with considerable influence included availability of equipment, library collection, teaching quality and the supply of teaching/learning materials. Similarly, Sojkin et al. (2011) in a study of Polish graduates identified social conditions and educational facilities among the key determinants of student satisfaction in higher education. Therefore, student satisfaction is not determined solely by the students' teaching and learning experiences but rather by their overall experiences at a particular higher education institution. This suggests that university education plays a role in developing social and communication skills that are likely to influence workplace performance; however, no previous research has demonstrated a causal relationship. A central contribution of this paper is to close the gap in the literature between the perceived quality of higher education experience with future labour market outcomes.

2. Data and Methods

The data used in this study is from the REFLEX[2] and HESGESCO projects covering eighteen countries.[3] It focuses on graduates in 2000 who were interviewed in 2005. The sample selected for the present study includes only those who studied for their third-level qualification on a full-time basis and who are in employment, aged between 25 and 40, in 2005. After further elimination of observations with missing values on essential variables, 23,207 observations are used in our empirical analysis.

Our objective is to investigate the effect of a positive higher education experience on job satisfaction five years after graduation while controlling for a range of socio-economic factors, accounting for non-random selection and endogeneity bias.[4] A list of the individual and job characteristics included can be found in Table 1 with summary statistics. Job satisfaction is measured by asking individuals to rate the extent to which they were satisfied in their current work on a scale of 1 (very dissatisfied) to 5 (very satisfied). A rating of 4 or 5 was deemed to be consistent with being satisfied in their current work (66% of the sample fell into this category). Satisfaction at higher education (HE) is based on the response to a question asking individuals would they choose the same study programme at the same institute again. A positive response, i.e. that the graduate would choose to study the same course at the same institution, is taken as an indication that the individual was satisfied with

[2] Further information can be found at the project websites:http://roa.sbe.maastrichtuniversity.nl/?portfolio=reflex-international-survey-higher-education-graduates; http://www.hegesco.org/.
[3] The countries included in this analysis are: Austria, Belgium, Czech Republic, Estonia, Finland, France, Germany, Hungary, Italy, Lithuania, Netherlands, Norway, Poland, Portugal, Slovenia, Spain, Turkey and United Kingdom.
[4] In identifying causal effects, one faces two separate challenges (non-random selection and endogeneity bias). It is not possible to jointly account for these but we use separate techniques to investigate the effect of a positive HE experience on job satisfaction.

their university experience (60% of the sample fell into this category).[5] The correlation coefficient between the job satisfaction and the satisfaction at HE variables is 0.20 showing a weak positive relationship. Table 2 shows the levels of job satisfaction and satisfaction at HE across the eighteen countries. Some interesting results are that: (i) respondents in Austria and Norway reported the highest level of job satisfaction (approx. 4 out of a maximum 5) with respondents in Turkey and Italy reporting the lowest level (approx. 3.5); (ii) the proportion of graduates satisfied with their jobs (providing a response of 4 or 5 to the question) in each country ranged from 50 per cent to 75 per cent and (iii) in terms of the proportion of respondents who were satisfied at HE, Austria and Belgium report the highest proportions (approx. 70 per cent) and Turkey and Lithuania reported the lowest (39 and 50 per cent, respectively).

From a methodological perspective, there are two potential sources of bias that confound the relationship between university experience and job satisfaction. First, it may be the case that individuals with a more adverse university experience also select into jobs with certain characteristics that are also correlated with job satisfaction. If the satisfaction with higher education variable is non-randomly distributed with respect to job satisfaction then this will obviously lead to biased estimates. This selection issue is also related to the problem of reverse causality, whereby individuals with certain observable attributes, or located in jobs with certain characteristics, have lower levels of job satisfaction which results in them expressing discontent with their educational choices. Second, it is arguable that unobserved traits, such as innate ability or psychological predispositions, will simultaneously drive both satisfaction with the university experience and job satisfaction thus leading to a standard endogeneity problem whereby one or more of the explanatory variables is correlated with the error term. Failure to control for either of these issues will result in biased estimates.

This paper attempts to identify the effect of a positive higher education experience on job satisfaction by using propensity score matching (PSM) to address possible bias arising from non-random selection (and individual unobserved heterogeneity through the application of post-estimation checks) and the special regressor method (SRM) to address potential endogeneity issues. The application of such procedures to this question is to our knowledge novel and allows us to control for possible types of bias to which estimates of the effect of a positive higher education experience on job satisfaction are susceptible, bringing us closer to a measure of causal influence.

