Non-Cognitive Skills and the Returns to Education

Do Non-cognitive skills explain part of the Returns to Education?

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Abstract

Returns to Higher Education are estimated to be around 6-9% in the UK, and while non-cognitive skills (such as locus of control, traits of work ethics, conscientiousness, self-esteem etc) and their impact on life-outcomes have been increasingly studied in psychology, sociology as well as economics, their effect on returns to higher education did not receive the focus it potentially deserves. Using the Longitudinal Study of Young People (LSYPE) this paper estimates the returns to Higher Education in the UK while controlling for these non-cognitive skills using standard OLS as well as Propensity Score Matching and Inverse Probability Weighted Regression Adjustment. Against expectation the inclusion of non-cognitive skills does not affect the estimates for returns to higher education greatly, and out of all non-cognitive skills included a high Locus of Control is the only trait that has a (statistically significant) positive impact on income. Having obtained a degree, therefore, far outweighs the effects of non-cognitive skills on income.

Introduction

It is common to assume that certain personality traits like initiative, persistence, motivation are desirable for successful outcomes in life and literature in psychology, sociology and economics has been increasingly trying to study the effect of such personality traits, otherwise known as non-cognitive skills, on various outcomes, by filling the gaps where previously only cognitive skills were accounted for. One such outcome is the return to Higher Education (HE) for which previous evidence has commonly demonstrated a return of around 10% (Harmon et al., 2003) and only controls for cognitive skills. While evidence on the returns of non-cognitive skills is increasing in recent years, it is nevertheless bound by data availability. The release of the Age 25 Survey, the latest survey of the Longitudinal Study of Young People in England (LSYPE), contains not only plenty information about the characteristics, traits and lives of the individuals but also the first observations on early labor market outcomes and offers hence the opportunity to explore the relationship between non-cognitive skills and the returns to HE.

The aim of this study is to explore the effect on non-cognitive skills on wages as well as the robustness of the returns to higher education estimate towards the inclusion of non-cognitive skills (which to my best knowledge has not been studied previously) using the most recent cohort data available for the UK. I use standard Ordinary Least Squares estimation as well as Propensity Score Matching and Inverse Probability Weighted Regression Adjustment to estimate these effects.

The paper is structured as follows: section 1 reviews related literature, section 2 describes the Data used and all variables in detail, section 3 presents preliminary relationships and some descriptive statistics and section 4 discusses the methodology applied. Section 5 presents the results obtained while section 6 outlines limitations and provides some further discussion before section 7 concludes.

1 Related Literature

The concept of non-cognitive skills is rooted in the field of personality psychology and hence an understanding of its implications in life requires/-draws back upon an interdisciplinary review of evidence. It is common to assume that your personality plays an important role in life and certain personality traits like initiative, persistence, motivation, and charm seem desirable for successful life-outcomes. Psychology literature formalizes the various facets of an individual's personality with the Big Five personality traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. It has become a widely used taxonomy of personality traits aiming to characterize them at the broadest level of abstraction. Within these broader definitions are a number of more narrowly defined personality characteristics some of which are more relevant in the scope of this research than others. As such competence, dutifulness, self-discipline, perseverance and work-ethic all represent different sides of Conscientiousness which in turn next to Openness to Experience have been shown to have a particularly strong association with successful outcomes in education (years of education, grades, test scores etc.) as well as successful labor market outcomes (Almlund et al., 2011). Almlund et al. (2011) also highlight locus of control (which is closely related to conscientiousness) and self-esteem, as two further personality traits that have been shown to particularly influence job performance and predict wages (Judge and Hurst, 2007; Drago, 2011; Duncan and Dunifon, 1998). Just as the study of non-cognitive skills and their impact grew in the fields of psychology and sociology it also gained popularity among economists which have been increasingly exploring the causal impacts of the non-cognitive skills.

One of the earlier contributions to the debate is Jencks' 1979 book "Who gets ahead – The Determinants of Economic Success in America" who discusses family background, academic ability education as well as non-cognitive traits. While the data may be dated now, Chapter 5, written by Peter Mueser, nevertheless highlights that non-cognitive skills, in particular in the form of self-assessed leadership, show to have a significant effect on wages but also cautiously abstains from singling out any one particular 'magic' trait. The data used for the study, Project Talent, was the largest and most comprehensive dataset on high school students in the US at the time and contained measures of personality based on the individual's self-assessment, but also their behavior, attitudes, and assessments by others. Mueser remains cautious and aware that his regressions are not rigorous causal models but it makes an important contribution in demonstrating that non-cognitive/personality traits add more to personal achievement than past research had indicated.

Heckman and Rubinstein (2001) highlight indirectly the power of non-cognitive skills on wages by attributing the observed difference of average wages earned by high school graduates and GED recipients (high school dropouts that exam certify as high school equivalents) to their difference in non-cognitive skills. Controlling for measured ability GEDs show to receive lower wages, on average, than high school graduates. With these results Heckman and Rubinstein were also calling upon subsequent studies to further study which skills in particular cause this difference in labor market success.

Heckman, Stixrud, and Urzua (2006) exploit the National Longitudinal Survey of Youth 1979 (NLSY79) and its records of the Rotter Locus of Control Scale and the Rosenberg Self-Esteem Scale as well as cognitive test scores to explore the returns to non-cognitive skills in a comprehensive manner. They address the econometrical difficulties of endogeneity/reverse causality between schooling and ability (and the limits of OLS) by estimating the distributions of latent cognitive and non-cognitive factors and using those to predict test scores of the individuals so that schooling cannot affect ability/test scores anymore. Using measured test scores, corrected test scores, and simply the estimated latent cognitive and non-cognitive factors in the wage regression, the standardized OLS coefficients for cognitive and non-cognitive ability vary by different schooling levels but are generally positive for non-cognitive skills and within the 2-10% range (depending on how ability enters the equation). Overall Heckman et al. (2006) demonstrate that non-cognitive skills raise wages through direct impact on productivity as well as indirectly through schooling and work experience and this based on locus of control and self-esteem as the deciding non-cognitive variables.

Heckman, Humphries, Urzua, Vermendi (2011) is in a way an extension to Heckman et al. (2006) since besides looking at labor market outcomes, they look at further life outcomes such as health and social outcomes based on a model of sequential schooling decisions. They use a slightly altered definition of non-cognitive skills that they call socio-emotional ability, which comprises measures of adverse adolescent behavior and argue (based on previous literature) that early behavior is related to non-cognitive traits and hence captures traits that help explain observed behavior. While the primary focus is to study the effect of educational choices on chosen outcomes, the inclusion of socio-emotional ability in the dynamic model indirectly demonstrates their important impact on the outcomes as well. Socio-emotional loadings are shown to have significant predictions of GPA and educational choices, and are significant for all the unconditional labour market models, except for labour force participation .

