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DISCUSSION PAPER SERIES

IZA DP No. 13248

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ABSTRACT

The Graduate Wage and Earnings Premia and the Role of Non-Cognitive Skills*

Estimates of the graduate earnings premium typically do not allow for the effect of non-cognitive skills. Since such skills are unobservable in most datasets there is a concern that existing estimates of the graduate premium are contaminated by selection on such unobservables. We use data on a young cohort of individuals that allows us to control for the effects of non-cognitive skills. We find that the inclusion of non-cognitive skills, themselves jointly significantly positive, reduces the estimated graduate premia by an insignificant 1-2 percentage points from an average of 10-12%. Our second contribution is motivated by the greater reliance on administrative datasets in recent research that has focused on annual earnings rather than hourly wages and our results show that the graduate earnings differential is significantly greater than the wage differential. Since we use estimation methods that are NOT robust to selection on unobservables, we adopt Oster (2016) tests to show that it would take an implausible degree of selection on unobservables to drive our estimated wage and earnings returns to zero, and that a plausible upper bound to returns is around one-quarter to one-third below the OLS returns. We further find heterogeneous returns by broad major group and elite university, and we find large degree class differentials.

JEL Classification: I23 I26, J24

Keywords: returns to higher education, non-cognitive skills

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1 Introduction

The financial returns to higher education has been the subject of considerable research. There is mounting evidence that the graduate earnings premium has remained large despite considerable increases in the supply side across successive birth cohorts from the 60's to the 80's in the US and from the 70's to the 90's in the UK (see Ashworth and Ransom (2018) and Blundell and Jin (2018)). Some recent research is underpinned by administrative data, such as Bhuller et al. (2017) in Norway, and Belfield et al. (2018a) in England, which both allow for more detailed research into the heterogeneity of returns. Administrative data sources usually contain only younger workers and so typically report lower estimates of graduate premia. However, almost all such work exclude consideration of non-cognitive skills. Heckman (2000) emphasised need for estimates of the returns to both cognitive and non-cognitive skills. There is now considerable evidence that traits such as initiative, persistence, and motivation contribute to successful outcomes and recent research (for example Cunha and Heckman (2007)) suggests that such "skills beget skills" implying that non-cognitive skills have a greater effect on the productivity and wage rates of graduates than of non-graduates.

The contribution of this paper is to estimate the effect of non-cognitive skills on the wages and earnings of both graduates and non-graduates, using an unusually rich cohort study, to examine the robustness of graduate wage and earnings premia to the inclusion of measures of non-cognitive skills. Our work is partly motivated by the increasing reliance placed on detailed administrative datasets (for example Britton et al. (2015)), which invariably do not contain information on non-cognitive skills. The usefulness of these datasets for estimating graduate premia depend on their robustness. Administrative datasets typically also lack information on hours and wage rates. The effects on both of hourly wage and longer term earnings are of interest, for different reasons, and our data allows us to compare these returns.

The latest wave of the Longitudinal Study of Young People in England (LSYPE) contains early labor market outcomes on cohort members, at age 25, while earlier waves contain considerable detail on the characteristics and traits of these young people as adolescents. Detailed educational achievements are matched from administrative sources. This offers the opportunity to explore the relationship between adolescent non-cognitive skills (locus of control, work ethic, self-esteem) and the financial returns, at age 25, to an undergraduate degree. In addition, the data is rich enough to explore the returns by institution type, broad degree major, and degree class. We distinguish between the graduate premium in terms of hourly wages (for those in paid employment), where our headline estimate is close to 10%, from the weekly earnings premium where our headline estimate is 18% - both estimated at this early stage of the life cycle. The significant difference between these graduate premia suggest that graduates utilize their human capital to a greater extent than non-graduates, by working longer hours per week, in addition to receiving a higher hourly wage. We find locus of control and work ethic positively affects wages and earnings respectively, but it would appear that non-cognitive skills affect the earnings of graduates and non-graduates to about the same extent. Thus, the inclusion of non-cognitive skills does not make a statistically significant difference to the estimated graduate wage and earnings premia, regardless of the specification.

When we consider heterogeneity in graduate premia by type of institution (distinguishing a well-defined set of elite institutions from the rest), and by broad major group (distinguishing between STEM, Arts & Humanities, and Social Sciences), we find large differentials within these cells but the insensitivity of graduate premia to non-cognitive controls in the headline estimates remains unchanged. Finally, we also estimate the effect of degree class. UK undergraduate degrees are classified into "First class" (approximately 20% of this graduate cohort), "Upper Second" class (approximately the next 50%), and below. Once we control for degree class, we find that non-cognitive skills are no longer significant determinants of the wages and earnings of graduates. This suggests that degree class acts as a sufficient statistic for non-cognitive skills. Finding that controlling for degree class makes the inclusion of non-cognitive skills insignificant is useful - since it implies that earnings premia, estimated from administrative data that does include degree class information as in the UK case, may not suffer from omitted variable bias from an inablity to control for non-cognitive skills.