[5] Four alternative negative responses were included in the survey (i) no, different programme at same college, (ii) no, same study at different college, (iii) no, different programmes at a different college, and (iv) no, would decide not to study.

2.1 Propensity Score Matching (PSM)

To address non-random selection, we begin by estimating a standard probit model examining the effect of higher education experience on job satisfaction,

$$JS_i^* = \beta_1 X_i + \beta_2 HE_i + \varepsilon_i \tag{1}$$

where $\mathrm{JS_i}$ is a latent variable which denotes an individual's probability of being satisfied in their job five years after graduation, X equals a vector of individual-specific independent variables, firm-specific indicators and employment characteristics, $\mathrm{HE_i}$ is a dummy variable measuring satisfaction at higher education and ε_i is an iid error term. We control for gender, field of study[6], education background, relative ability, work experience, family characteristics, job characteristics, migrant status and country.

However, as discussed there are strong grounds for believing that the estimate generated using a standard probit model may be biased. Therefore, we undertake further analysis to examine potential biases relating to either sample selection and unobserved individual heterogeneity. For example, if individuals who are dissatisfied at university also had observable individual or job characteristics that systematically influenced the probability to have lower job satisfaction, these influences will tend to confound the estimate of HE satisfaction on job satisfaction. To overcome this estimation risk, we adopt a propensity score matching (PSM) approach. The PSM method ensures that treated individuals i.e. those who report being satisfied with HE are compared with members of a non-treated control group (those who are dissatisfied with HE) who are similiar in terms of all observable characteristics relevant for describing allocation to the control group.

PSM involves a two-stage estimation process. In the first stage, the principle characteristics that influence the probability of being in the treatment and control groups are assigned a "propensity score" based on their estimated probability of receiving treatment (satisfaction at higher education). The first stage equation controls for gender, relative ability, years of higher education, field of study, migrant status, Hesgesco year dummy, unemployment, number of employers, country fixed effects and job characteristics including sector, hours of work, public sector, firm size, experience in months, supervisor status, job security, and field match.

[6] We distinguish a maximum of seven fields of study for each country: (i) education, humanities and arts, (ii) social sciences, business and law, (iii) science, mathematics and computing, (iv) engineering, manufacturing, and construction, (v) health and welfare, (vi) agriculture and veterinary, and (vii) services. Therefore, the reported effects are over and above those related to field of study.

The propensity score is defined as the conditional probability of receiving a treatment given certain determining characteristics,

$$p(X) = Pr\{D = 1/X\} = E\{D/X\} \qquad (2)$$

where D is a binary term indicating exposure to the treatment, in this case satisfaction at higher education, and X is a vector of determining characteristics. In the second stage, individuals in the treatment group are "matched" with counterparts in the control group that have similar propensity scores and their actual outcomes (job satisfaction) are compared. Rosenbaum and Ruben (1983) show that matching individuals on the basis of propensity scores is equivalent to matching on actual characteristics. Essentially, the only observable distinguishing factor separating the control and treatment groups will be the degree of satisfaction with the HE experience. There are a number of PSM algorithms that can be estimated but no single method is generally considered to be superior. In this instance, pairs of treated and untreated subjects are formed with individuals whose propensity scores differ by at most a pre-specified amount[7]; we employ a caliper width estimator. All our PSM models are estimated applying common support.

The main limitations of the PSM approach are: (a) it may not be possible to eradicate all observable differences between the control and treatment groups and (b) matching helps control only for observable differences and not unobservable differences, thus unobserved heterogeneity remains a problem. The estimated treatment effect is conditioned on the propensity score. Therefore, we check to ensure that this is equivalent to conditioning on the individual covariates by testing that all observable differences between the control and treatment groups have been eradicated post-matching. Our post-estimation check ensures that all important statistically significant differences within individual characteristics across the treated and untreated samples are eliminated post-matching. This ensures that any additional conditioning on observable characteristics will not provide any new information on the treatment decision. Specifically, shown in Table 3, we measure the extent to which the pseudo R2 of the stage 1 probit falls towards zero when estimated on the matched sample. Our estimation approach is to continually tighten the calliper until the point is reached where the stage 1 equation estimated on the matched sample is statistically insignificant. This approach ensures that there remains no systematic difference in the distribution of the covariates between both groups (treatment and control).