Flossmann, Piatek, Wichert (2007) follow closely the methodology of Heckman et al. 2006 and find that non-cognitive skills (also) matter in the determination of wages in Germany, based on the 1999 wave of the German Social Economic Survey (GSOEP). Subject to data availability on non-cognitive skills Flossmann et al. (2007) exploit attitude questions closely related to the locus of control and use these (i) to construct a simple additive variable/index for the non-cognitive skill of the individual (ii) for their measurement system to obtain the distribution of the latent factor and which is then used in the estimation to address endogeneity as well as measurement error concerns. There is no difference in effect of non-cognitive skills between men and women, revolving at a return of just under 4%.

A previous paper that has been studying non-cognitive skills by exploiting LSYPE (the same dataset used here) was written by Mendolia and Walker (2014) . It explored the impact of personality traits like locus of control, self-esteem, and work ethics (at age 15/16) on subject choices and school performance at age 17/18. The continuation of the survey until age 25 allows me to take the analysis of these non-cognitive skills to the next level and look at wages. Since Mendolia and Walker (2014) found a significant impact of the individual's locus of control and self-esteem on performance in high school it establishes a promising start for this research.

To my knowledge no previous evidence demonstrates whether the returns to (higher) education is robust to the inclusion of non-cognitive skills. The returns to higher education in the UK have been typically shown to be between 6-10%/7-9% (Harmon et al., 2003). The aim of this study is to explore the effect on non-cognitive skills on wages as well as the robustness of the returns to higher education estimate towards the inclusion of non-cognitive skills using the most recent cohort data available for the UK. The availability of questions in surveys regarding locus of control and self-esteem makes these traits the most commonly studied non-cognitive skills in relation to outcomes such as educational or economic success. The advantage of LSYPE is that it contains a variety of different attitude questions/statements, that can be exploited for some principle component analysis and possibly give a better depth to the skills.

2 Data

The main source of data is the Longitudinal Study of Young People (LSYPE). It is a large-scale cohort study that follows the lives of around 16,000 people born in 1989-90 in England. Cohort members were aged 13-14 when the study began in 2004 and were followed/interviewed every year until 2010, aged 19-20. They were then revisited in 2016, aged 25, to provide some insights into the lives of the young adults. Treating the data as a cross-section provides plenty information on the educational and labour market experiences, economic circumstances, family life, physical health and emotional wellbeing, social participation and attitudes of the individuals. Crucial to this research is the release of the Age 25 survey as it allows to connect and study how educational choices and outcomes of the individuals as well as non-cognitive traits and other individual and family characteristics have influenced their lives so far in terms of labour market outcomes/economic well-being, i.e. assessing the returns to early life-decision and attitudes.

Surveys 1-7 were managed by the Department for Education (DfE), while survey 8 (Age 25 survey) was carried out under the management of the Centre for Longitudinal Studies at the UCL Institute of Education.

2.1 Outcome Variable

This study is interested in the returns to educational outcomes as a function of cognitive as well as non-cognitive skills. The main outcome variable is the individuals' income from full-time and part-time employment (at time of interview – aged 25). I take the logarithm of the gross hourly wage, computed by the ratio of the gross weekly pay and the hours worked per week by the individual.

2.2 Cognitive Skill Measures

In terms of the cognitive skill measures I use various different variables in the wage specifications (see Section 3) depending on applicability. LSYPE has information on what qualification the individual has acquired to date. To capture the overall returns to Higher Education (HE) I exploit the variable that reflects whether the individual has completed at least a First Degree, meaning individuals who have obtained at least a First degree level qualification (including foundation degrees, graduate membership of a professional institute, PGCE) and does not exclude individuals having completed a University Higher Degree (e.g. MSc, PhD). Conditional on having obtained a degree LSYPE also reports whether the individual has been awarded the degree by a Russel Group University or by another Higher Education (HE) institution allowing me exploit these as two separate sub-treatments. The Age 25 Survey further specifies what subjects the individuals studied at university (First Degree only) which I group into STEM, Social Sciences, and Arts and Humanities to study the differences in returns on more specific subject areas.

Other explanatory variables used in the specifications are dummies for gender (1=female), regional dummies (a dummy for north, south, and midlands of England respectively) and dummies for the individual's ethnicity (non-white vs. white). Figure 1 shows the descriptive statistics of the outcome variable and cognitive skill measures by gender discussed so far. The variables are weighted given the most recent survey wave. Furthermore, all variables apart from the log hourly income are dummy variables and N is showing the positive observations (excluding the zeroes) for these dummies.

Figure 1: Descriptive Statistics of outcome variable and cogn. skill measures

			Male		Female	
Variable	Description	N	mean	sd	mean	sd
Log hourly income	Log of gross hourly wage	5,159	2.426	0.397	2.352	0.376
Degree	ind. has obtained at least first degree	2,660	0.255	0.436	0.286	0.452
No degree	ind. has not obtained at least a first degree	2,073	0.316	0.465	0.301	0.459
Missing degree	observation for degree missing	2,869	0.429	0.495	0.413	0.492
Russel	ind. was awarded degree by Russel Group University	442	0.052	0.222	0.055	0.227
other HEI	ind. was awarded degree by other Higher Education Institution	1,296	0.129	0.335	0.161	0.367
STEM	ind. was awarded a STEM subject degree	688	0.083	0.276	0.071	0.257
Social Sciences	ind. was awarded a Social Science subject degree	523	0.050	0.218	0.062	0.240
Arts & Humanities	ind. was awarded an A&H subject degree	543	0.049	0.216	0.083	0.276

2.3 Non-cognitive skills

Non-cognitive ability is difficult to measure not least because there is no overarching agreement on how to define non-cognitive skills and while reference points from the Psychology literature exist (i.e. Big Five) it is not feasible to express non-cognitive ability through one measure only. Non-cognitive skills are usually the interaction and combination of at least a few 'key skills'. LSYPE offers a few opportunities to capture the non-cognitive skills of the individual.

A commonly used measure in related literature (not least because of its availability in recent datasets) is a form of the Locus of Control Scale, first introduced by Rotter (1966), which aims to reflect how much control the individual believes to have over his/her life. LSYPE asks cohort members in Wave 2, Wave 4, Wave 7 and Wave 8 a series of attitude questions that are meant to capture the concept of locus of control. Figure 2 gives an overview of these questions/statements that remain the same across the waves allowing for comparability across time.

Note that the individual can either strongly agree (SA), agree (A), disagree (D), or strongly disagree (SD) with each statement which are coded from 1 to 4. Summing the responses to these four questions gives an overall score on the Locus of control scale (Lefcourt, 1991). For the direction of the statements to match up, statement 1,2 and 4 were recoded as follows: 1=4, 2=3, 3=2, 4=1. A higher overall score therefore indicates a more internal locus of control – meaning the individual has greater confidence in the fact that he/she can influence his/her destiny, vice versa for a person with a low score and therefore a more external locus of control.