Since we use methods that rely on NO selection on unobservables, we employ Oster (2016) tests to show that it would take an implausible degree of selection on unobservables to drive our estimates to zero, and our estimated lower bounds to returns are approximately one-quarter to one-third below the OLS estimates, whether non-cognitive skills are controlled for or not. While these differences are not statistically significant, they are economically meaningful. Nonetheless, our estimates cannot claim to be causal because there always remains unobservables no matter how rich the data. We think of our estimates as tightening the upper bound on returns.

The paper is structured as follows: Section 2 reviews related literature; Section 3 describes the data and variables; Section 4 discusses the method; and Section 5 presents and explains the results. Section 6 outlines the limitations, provides some directions for further research, and concludes.

2 Related Literature

It is common to assume that personality plays an important role in life and that certain personality traits like initiative, persistence, and motivation seem desirable for successful life-outcomes. Much of the psychology literature collapses the various facets of an individual's personality into the so-called Big Five personality traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. This has become a widely used taxonomy of personality traits. Within these broader definitions are a number of more narrowly defined personality characteristics some of which are more relevant to the scope of this research than others. Competence, dutifulness, self-discipline, perseverance and work-ethic all represent different aspects of conscientiousness which has 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 highlights locus of control 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). Heckman and Rubinstein (2001) has attributed the lower wage GED graduates compared to high school graduates to the effect of non-cognitive skills. The former are high school dropouts that subsequently certify as high school equivalents.

Heckman et al. (2006) exploit the National Longitudinal Survey of Youth 1979 (NLSY79), which includes 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 more detail. They address the econometric difficulties of endogeneous schooling by estimating the distributions of latent cognitive and non-cognitive factors and use those to predict the test scores of the individuals so that schooling can no longer directly affect ability/test scores. Using measured test scores, corrected test scores, and the estimated latent cognitive and non-cognitive factors in the wage regression, the standardized OLS coefficients for non-cognitive ability vary by schooling level but are generally positive. Heckman et al. (2006) demonstrate that non-cognitive skills raise wages through a direct impact on productivity as well as indirectly through schooling and work experience, and that the most important of such skills are locus of control and self-esteem.

Heckman et al. (2010) is an extension to Heckman et al. (2006) and, besides looking at labor market outcomes (based on a model of sequential schooling decisions), it looks at further life outcomes, such as health, and social outcomes. Socio-emotional abilities are shown to be significant predictors of high school GPA, educational choices, and later life outcomes.

Flossmann et al. (2007) use the 1999 wave of the German Social Economic Survey (GSOEP) and follow the methodology in Heckman et al. (2006) closely. They find that non-cognitive skills also matter for the determination of wages in Germany and they also exploit attitudinal questions that are closely related to the locus of control to construct a simple additive index of the non-cognitive skills of the individual. They also obtain the distribution of the latent factor which is then used in the estimation to address endogeneity as well as measurement error concerns.

Lindqvist and Vestman (2011) use administrative Swedish data and information from the compulsory military draft to study the effect of cognitive and non-cognitive ability on wages, unemployment and earnings. The non-cognitive ability measure comes from an interview carried out by a trained psychologist to assess the conscript's ability to function in armed combat. Lindqvist and Vestman (2011) argue that the latter ability, which includes persistence, social skills and emotional stability, are also valued and rewarded in the labour market. The effects of cognitive ability and non-cognitive skills on wages and earnings are found to be similar, with cognitive ability being the stronger predictor. Cognitive ability is a stronger predictor of wages/earnings for skilled workers while non-cognitive skills have a stronger effect at the lower end of the earnings distribution. Non-cognitive skills are also the stronger predictor of unemployment. Controlling for educational attainment, the relative importance of cognitive and non-cognitive ability is reversed. Edin et al. (2018) went on to study the relative returns to cognitive and non-cognitive skills over time using the same data. They observed an increase in the returns to non-cognitive skills from around 7% to 14%. Edin et al. (2018) and explored the specific type of occupations that experienced greater increases in the relative returns to non-cognitive skills. The question, of how much the returns to educational attainment change when non-cognitive skills are accounted for, remains unanswered

Lin et al. (2018) uses NLSY79 to show the effects of cognitive skills (measured by AFQT) on labour income and finds that adding controls for non-cognitive skills (locus of control, self-esteem and sociability) reduces returns at age 25 from approximately 26% with no controls to 22% when NC skills are added.