[7] The appropriate caliper depends to some extent on the data set to which it is being applied; it should be tight enough to produce close matches for efficiency, but not so tight that it becomes impossible to match a number of treated individuals, which could introduce both inefficiency (due to the reduced sample size) and selection bias. We started with a caliper of 0.1 and tightened to 0.05 until we were content with our post-estimation checks that our data were well-balanced.

The second potential concern, which our PSM approach does not directly address, relates to selection on unobservables. Therefore, further sensitivity analysis is applied to test the sensitivity of our estimated treatment effects to the existence of such hidden bias relating to individual unobserved heterogeneity bias. The reliability of any propensity score matching estimate is dependent upon the Conditional Independence Assumption (CIA) being met. This assumption implies that selection to the treatment is based solely on observables within the dataset and where all variables that simultaneously impact both the treatment and outcome variable are also observed. Given that the REFLEX dataset contains an extensive range of information on personal, job and background characteristics (included in our first stage model), we are confident that the variables at hand sufficiently incorporate all key aspects of the allocation to treatment processes. Nevertheless, despite this, it is not possible to completely rule out the possibility that our estimates are unaffected by one or more unobserved effects that simultaneously influence both the treatment and outcome variables. While we cannot explicitly eliminate such influences, as we might do for instance by estimating a fixed effects model within a panel environment, we can test the sensitivity of our estimated treatment effects to the existence of such hidden bias. Our broad higher education satisfaction PSM estimates are checked for robustness to unobserved heterogeneity bias using the “mhbounds” procedure in Stata (Becker and Caliendo, 2007). This procedure allows us to introduce an unobserved factor that simultaneously increases the likelihood of job satisfaction and increases the likelihood of allocation to the treatment group (termed positive selection bias) to assess if our estimated treatment effect remains statistically reliable. Effectively, the sensitivity test measures the extent to which an unobserved factor must influence the odds of being allocated to the treatment group before the estimated treatment effect becomes statistically unreliable.

2.2 Special Regressor Model (SRM)

Endogeneity of the satisfaction at higher education variable is the second form of potential bias that may occur as, in this setting, satisfaction with higher education is likely to be influenced by unobserved factors such as innate ability that will also positively affect job satisfaction leading to biased estimates. While the post-estimation PSM methods provide a sensitivity check on such influences, they do not explicitly control for it. In addition, the dependent variable (job satisfaction) and the explanatory variable of interest (satisfaction with higher education) are both binary which complicates the problem of explicitly controlling for such biases further. Consistent estimation requires the adoption of effective instruments within a framework that facilitates a binary outcome and a potentially endogenous variable. In this context, a Linear Probability Model (LPM) cannot account for endogeneity or ensure that estimated coefficients are consistent with a probability range between 0 to 1. Standard instrumental variable (IV) techniques, while accounting for endogeneity, may still generate inconsistent coefficient estimates where the outcome and endogenous variables are binary as the coefficients will not be properly bounded (Wooldridge, 2010).

Given these limitations, we adopt the SRM approach which allows us to address endogeneity and generate consistent estimates in the current context within an instrumental variables framework. A further advantage of the SRM method is that it does not impose restrictions on the model error and does not require the relationship between the endogenous and exogenous regressor to be specified. Again, in this analysis, we control for a large number of individual-specific independent variables, firm-specific indicators and employment characteristics. We also control for relative ability, however, we cannot be confident that this will encapsulate all aspects of innate ability.[8] The consistency of the SRM relies on the presence of a special regressor, V, in this case the age variable[9], which must satisfy three properties. First, V is exogenous and appears additively to the error. Second, V is continuously distributed and has large support, taking a wide range of values (ages 25 to 40), satisfying the second condition. Third, though not strictly necessary, V has a thick tailed distribution (in this case a kurtosis of 4.2). The SRM approach (Lewbel et al., 2012) is formally specified below:

$$\mathrm{JS} = \mathrm{I}(\beta'\mathrm{HE} + \gamma'\mathrm{X} + \mathrm{V} + \varepsilon \geq 0) \tag{3}$$

$$\mathrm{V} = \omega'\mathrm{HE} + \pi_1\mathrm{X} + \pi_2\mathrm{Z} + \mu \tag{4}$$