Figure 2: Locus of Control statements

No.	Locus of Control Statement	Score			
1	"If someone is not a success in life, it is usually their own fault"	SA (=4)	A (=3)	D (=2)	SD (=1)
2	"I can pretty much decide what will happen in my life"	SA (=4)	A (=3)	D (=2)	SD (=1)
3	"How well you get on in this world is mostly a matter of luck"	SA (=1)	A (=2)	D (=3)	SD (=4)
4	"If you work hard at something you'll usually succeed	SA (=4)	A (=3)	D (=2)	SD (=1)

SA – strongly agree, A – agree, D – disagree, SD – strongly disagree

Summing the scores over the four statements in each wave, I construct an additive Locus of Control variable for each wave, with a minimum score of 4 and a maximum score of 16. For the main analysis in this paper I choose to include the overall score of the locus of control from wave 2 (individuals aged 14/15), because observations from wave 4 are too low, and wave 7 and 8 pose a problem with endogeneity in this context since these scores would have been measured during the time of going to university. The mean of Wave-2-Locus-of-control averages to a score around 12.

I have grouped further attitude statements across the different waves into the following topics: feelings about school (contained in wave 1, wave 2, wave 3 and to a certain extent in wave 4), self-confidence in terms of the future (job/university), and a more direct interpretation of self-esteem in Wave 4. The three attitude statements on feelings about school are seen in Figure 3. Similarly to the locus of control, I generate additive variables that reflect in this case what I call "school importance". For the directions of the statements to match up again, I recode the first, second and fourth statement the following way: 1=4, 2=3, 3=2, 4=1. The higher the score on this scale, the more important school is to the individual.

Figure 3: Statements on 'School Importance'

No.	Statement on feelings about school (wave 1, 2, 3)	Score			
1	"School is a waste of time for me"	SA (=1)	A (=2)	D (=3)	SD (=4)
2	"School work is worth doing"	SA (=4)	A (=3)	D (=2)	SD (=1)
3	"I work as hard as I can in school"	SA (=4)	A (=3)	D (=2)	SD (=1)

SA – strongly agree, A – agree, D – disagree, SD – strongly disagree

additive variable for each wave (min=3, max=12)	N	mean	sd
school importance wave 1	4926	10.33	1.35
school importance wave 2	4557	9.94	1.47
school importance wave 3	4517	10.07	1.46

In Wave 4, there are similar question regarding feelings towards school like "Working hard now, will help me get on later in life" or "Doing well in school means a lot to me" but due to low observations number is not representative enough. On the other hand LYSPE reports its own variable for Wave 4 called 'attitude towards school' which is a derived variable and shows a score from 0 until 20. Again, the higher the score the more positive towards school the individual is. I reserve this further definition for robustness checks.

Wave 4 further reports self-confidence regarding getting a job or going to university, but again the observation count is too low. Instead I will rely on a more direct interpretation of self-esteem. Figure 4 provides an overview of the questions, scores, and a derived additive variable I generate from the four available statements. The higher score on this scale of 'self-esteem' the higher the self-esteem of the individual.

Figure 4: Statements on Self-Esteem - Wave 4

No.	Statements about individual's self-esteem	Score			
1	"Whether Young Person (YP) felt unhappy or depressed"	not at all (=4)	no more than usual (=3)	rather more than usual (=2)	much more than usual (=1)
2	"Whether YP has been losing confidence in self"	not at all (=4)	no more than usual (=3)	rather more than usual (=2)	much more than usual (=1)
3	"Whether YP has thought of themselves as a worthless person recently"	not at all (=4)	no more than usual (=3)	rather more than usual (=2)	much more than usual (=1)
4	"Whether YP has felt reasonable happy"	more so than usual (=1)	about the same as usual (=2)	less so than usual (=3)	much less than usual (=4)

additive variable (min=4, max=16)	N	mean	sd
self-esteem	4492	13.11	2.65

2.4 Preliminary Relationships between Locus of Control and different outcomes

This section presents preliminary relationship between the Locus of Control and different outcomes such as the mean of weekly gross income, the individual's final UCAS score, as well as university degree classification.

Figure 5 displays the mean of weekly gross pay (£) graphed on the Locus of Control score (at age 14/15) by gender and by degree status. The tails of the locus of control distribution were grouped due to very limited observation counts in the extreme cases. There seems to be an indication for an increasing mean of income the higher the locus of control is, meaning the more internal the individual perceives himself to be and believes he can change his destiny the higher the mean income. This positive relationship seems to the strongest for males that hold a degree and to a certain degree for females with a degree. The positive relationship is less convincing for males without a degree and somewhat non-existant for females without a degree.

Figure 6 looks more closely at whether there are differences in the previously observed relationship depending on the type of Higher Education Institution. Figure 6 makes a distinction between a Degree obtained from a Russel Group university versus a degree obtained from another university.

The positive relationship between income and locus of control is again noticeable for men, even though more prominent when having obtained a Russel degree and showing a slight dip in the left tail of the locus distribution in the other HEI category. There is no clear relationship visible for women.

Figure 5: Mean of weekly gross pay (£) and Locus of Control (by gender and degree)

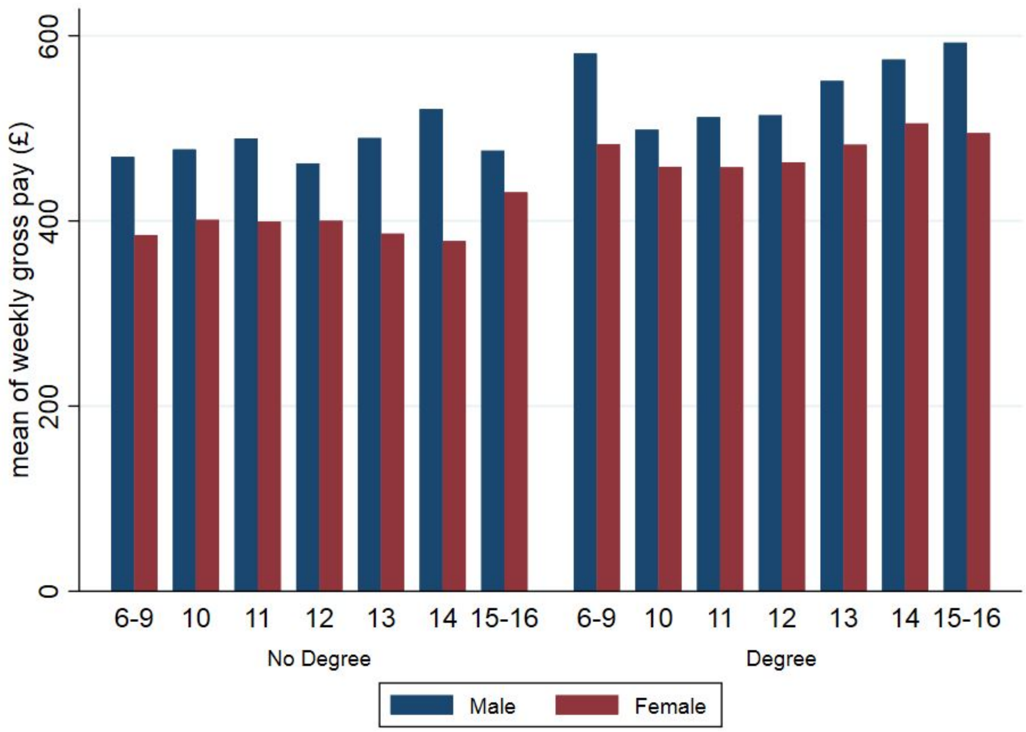


Figure 6: Mean of weekly gross pay (£) and Locus of Control (by gender and HEI type)