Belfield et al. (2018a) is the most recent, and comprehensive analysis of the graduate premium in the UK. While it uses an administrative dataset that contains extensive pre-treatment measures of cognitive ability it contains no controls for pre-treatment non-cognitive skills. Since that study used estimation methods that are not robust to selection on unobservables it is important to examine its potential robustness by using other data to explore the role of NC skills. The aim of this study is to explore the effect on non-cognitive skills on wages and earnings as well as the robustness of the estimates of returns to higher education to the inclusion of non-cognitive skills, and we do so using the most recent cohort data available for the UK. [1]

3 Data

Our data comes from the Longitudinal Study of Young People in England (LSYPE). This 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 interviewed every year until 2010, aged 19-20. The sampling was stratified with secondary schools being selected at random and from all schools, and pupils within each school selected at random. LSYPE selected observations to be representative of the English school population, but specific groups were oversampled - in particular, youths from low socioeconomic backgrounds and minorities (see Department for Education (2010)). More details can be found in Centre for Longitudinal Studies (2018) and Anders (2012). The LSYPE pupils were revisited in 2016, aged 25, to provide some insights into their lives as young adults. Treating the data as a cross-section provides information on the educational and labour market experiences, economic circumstances, family life, physical health and emotional wellbeing, social participation, attitudes of the individuals, and non-cognitive skills. The availability of survey questions in earlier waves about locus of control (LoC) and self-esteem makes these traits the most commonly studied non-cognitive skills in research on outcomes such as educational or economic success.

LSYPE achieved cross-sectional responses rates ranging from 48% (in Wave 8), to 84% (in Wave 2). For waves 1 to 7, the sample issued (response rate denominator) at each wave comprised respondents from the immediately preceding wave who agreed to be re-contacted. Despite reasonably good cross-sectional response rates, the sample size was reduced to 7,707 by Wave 8 from an initial 15,774 responses at Wave 1. The fact that many of the participants in Wave 8 had not participated in each wave, due to the sequential sampling method, means that out of the 7,707 Wave 8 participants, many do not have a complete history from participation in all waves.

[1] The only other UK work that we know of is the recent descriptive report by Boero et al. (2019) which finds, like us, that non-cognitive skills do not seem to affect the graduate premium.

This type of attrition could pose a problem for our study if, conditional on observed covariates, survey attrition is related to higher education and wages/earnings.[2]

3.1 Degree Attainment

We define a graduate as an individual who has (successfully) completed at least an undergraduate degree.[3] Conditional on having obtained a degree, LSYPE also reports whether the individual has been awarded a degree by an elite "Russell Group" university (that approximately 25 per cent of students attend) or otherwise. LSYPE wave 8 at age 25 further specifies the subjects that individuals studied at university - which we group into STEM, Social Sciences, Arts and Humanities, and other majors.[4] Our data also records degree class obtained on course completion. Other explanatory variables used in the specifications are controls for gender (female=1), regional controls (which we collapse into north, south, versus midlands) and controls for individual ethnicity (which we collapse into non-white vs. white).

Figure 1 shows the HE participation rate in the overall sample of those in paid employment. The LSYPE participation rates, using survey weights, are broadly in line with the aggregate data for the 2009/2010 university entrant cohort from HESA administrative (Department for Education, 2019). Figure 2 shows the breakdown of HE graduates by elite (Russell Group) vs non-elite institutions, conditional on degree attainment. Figure 3 shows the breakdown by majors which again matches the administrative data well. Figure 4 shows the proportions of individuals obtaining a first class, upper second, and lower second / third class. This also matches administrative data well for this cohort.[5]

[2] While it is not possible to completely rule out this possibility, because it relates to unobserved selection, we conduct analyses with and without the survey weights provided, and we also fit a model predicting participation in the final sample, based on initial characteristics and the treatment variable. We find no significant differences when we do so.

[3] We also include individuals having completed a postgraduate degree (e.g. MSc, PhD) but we do not condition on them in the analysis. That is, our estimates include the option value of the possibility of post-graduate qualifications.

[4] UK students typically specialise intensively in a single major throughout their three years of higher education straight from senior high school at 18.

[5] These figures are all conditional on not dropping out by age 25. Drop out rates are around 6%. Walker and Zhu (2013) find dropout earnings are close to those who never go to university conditional on work experience.