where JS represents the binary decision variable job satisfaction, HE represents the binary variable of satisfaction with higher education variable, vector X includes all other exogenous variables, and ε has a zero mean distribution. The special regressor, V, should be such that $E(\mathrm{JS}|\mathbf{X},\mathrm{V})$ increases with V. Since job satisfaction decreases with an increase in age within this range (ages 25 to 40), we define V as minus the age and normalise V such that it is of mean zero (See Figures 2.1 and 2.2). $\mathrm{I}(.)$ is the indicator function taking the value of one if the latent variable $\beta'\mathrm{HE} + \gamma'\mathrm{X} + \mathrm{V} + \varepsilon$ is positive and zero otherwise. Z is a vector of instruments, β and ω are vector parameters and π_1 and π_2 are matrices of reduced form parameters.

[8] In terms of student grades due to differences across countries, a question on the relative grade was used: “How do you rate your average grade compared to other students who graduated from your study programme?”

[9] Dong and Lewbel (2015) illustrate the use of the special regressor model with an empirical application estimating migration probabilities within the US using the age variable in a similar way to how we use it here (defining the special regressor V to be the negative of age minus its mean to ensure it has a positive coefficient and mean zero).

Practically, we estimate this model in four stages: (i) we estimate π_1 and π_2 for Equation (4) using OLS and get the residuals for each observation ($\hat{\mu}_i = V_i - S_i'\hat{\pi}$) where V_i takes both negative and positive values with a mean of zero; (ii) the density function for $\hat{\mu}_i$ is estimated using a kernel density estimator[10], $f(\hat{\mu}_i)$; (iii) construct $\widehat{T}_i = [JS_i - I(V_i \geq 0)]/f(\hat{\mu}_i)$;[11] and (iii) run a linear 2SLS of $\widehat{T}_i$ on HE_i, X_i, V_i and Z_i using the instruments to get an unbiased and consistent estimate of $\hat{\beta}$. For comparative purposes we also estimate the relationship using a basic probit model (Table 5).

Obviously, the SRM approach, as with any IV method, requires valid instruments. We instrument university satisfaction using two variables that measure: (i) the reported freedom of graduates in composing their own degree programme and (ii) if the programme was generally regarded as demanding. Arguably, having the flexibility to organise ones degree programme will increase its perceived intrinsic value; however, there are no obvious grounds to believe that such flexibility, which stems from the educational provider, will be related to factors that will influence subsequent job satisfaction. The question related to the demands of the course reflects general perceptions, rather than the students own experience of it, therefore the measure will reflect course status which will again influence satisfaction with it without having any obvious link to factors related to job satisfaction, particularly given that we explicitly control for relative ability in our models. The responses to the variables selected as instruments were captured on a 1 to 5 scale and for our purposes were reduced to binary outcome variables for responses of 4 and 5 respectively. The instruments pass all tests related to both the strength and validity within the SRM frameworks (shown in Table 3).

3. Results

Table 3 shows positive and highly significant effects of satisfaction at higher education on job satisfaction five years after graduation across all models after controlling for a wide range of personal and job characteristics. The marginal effects range from 12% to 16%, indicating that individuals who were satisfied with their HE experience were between 12 to 16 percentage points more likely to be satisfied in their jobs 5 years after graduation. We first report the results for the probit and PSM models followed by the SRM results using both instruments simultaneously and then separately using the individual instruments. The basic probit model (Table 4), which ignores any regressor endogeneity and provided here as a baseline

[10] To estimate the density, the Epanechnikov kernel function was used and the bandwidth was given by the Silverman's rule of thumb.

[11] Since $\widehat{T}_i$ construction involves dividing by the density function and outliers can lead to high standard errors, we trim the outliers (Lewbel et al., 2012). In all cases, 95% winsorisation was applied to the data. As a robustness check, we estimated the coefficients and standard errors under the winsorisation and trimming techniques at different levels (1, 2.5, and 5).

benchmark, indicates that after controlling for a wide range of factors, individuals who were satisfied with their HE experience were 16 percentage points more likely to be satisfied in their jobs 5 years after graduation. The model is well specified and shows that job satisfaction was higher among migrants, those with higher relative ability, more labour market experience, in public sector employment, those working increased hours, with a supervisory role, in occupations matching their field of study, with job security and in large firms with over 1000 employees. While previous unemployment spells significantly lowered job satisfaction. The estimated marginal effect of negative age is modest but statistically significant. Sector and country dummies were included and also played significant roles.[12]