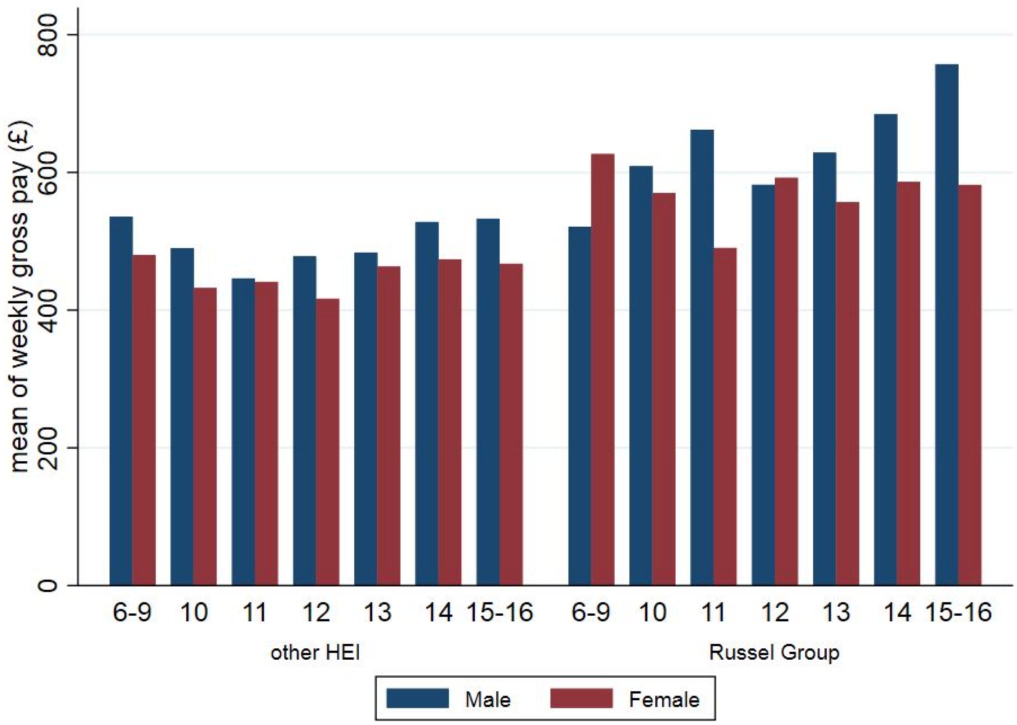


Figure 7 shows the mean of the UCAS points (obtained from best three A Levels) as the outcome variable and how it varies with respect to locus of control. For Males a positive relationship between the locus of control score and the mean A-Level points can be observed between locus scores 11-16. Scores 6-11 show a negative relationship. For Females the A-Level points seem to rise with a higher locus of control score up until score 12, where it then tails off and even decreases slightly again. As previously noted though the observation counts per score are not equally distributed (even after grouping the tails) meaning that these are solely preliminary relationships and impressions might very well be skewed by outliers/uneven observation counts. While it makes sense to assume that a higher locus of control score (=more internal attitude to life) is associated with a higher A-Level points the graphs are less clear about it.

A slightly clearer picture transpires once I substitute locus of control for how highly the individual values school ("school importance") taken from wave 3. Figure 8 shows this relationship which now mostly identifies a positive relationship between the individual's UCAS score and his 'school importance' score (described in Section 2.3). The interpretation is intuitive since it means that the more you value/recognize the importance of school (the higher the score on the x-axis) the higher is the UCAS score achieved. For males a dip is observed again at the beginning of the school-importance distribution but once again, the left tail of the school-importance-distribution suffers from low observations which could explain the irregularity.