The first stage PSM models including individual, programme and job characteristics indicate a range of factors associated with HE satisfaction. As we are attempting to eradicate the extent to which satisfaction at HE is potentially correlated with a range of personal and job characteristics that also influence job satisfaction, a full range of controls are included in the model. Matching on both individual and job characteristics minimises the risk that individuals are negatively reflecting on their HE experience as a consequence of being predominantly located in jobs or sectors with low levels of job satisfaction (Table 4, Row 2). Higher education satisfaction was greater among males, those with higher relative ability, in occupations matching their field of study, in supervisory roles, secure positions, with longer durations of HE study and labour market experience. Meanwhile, periods of unemployment and an increased number of employers lowered the reported satisfaction with higher education. Sector, field of study and country dummies were again included and also played significant roles.

The PSM estimate is directly in line with that from the probit model, suggesting that selection bias in not an issue. Table 4 includes the post-estimation MH bound test statistics and the estimated effects appear very robust to unobserved heterogeneity bias. The reported MH bound test statistic of 2.2 shows that in the case of an unobserved factor increasing the likelihood of job satisfaction by a factor of 120 percent our estimate is still reliable at a 95 percent level of confidence.[13] Therefore, given the dataset includes such a rich set of variables, the test statistics reported above and the SRM model results to be discussed below, we are confident that the PSM estimate is robust to both sample selection and unobserved heterogeneity.

Further comparisons shows that the SRM estimates are also in line with Probit and PSM estimates (Table 5). The Anderson under-identification test and the Sargan-Hansen test for

[12] Extended tables available on request from the authors.
[13] Mavromaras. McGuinnness and Fok (2009) use similar sensitivity analysis and comment that an MH bound test statistic of 2 are particularly strong given the minimum wage study by Card and Kruger found that results become unreliable with lower values of between 1.34 and 1.5 (Rosenbaum, 2002).

over-identification were performed and confirmed the validity of the two instruments.[14] The SRM results show satisfaction with higher education experience to be associated with a 12 to 13 percent increase in the probability of job satisfaction five years after graduation. Regarding the other covariates in the model[15], a positive effect with job satisfaction is found for males[16], years in higher education, public sector employment, job security, labour market experience, supervisory roles and previous unemployment spells. In terms of field of study, compared to arts, humanities and education a significant negative effect is found for three fields: social sciences, business and law; science, mathematics, and computing; and services. Average relative grade is also found to have a negative impact on job satisfaction five years after graduation.

4. Conclusion

After controlling for a wide range of personal and job characteristics, as well as the potential bias arising from individual unobserved heterogeneity or potential endogeneity, our results show that graduates who have a positive higher education experience tend to be more satisfied in their work life. The analysis confirms that a positive university experience is important for success in future employment and suggests that emphasis should be focused on the utility of participating in third-level education along with academic outcomes.

These findings have relevant implications for policy, as they recognise the importance of the provision of education facilities, support services and a social environment that create a positive experience for students at higher educational institutions. With respect to course composition, the study provides clear evidence of a need for greater flexibility to allow autonomy for students in the composition of their studies while providing the relevant skills for future labour market experiences. In terms of career guidance, the research supports the view that by investing more heavily in career-support functions, higher level institutions can play an important role in assisting graduates with their career decisions, which can have long-term impacts for success in future employment.

[14] The null hypothesis for the Anderson test is that the equation is under-identified and the null hypothesis of the Sargen-Hansen test is that the instruments are valid. These tests for instrument validity were incorporated by Bontemps and Nauges (2016) into the *sppecialreg* procedure (Baum, 2012).

[15] Note that the sign on the marginal effects change between the probit and SRM models for a couple of the other significant covariates, namely, relative average grade and unemployment spells. However, the marginal effect on the main variable of interest (satisfaction with college) does not change.

[16] This result is counter to a number of early studies showing that women have higher levels of job satisfaction than men (Clark et al., 1997).

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Tables

Table 1: Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable					
Satisfied in Current Job (5 years after graduation)	23,090	0.66	0.47	0	1
Independent Variables					
Satisfied at Higher Education	22,692	0.60	0.49	0	1
Individual Specific Characteristics					
Male	23,207	0.40	0.49	0	1
Age	23,207	29.2	2.45	25	39
Years of Higher Education	23,044	4.30	0.94	3	7
Relative Average Grade	20,457	3.58	0.73	1	5
Migrant	23,207	0.03	0.16	0	1
Hegesco Year Dummy	23,207	0.21	0.41	0	1
Fields of Study					
General, Education and Humanities*	23,207	0.31	0.46	0	1
Social Sciences, Business and Law	23,207	0.31	0.46	0	1
Science, Mathematics and Computing	23,207	0.10	0.31	0	1
Engineering, Manufacturing and Construction	23,207	0.18	0.39	0	1
Agriculture and Veterinary	23,207	0.03	0.17	0	1
Health and Welfare	23,207	0.13	0.34	0	1
Services	23,207	0.03	0.17	0	1
Job- Specific Characteristics					
Hours Worked (Weekly)	22,985	37.39	8.24	1	98
Field Match	23,049	0.31	0.46	0	1
Public Sector	22,870	0.43	0.49	0	1
Firm Size (<100)*	23,207	0.35	0.48	0	1
Firm Size (100-249)	21,589	0.12	0.33	0	1
Firm Size (250-999)	21,589	0.16	0.37	0	1
Firm Size (1000+)	21,589	0.34	0.47	0	1
Supervisor Role	22,922	0.33	0.47	0	1
Job Security	23,207	0.33	0.47	0	1
Number of Employers	21,622	2.23	2.08	0	83
Unemployment Spell	23,017	0.39	0.49	0	1
Labour Market Experience (Months)	21,015	50.83	14.42	0	84
Sectors					
Education*	22,390	0.14	0.35	0	1
Manufacturing	22,390	0.14	0.35	0	1
Wholesale and Retail Trade	22,390	0.05	0.22	0	1
Financial Intermediation	22,390	0.05	0.23	0	1
Real Estate, Renting and Business	22,390	0.16	0.37	0	1
Public Administration and Defense	22,390	0.09	0.29	0	1
Health and Social Work	22,390	0.15	0.36	0	1
Other Sectors	23,207	0.14	0.35	0	1

*** Identify Base Categories**

Table 1 Cont'd: Summary Statistics

Variables Continued	Obs	Mean	Std. Dev.	Min	Max
Countries					
Austria	23,207	0.03	0.18	0	1
Belgium	23,207	0.04	0.2	0	1
Czech Republic	23,207	0.16	0.37	0	1
Estonia	23,207	0.02	0.13	0	1
Finland	23,207	0.06	0.24	0	1
France	23,207	0.04	0.21	0	1
Germany	23,207	0.04	0.20	0	1
Hungary	23,207	0.04	0.19	0	1
Italy	23,207	0.06	0.24	0	1
Lithuania	23,207	0.03	0.17	0	1
Netherlands	23,207	0.09	0.29	0	1
Norway	23,207	0.06	0.24	0	1
Poland	23,207	0.03	0.16	0	1
Portugal	23,207	0.02	0.12	0	1
Slovenia	23,207	0.07	0.25	0	1
Spain	23,207	0.10	0.31	0	1
Turkey	23,207	0.05	0.21	0	1
United Kingdom	23,207	0.05	0.21	0	1

Table 2: Satisfaction Variables by Country

	Country	Job Satisfaction Rank	Job Satisfaction	Satisfaction at HE	%
		Scale of 1 (very dissatisfied) to 5 (very satisfied)	Collapsed to Binary 0-1	Binary 0-1	
1	**Austria**	4.006	0.748	0.702	3.46
2	**Belgium**	3.871	0.726	0.699	4.22
3	**Czech Republic**	3.873	0.705	0.637	16.17
4	**Estonia**	3.861	0.691	0.550	1.80
5	**Finland**	3.711	0.651	0.594	5.98
6	**France**	3.845	0.681	0.668	4.50
7	**Germany**	3.867	0.716	0.632	4.40
8	**Hungary**	3.700	0.627	0.586	3.95
9	**Italy**	3.582	0.561	0.653	6.23
10	**Lithuania**	3.850	0.681	0.502	2.82
11	**Netherlands**	3.763	0.675	0.623	9.40
12	**Norway**	3.937	0.721	0.640	6.37
13	**Poland**	3.659	0.643	0.590	2.68
14	**Portugal**	3.668	0.634	0.565	1.52
15	**Slovenia**	3.727	0.643	0.519	6.76
16	**Spain**	3.687	0.621	0.519	10.41
17	**Turkey**	3.369	0.499	0.389	4.82
18	**United Kingdom**	3.734	0.649	0.633	4.50
	Total	3.766	0.661	0.600	100.00
	#				23,207