Figure 7: UCAS points and Locus of Control

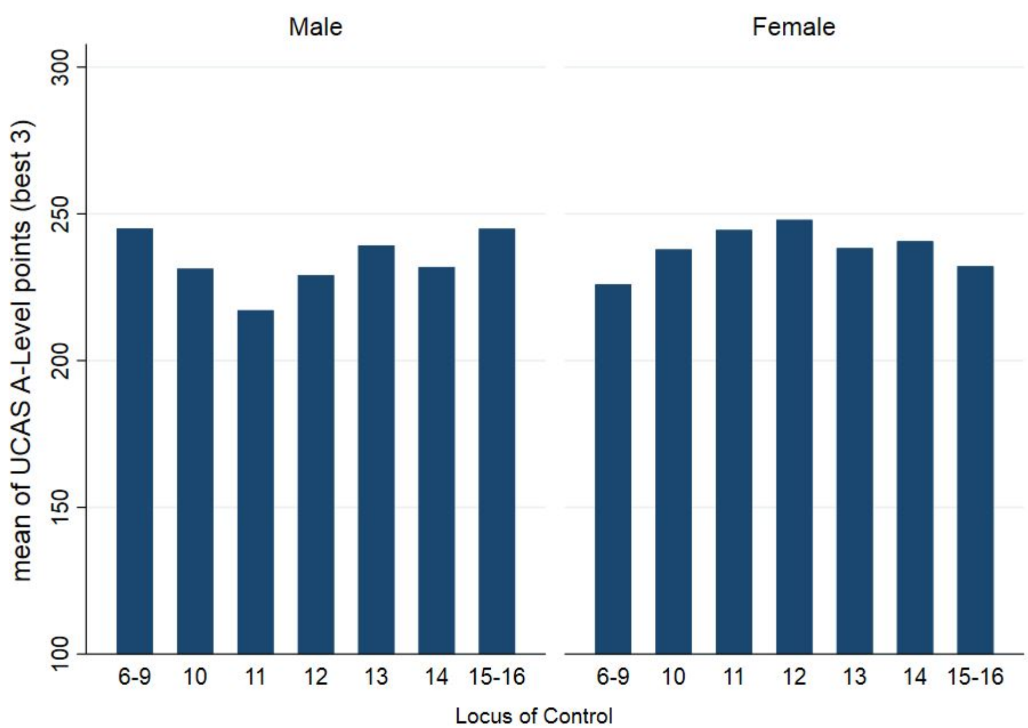
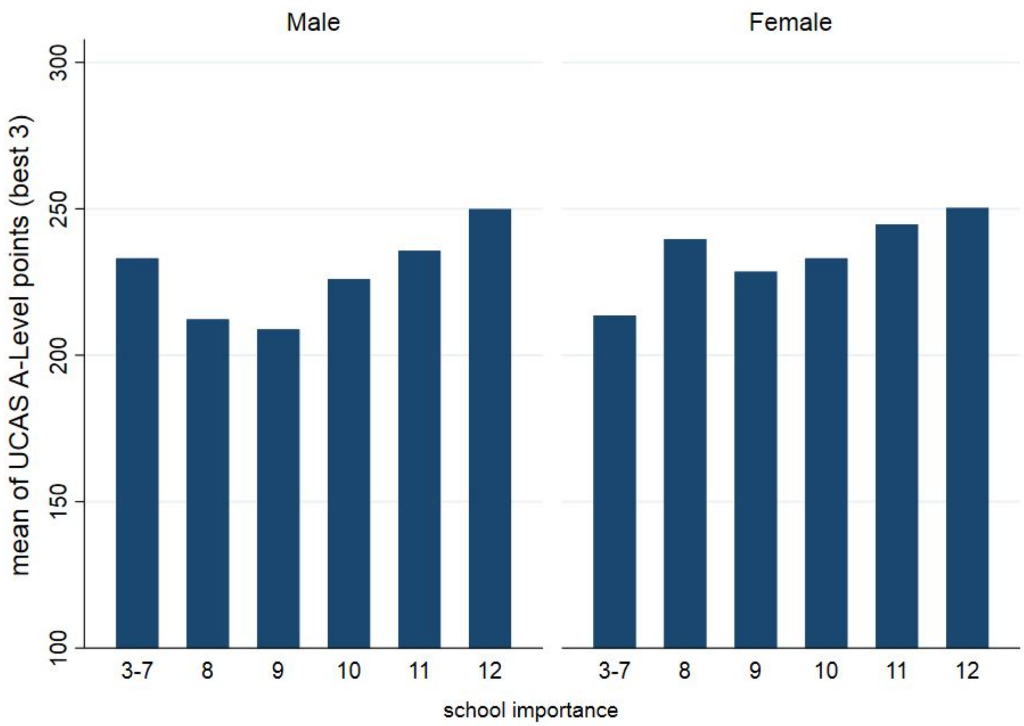


Figure 8: UCAS score and ’School Importance’



Given ’school importance’ was a somewhat better indicator of a high UCAS score than locus of control, I also explore the relationship between locus of control and ’school importance’. Figure 9 uses the locus of control score constructed from wave 2 statements and ’school importance’ score constructed from wave 3 statements. A clear positive relationship between the two transpires which suggests that they are potentially combinatory or possibly interchangeable if necessary (I will explore this in further robustness checks outlines in Section 6). Lastly I also analyze the relationship between the mean locus of control and the classification obtained in Figure 10. It can be seen that the higher the locus of control (=the higher the sense of ownership over ones life) the higher up you are on the degree classification scale.

Figure 9: Locus of Control and 'School Importance'

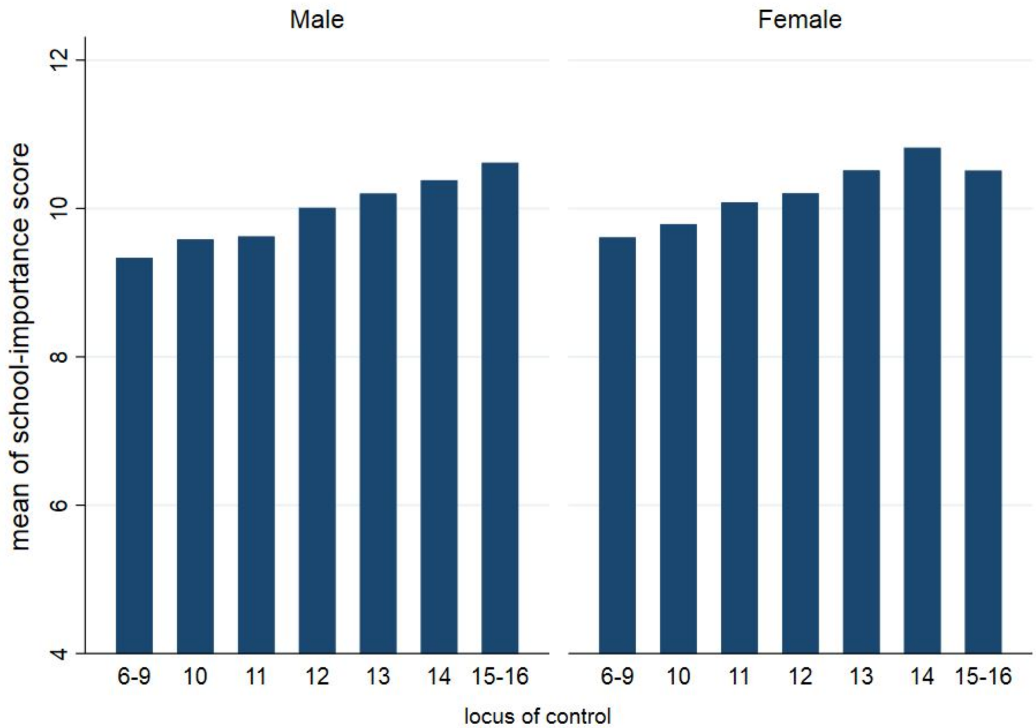
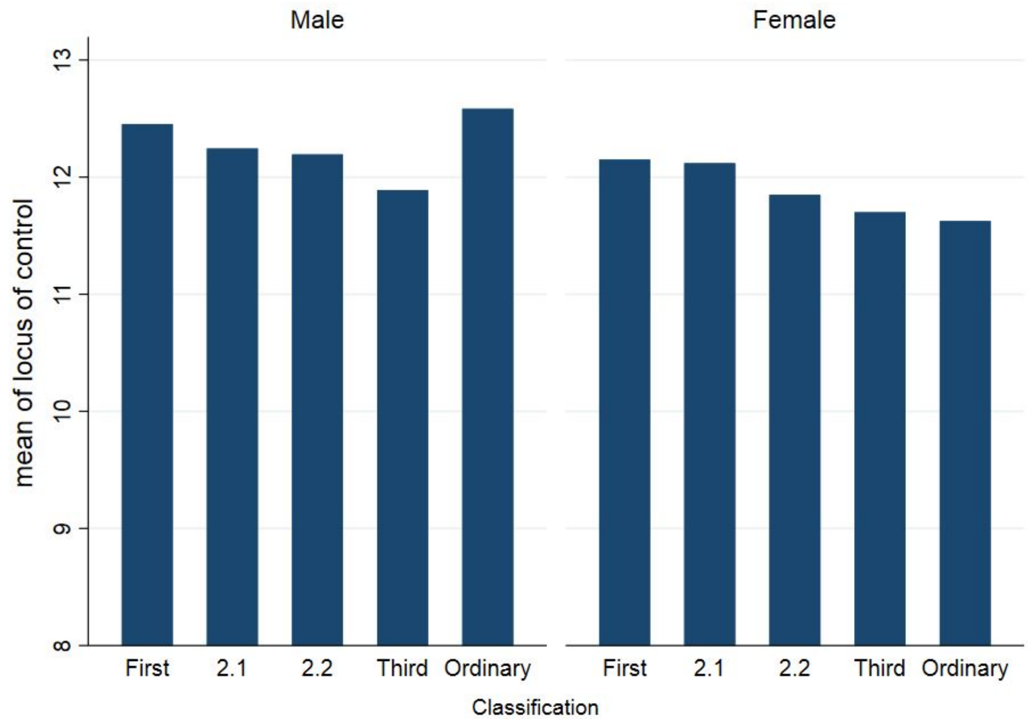