Table 3: Abbreviated Estimation Results (Marginal Effects) and Post-estimation Tests

Dependent Variable: Satisfaction in Current Job	**(1) PROBIT**	**(2) PSM (ATT)**	**(3) SRM IV(Freedom &Demand)**	**(4) SRM IV(Freedom)**	**(5) SRM IV(Demand)**
Satisfaction with College (Robust Std.Err.)	0.16*** (0.008)	0.16*** (0.01)	0.12*** (0.014)	0.12*** (0.025)	0.13*** (0.016)
N	15,848	15,848	15,737	15,761	15,788
F Statistic (Prob>F)	30.84 (0.000)	996.07 (0.000)	-	-	-
Pseudo R2 (Pre)	-	0.047 (0.000)	-	-	-
Pseudo R2 (Post)	-	0.002 (0.443)	-	-	-
MHbounds	-	2.20	-	-	-
Under-Identification Test:					
Anderson Canon. Corr. LM Statistic (Chi-sq(2) P-Val)	-	-	164.017 (0.000)	39.394 (0.000)	120.26 (0.000)
Weak-Identification Test:					
Cragg-Donald Wald F Statistic (10% Maximal IV Size)	-	-	82.619 (19.93)	39.374 (16.38)	120.830 (16.38)
Over-Identification Test:					
Sargan Statistic (Chi-sq(1) P-Val)	-	-	0.454 (0.5005)	-	-

*** Significant at 1% level. Other control variables in all models include: gender, age, years of education, seven dummy variables for field of study, relative average grade, experience, unemployment, number of employers, migrant status, four dummy variables for firm size, hours of work, public service, supervisor role, job security, field match, HEGESCO year, seven dummy variables for sectors, and eighteen country dummy variables.

Table 4: PSM Estimates for Job Satisfaction[17]

	Dependent Variable: Job Satisfaction	**PSM (ATT)**	**PSM (Unmatched)**	**Pseudo R2 (Pre)**	**Pseudo R2 (Post)**	**MHbounds**	**#**
1	**Satisfaction with Higher Education** ***(Matched on Individual Pre-Job Characteristics)***	0.180*** (0.007)	0.193*** (0.007)	0.022***	0.001	2.25	19,798
2	**Satisfaction with Higher Education** ***(Matched on Individual and Job-Specific Characteristics)***	0.157*** (0.01)	0.187*** (0.001)	0.047***	0.001	2.20	15,737

[17] First stage probits for the PSM are available by request from the authors.

Table 5: Probit and SRM Estimates for Job Satisfaction – Estimated Marginal Effects[18]