Figure 10: Locus of Control and degree classification



3 Methodology

To assess the effect of non-cognitive skills on wages at age 25, I specify a standard wage equation with different measures of cognitive as well as non-cognitive skills/traits. I begin by estimating the equation using Ordinary Least Squares, followed by obtaining estimates through Propensity Score Matching (PSM) as well as Inverse Probability Weighted Regression Adjustment to address the shortcomings of a simple OLS regression discussed below and to obtain estimates less likely to be affected by selection bias.

3.1 Ordinary Least Squares

For the Ordinary Least Squares regression, I specify the following linear model:

$$Y_i = \alpha + \beta C_i + \gamma NC_i + \delta X_i + \epsilon_i$$

Where Y_i is the outcome variable log hourly wage of the individual, C_i and NC_i are the individual's cognitive and non-cognitive skills respectively (discussed in Section 2), and X_i are individual characteristics (gender, ethnicity, and region). The model is estimated for a sample of working individuals at age 25. The non-cognitive skills included in the main regressions throughout this paper are: locus of control measured at age 14/15 (a year before GCSEs), a proxy for conscientiousness, and a proxy for self-esteem (Section 2)[1 2].

3.1.1 Propensity Score Matching

I also employ Propensity Score Matching (PSM) to address the possible selection bias that arises due to the fact that students self-select into pursuing higher education. The idea of Propensity Score Matching is to focus on individuals that are more comparable based on their distribution of covariates, by modeling the treatment group and match individuals with a similar probability of receiving treatment (pursuing higher education) from both the treated and control group. Estimates of the treatment effect are obtained from the difference between the treated and the more adequate control group - reflecting the Average Treatment on Treated (rather than the Average Treatment Effect as OLS would do). And while Propensity Score Matching is based on the strong assumption of conditional independence, meaning selection is solely based on observables and all covariates which impact treatment and potential outcome are observed, it is argued to nevertheless reduce selection bias by comparing treated and control individuals with a

[1] A test of robustness to alterations of the definition of non-cognitive skills was also performed, where I change the proxy for conscientiousness to the variable 'school importance' (from different waves as well), and also use variables obtained through Principle Component analysis of the non-cognitive skills available (where I obtain a proxy for locus of control, work ethic, and self-esteem). These changes do not affect the stability of the estimates for the return to a degree, nor do they change the magnitude. Results are available upon request.

[2] Since the estimation arguably suffers from a limited sample size I further include 'missing-dummies' in the OLS specification with the main goal of retaining a greater sample size. These missing-dummies are constructed á la the dummy variable adjustment method (Allison, 2001), where a dummy is equal to 1 if the observation is missing and 0 otherwise. I include missing-dummies for missing observations regarding whether the individual has obtained a degree or not, and for missing observations across the non-cognitive skills mentioned previously. I acknowledge that including these dummies may give biased estimates if the observations are not missing at random. I have also estimated all specifications without these dummies and the stability of the degree-return estimates is not affects. Results are available upon request.

higher overlap in distribution of covariates. To model the treatment group - individuals going to university - I control for the main and second parent's education, the individuals gender, ethnicity, and region of living and model a second treatment group with additionally controlling for non-cognitive skills (locus of control, conscientiousness, self-esteem). These variables are likely to influence treatment decision and outcome variable simultaneously and are arguably unaffected by participation (or anticipation of it). I base the latter argument on the fact that non-cognitive skills are likely to only undergo modest changes over the years on average (Caliendo et al., 2015) which allows me to use proxies for non-cognitive skills measured before treatment and assume that they will not change much. I employ PSM with the Stata code *teffects psmatch*.

4 Inverse Probability Weighted Regression Adjustment

I also use a weighting procedure, the Inverse Probability Weighted Regression Adjustment, as an alternative bias-reducing method. Similar to Propensity Score matching IPWRA accounts for the nonrandom treatment assignment - selection into Higher Education - by making the control and treatment groups more comparable. Compared to Propensity score matching, the Inverse Probability Weighted Regression Adjustment method fits the conditional model for the outcome through weighting instead of matching. Even though a propensity score estimator performs equally efficient compared to an IPW-estimator (Tan, 2007), the advantage of using IPWRA is opportunity to model both the outcome and the treatment, which allows for the covariates of the outcome and treatmend model to not be the same. At the same time IPWRA is characterized by the double-robust property, meaning that if either treatment model or outcome model are misspecified the estimates of the treatment effect will nevertheless be consistent. The outcome is modelled by controlling for non-cognitive skills, gender, region of living, and the treatment is modelled by controlling for non-cognitive skills, parents' education, gender, region of living. To compare how much the treatment effect is affected by the inclusion of non-cognitive skills I exclude the non-cognitive skills when modelling outcome and treatment in a separate estimation. But the main reason for employing IPWRA here is that it allows for multiple treatments compared to PSM. This allows Russel Group universities and other Higher Education Institutions to be treated as two different treatments, as well as the different subject areas to be treated as 3 treatments (STEM, Social Sciences, Arts & Humanities). Combining the previous treatments it allows to lastly estimate the effect of 6 treatments, namely the subjects by the institution type (Russel Group versus non-Russel Group). I employ IPWRA with the Stata code *teffects ipwra*.

5 Results

The following section presents the estimation results for the returns to higher education and how it changes when controlling for non-cognitive skills. I will demonstrate the results obtained with Ordinary Least Squares and Propensity Score Matching in Table 1 for a pooled sample as well as by men and women, and present and compare estimates obtained with Ordinary Least Squares and Inverse Probability Weighted Regression Adjustment in Table 1 for different subject categories and institution types (Russel Group vs. other Higher Education Institution). All returns shown are relative to individuals who have not obtained a degree[3].

Table 1 is structured as follows: It shows OLS and PSM estimates for the returns to a degree for men and women as well as a pooled sample. For each sample specification (1) does not control for non-cognitive skills (locus of control, conscientiousness, self-esteem) and specification (2) does. The OLS sample size is bigger since it allows to control for missing observations with 'missing-dummies' discussed in Section 3.

Estimates across all samples and both estimation methods draw a consistent picture: controlling for non-cognitive skills does not alter the effect of a degree on income. OLS estimates for men show a return of 10.1% without non-cognitive skills and 9.9% with. For women the estimate shows to be slightly higher at 13.2% and 12.7% without and with non-cognitive skills, which averages to 11.5% and 11.2% without and with non-cognitive skills for the pooled sample. Out of the non-cognitive skills used in the specifications only locus of control seems to be (highly) statistically significant. An F-test for the effect of the three non-cognitive skills combined being zero can be rejected for all samples[4], but if locus of control were to be excluded from the

[3]I also test whether the return estimates change significantly if I run the specifications on a subsample where I only include people who have a realistic chance of attending university which I define as individuals who have entered sixth form (or its equivalent). The returns are slightly lower at around 8% on average but in line with results presented here do not change when controlling for non-cognitive skills.

[4]Pooled sample: $F(3, 4120) = 8.76$, p ¡ .001; Men: $F(3, 1867) = 5.46$, p ¡ .001, Women: F(3,

set of non-cognitive skills the null hypothesis cannot be rejected. The size of the locus of control coefficient itself is difficult to interpret in real terms, but it is clear that a higher locus of control, meaning the more internal a person rates himself to be, translates into a positive effect on income.

PSM estimates for the effect of a degree on income can be seen to be slightly lower than OLS estimates with returns being around 9-10% across all samples, but wherever statistically significant these estimates do not vary greatly after controlling for non-cognitive skills.

Overall the average return to a university degree can be summarized here to lie around 10% which is in line with estimates previously found for the UK (Harmon et al. 2003).

Table 2 is structured in a similar manner to Table 1. It shows OLS and IPWRA estimates for the returns to a degree across all individuals but for different subject categories (STEM, Social Sciences, and Arts & Humanities), and institution types (Russel Group vs. other Higher Education Institutions). Similarly to Table 1 estimates presented in column (1) below each institution type show the returns to a degree where non-cognitive skills are not controlled for and the estimates presented in column (2) show the returns where the previously mentioned non-cognitive skills are taken into account of.

Starting with the return estimates for all subjects pooled across the higher education institution types (first row), OLS and IPWRA estimates are not drastically different (where statistically significant) with IPWRA estimates being slightly lower. Furthermore, in line with results seen previously, estimates of the effect of a degree do not change significantly after controlling for non-cognitive skills. The average return to a degree for all Higher Education Institutions ranges from 9% (OLS-estimate) to 11% (IPWRA-estimate). For a degree obtained from a Russel Group university OLS estimates a return of 21.7% without controlling for non-cognitive skills and 21.3% after taking them into account, while IPWRA shows a slightly lower return of 17% and 15.2% without and with non-cognitive skills respectively. For other HE institutions (exclcuding Russel Group universities) OLS shows that the return to a degree is around 6% while IPWRA estimates are not significant in this case.

Analyzing the returns by degree subjects Table 2 differentiates between STEM subjects, Social Sciences, and Arts and Humanities. Averaged across all Higher Education Institutions STEM and Social Science subjects are shown to give a return of around 14.5% estimated with OLS and a return

2242) = 5.49, p ¡ .001

of around 11% estimated with IPWRA. The difference between estimated that take into account non-cognitive skills and those that do not is negligible. The estimates for Arts and Humanities are not significant in neither OLS nor IPWRA.

Lastly, Table 2 also presents the effects of different degree subjects obtained from different institutions (Russel Group vs. other HEI). OLS estimates for STEM subjects obtained from a Russel Group university hardly show any difference after controlling for non-cognitive skills, with the return being around 26%, while IPWRA estimates show an overall lower return to the degree with a return of 19.2% without NC-skills and 17.9% with NC-skills (reflecting a slight difference when controlling for these skills). A STEM degree obtained from other Higher Education Institutions gives a return of around 10% with OLS (no significant different after inclusion of NC-skills) and 7% estimated with IPWRA and controlling for NC-skills (compared to 8.7% without).

A Social Science degree obtained from a Russel Group university shows to give a return of around 22% if estimated with OLS, where once again no difference to the effect of a degree can be observed after controlling for non-cognitive skills. Estimating the same degree with IPWRA the return is slightly lower with 17.5% without the inclusion of NC-skills and 13.9% with. There seems to be a bigger difference in degree returns caused by controlling for NC-skills, but the latter estimate is 'only' significant at the 5% level compared to previous estimates all being highly significant. A Social Science degree obtained from a university other than a Russel Group one gives a return of 11% (OLS) while IPWRA estimates are not statistically significant.

Analyzing the returns to a degree in Arts and Humanities, OLS and IPWRA estimates are difficult to compare since: the return of an Arts and Humanities degree obtained from a Russel Group university is only statistically significant if estimated with OLS and the return of that same degree obatined from a university other than Russel Group one is only statistically significant if estimated with IPWRA. What defintiely stand out though is how big the difference in returns between the degree obtained from Russel university versus another Higher Education Institution is. The former shows to give a return of around 14% while the latter shows a negative return of around -8%.

Table 1: Returns to having obtained a degree - OLS and PSM estimation

	OLS						PSM					
	Pooled		Men		Women		Pooled		Men		Women	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.115***	0.112***	0.101***	0.099***	0.132	0.127***	0.096***	0.090***	0.105***	0.080*	0.029	0.088***
	(0.016)	(0.016)	(0.024)	(0.024)	(0.022)	(0.022)	(0.018)	(0.024)	(0.027)	(0.037)	(0.026)	(0.040)
Locus of control		0.023***		0.025***		0.021***		✓		✓		✓
		(0.005)		(0.007)		(0.006)						
Conscientiousness		-0.008		-0.025		0.008		✓		✓		✓
		(0.011)		(0.016)		(0.015)						
Self-Esteem		-0.001		0.001		-0.003		✓		✓		✓
		(0.004)		(0.008)		(0.004)						
R-sqr	0.074	0.083	0.071	0.084	0.067	0.076	-	-	-	-	-	-
N	4133	4133	1879	1879	2254	2254	2207	2207	1009	1009	1198	1198