Dependent Variable: Satisfaction in Current Job	**(1) PROBIT**	**(1) SRM IV(F&D)**	**(2) SRM IV(Freedom)**	**(3) SRM IV(Demand)**
Satisfaction with College	0.16***	0.12***	0.12***	0.13***
	(0.008)	(0.014)	(0.025)	(0.016)
Individual-Specific Characteristics[19]				
Age *(negative values of)*	0.01***	0.02***	0.02***	0.02***
	(0.002)	(0.005)	(0.009)	(0.005)
Male	0.00	0.01***	0.01**	0.01**
	(0.009)	(0.004)	(0.007)	(0.004)
Migrant	0.06**	0.00	0.00	0.00
	(0.023)	(0.006)	(0.009)	(0.006)
Relative Average Grade	0.01***	-0.01***	-0.01***	-0.01***
	(0.005)	(0.002)	(0.003)	(0.002)
Years of Higher Education	-0.00	0.01***	0.02**	0.01***
	(0.005)	(0.004)	(0.007)	(0.004)
Hegesco Year Dummy	0.05	0.00	-0.00	0.00
	(0.038)	(0.012)	(0.011)	(0.008)
Field of Study (Base Case: Education, Humanities and Arts)				
Social Sciences, Business and Law	0.00	-0.01***	-0.01***	-0.01***
	(0.013)	(0.004)	(0.005)	(0.004)
Science, Mathematics and Computing	0.01	-0.01**	-0.01*	-0.01**
	(0.015)	(0.003)	(0.005)	(0.004)
Engineering, Manufacturing and Construction	-0.00	-0.00	-0.00	-0.00
	(0.014)	(0.005)	(0.007)	(0.005)
Health and Welfare	-0.01	-0.01	-0.01	-0.01*
	(0.018)	(0.006)	(0.007)	(0.005)
Agriculture and Veterinary	-0.00	0.01	0.01	0.01
	(0.025)	(0.007)	(0.010)	(0.006)
Services	-0.02	-0.01*	-0.02	-0.01**
	(0.025)	(0.008)	(0.010)	(0.007)
Job-Specific Characteristics				
Hours Worked (Weekly)	0.00**	0.00	0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.000)
Public Sector	0.04***	0.01**	0.01**	0.01**
	(0.011)	(0.004)	(0.004)	(0.003)
Supervisor Role	0.07***	0.01**	0.01*	0.01**
	(0.008)	(0.004)	(0.007)	(0.003)
Field Match	0.08***	-0.00	0.00	-0.00
	(0.009)	(0.004)	(0.007)	(0.003)
Firm Size (100-249)	-0.02	-0.00	-0.00	-0.00
	(0.013)	(0.004)	(0.003)	(0.004)
Firm Size (250-999)	-0.02	-0.00	-0.00	-0.00
	(0.012)	(0.004)	(0.004)	(0.003)
Firm Size (1000+)	0.02**	0.00	0.00	0.00
	(0.010)	(0.003)	(0.003)	(0.003)
Job Security	0.07***	0.01**	0.01*	0.01**
	(0.008)	(0.004)	(0.006)	(0.004)
Number of Employers	0.00	0.00*	0.00*	0.00*
	(0.003)	(0.001)	(0.001)	(0.001)
Labour Market Experience (Months)	0.00**	0.00***	0.00**	0.00***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment Spell	-0.03***	0.01***	0.01***	0.01***
	(0.009)	(0.003)	(0.003)	(0.002)
Country Dummies Included	YES	YES	YES	YES
Sector Dummies Included	YES	YES	YES	YES
Constant		-0.13***	-0.14***	-0.12***
		(0.026)	(0.044)	(0.029)
Observations	15,848	15,737	15,761	15,788
Number of countries	18	18	18	18
Prob > F	0.00	0.00	0.00	0.00
Pseudo R-Squared	0.06	-	-	-

[18] Standard errors for the special regressor models were calculated using bootstrap techniques (100 reps).

[19] As age is chosen as the special regressor, we define it to be the negative of age, minus its mean (ensuring it has a positive coefficient and mean zero).

Figures

Figure 2.1: Kernel Density of Age (demeaned value)

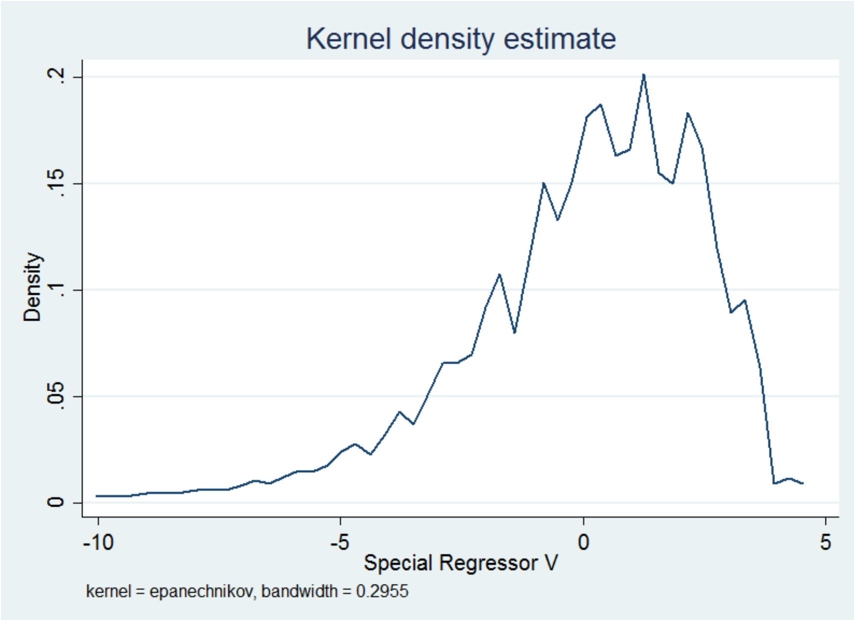

Figure 2.2: Kernel Weighted Local Polynomial Regression of JS on V