Note: The dependent variable is log of gross hourly wage. Specification (1) does not control for non-cognitive skills, while specification (2) does. Non-cognitive skills included are: Locus of control, a proxy for conscientiousness, and a proxy for self-esteem where the higher the score the more non-cognitive skills the individual has. All specifications include the following additional controls: gender, ethnicity as well as regional dummies. OLS specifications further control for missing values in the sample for degree-observations as well as non-cognitive skill observations (see Section 3). PSM obtains the average treatment effect on treated. All observations are weighted by the most recent LSYPE sample weights.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Returns to having obtained a degree - OLS and IPWRA estimation

	OLS						IPWRA					
	all HEIs		Russel Group		other HEI		all HEIs		Russel Group		other HEI	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
All subjects	0.115***	0.112***	0.217***	0.213***	0.063***	0.061**	0.093***	0.087***	0.170***	0.152***	0.038	0.019
	(0.016)	(0.016)	(0.026)	(0.026)	(0.018)	(0.018)	(0.018)	(0.020)	(0.032)	(0.038)	(0.027)	(0.034)
STEM	0.147***	0.143***	0.264***	0.260***	0.104***	0.100***	0.111***	0.103***	0.192***	0.179***	0.087**	0.070*
	(0.022)	(0.022)	(0.038)	(0.038)	(0.024)	(0.024)	(0.022)	(0.024)	(0.041)	(0.044)	(0.031)	(0.036)
Social Sciences	0.144***	0.142***	0.228***	0.221***	0.110***	0.111***	0.112***	0.106***	0.175**	0.139*	0.076	0.060
	(0.026)	(0.026)	(0.044)	(0.044)	(0.030)	(0.030)	(0.026)	(0.028)	(0.060)	0.064	0.039	0.043
Arts & Humanities	0.021	0.019	0.142***	0.139***	-0.026	-0.027	-0.017	-0.022	0.072	0.048	-0.079*	-0.087*
	(0.024)	(0.024)	(0.042)	(0.042)	(0.026)	(0.026)	(0.027)	(0.028)	(0.049)	(0.048)	(0.039)	(0.039)

Note: The dependent variable is log of gross hourly wage. Specification (1) does not include non-cognitive skills, while specification (2) does. Non-cognitive skills included are: Locus of control, a proxy for conscientiousness, and a proxy for self-esteem (where the higher the score the more non-cognitive skills the individual has). All specifications include the following additional controls: gender, ethnicity as well as regional dummies. OLS specifications further control for missing values in the sample for degree-observations as well as non-cognitive skill observations (for reasoning see Section 3). IPWRA obtains the average treatment effect on treated. All observations are weighted by the most recent LSYPE sample weights.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Limitations, Discussion & further plans

While LSYPE is very rich in different types of information about the cohort members, the latest survey, the Age 25 Survey, contains a sample of only around half of the originally 16,000 questioned young people. After data trimmings and impositions of certain requirements, or simply incomplete information, the estimations suffer from an arguably limited sample size. Mainly for this reason the missing-dummies described in Section 3 were used for the OLS specifications. It should be noted that this might bias estimates but re-estimating the specification without 'controlling for' missing observations does not change the fact that the return to a degree is stable towards the inclusion of non-cognitive skills. Furthermore the available sample size greatly limits what can be explored.

While it is not unusual to exploit labor outcomes at age 25, one should bear in mind that individuals are still relatively very early in their career path and some would have just finished university while others, who did not pursue Higher Education would have had the chance to climb the career ladder for a longer period of time meaning the length of experience in the labour market varies greatly across individuals and we are comparing individuals at different stages in their working life.

There are a few robustness checks that have been explored/implemented but are not reported in this paper (yet; available upon request though). I test the robustness to including different definitions of non-cognitive skills in the specifications such as using the school-importance score instead of the current proxy for conscientiousness or leaving out the measure for self-esteem. The results obtained do not show any great difference compared to the current results (I am yet to finalize the presentation of these robustness checks). With the aim to reduce the number of measures for non-cognitive skills I also apply the Principle Component Analysis to a selection of non-cognitive skills, as a further robustness check to the ways non-cognitive skills are included in the regressions. Once again, the results obtained are not much different from the results presented so far.

It would further be interesting for comparability to follow Heckman, Stixrud, and Urzua (2006) in methodology and also estimate a latent factor model.

For future research beyond the scope of this paper one could also look at outcome variables beyond labor market outcomes. LSYPE offers information on crime behavior and health measures for example. It could be worth looking into, even though this would deviate from returns to education and concentrate on the returns to non-cognitive skills on various life-outcomes.

7 Conclusion

The aim of the study is to explore the robustness of the estimate of the return to Higher Education to the inclusion of non-cognitive skills such as Locus of control, conscientiousness and self-esteem and to then re-estimate the returns to Higher Education with a 'corrected' specification using OLS as well as Propensity Score Matching and Inverse Probability Weighted Regression Adjustment. I exploit the most recent large-scale cohort study in the UK, the Longitudinal Study of Young People (LSYPE), which follows the lives of individuals since 2004 (aged 13-14) and had recently released the Age 25 Survey, containing not only updated information on the individual's life but also includes for the first time labor market outcomes such as wages, employment status, job type. The samples explored were a pooled sample, as well as by men and women, and I explored 6 treatments, namely: at least a First Degree, Russel Group Degree, other HE institution degree, and a STEM, Social Sciences, Arts and Humanities degree.

Throughout all estimation methods used (OLS, PSM and IPWRA) results do not seem to suggest that previously estimated returns to Higher Education might have been overestimated, since controlling for non-cognitive skills leaves estimates practically unchanged. The estimates for the returns to higher education are in line with previous literature averaging at around 10%. Propensity score estimates as well as IPWRA estimates are generally slightly lower than OLS estimates. Non-cognitive skills reduce the estimate for the returns to a degree by at most 2% (in a couple instances), even though most of the time the difference was negligible. The non-cognitive skill that stood out, by being the only statistically significant non-cognitive skill trait, was locus of control. Least predictive power on income seems to have self-esteem. Interpretation of the estimates of the non-cognitive skills is a little less intuitive since it is a 'man-made' quantitative score trying to describe a qualitative trait, but what can be taken away is that especially locus of control should not be overlooked in future research.

Overall these results are very interesting since they go against what one would likely expect, since high non-cognitive skills are associated with-/desired for success in ones personal as well as professional life. Schools, universities, employers turn with increased attention towards the development of these skills as they are commonly known to play a vital part in different areas of life. To see that in the wage equation these skills do not quantifiably affect the estimate for returns to higher education is definitely interesting and shows that obtaining a degree heavily drives impact on income.

This should not mean that non-cognitive skills are hence not important as they do not affect income greatly, it is merely a reflection of the fact that having a degree far outweighs the effects of non-cognitive skills but not that these skills are not having an impact at all.

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