Figure 1: Overall HE participation rate

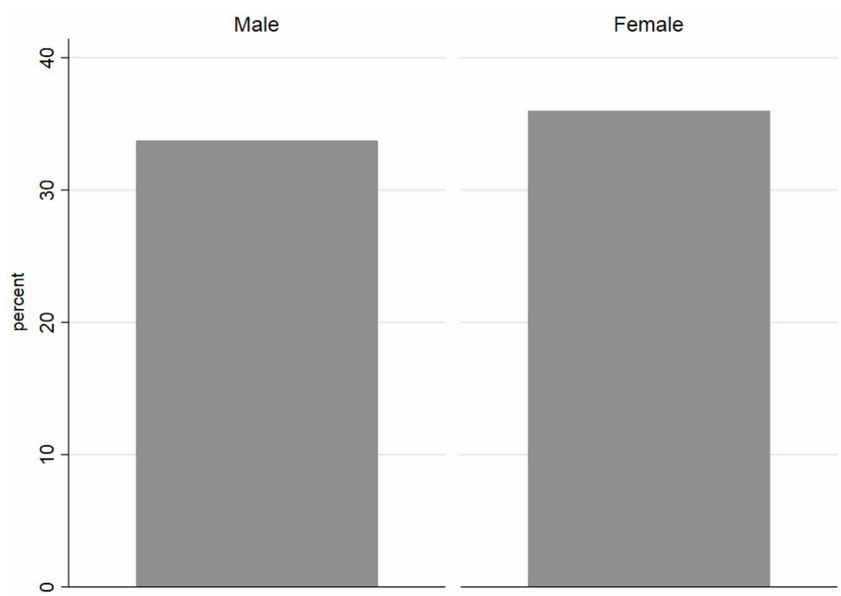


Figure 2: HE participation rates including Russell vs other HEI proportions

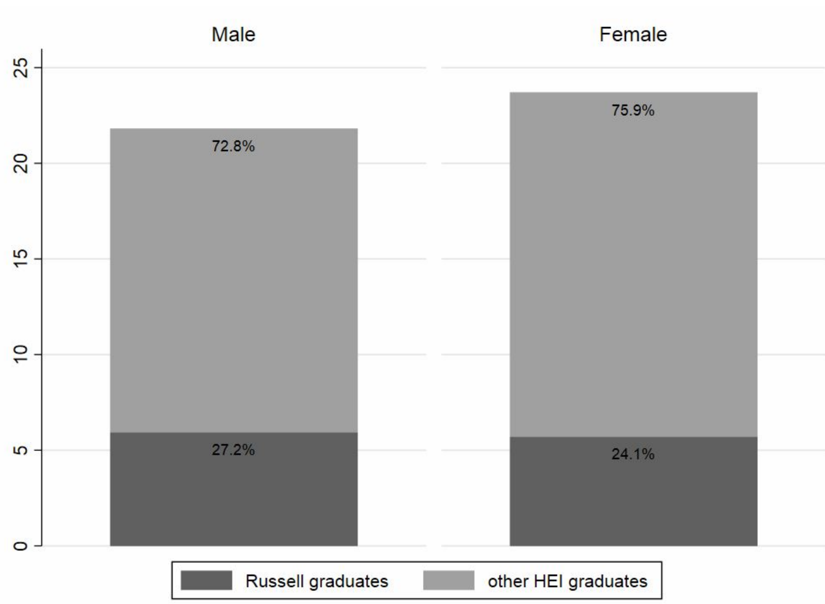


Figure 3: HE participation rates for subject groups

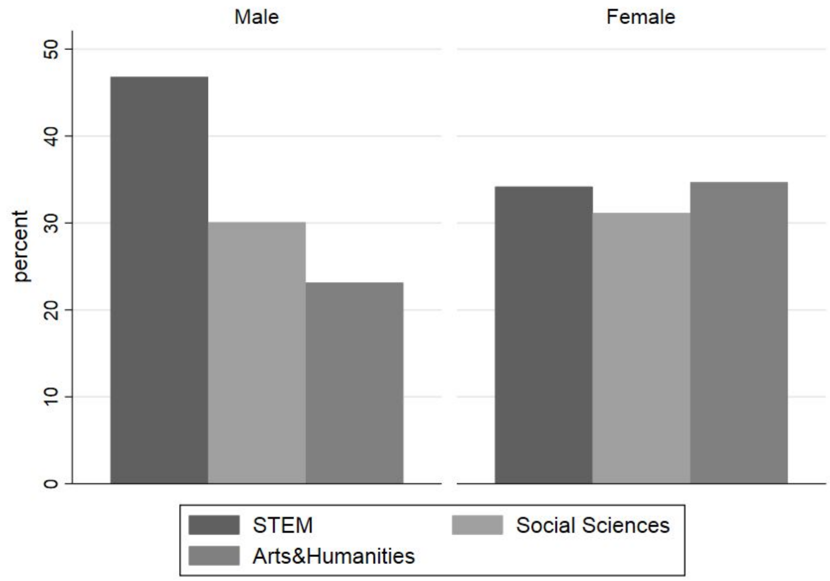
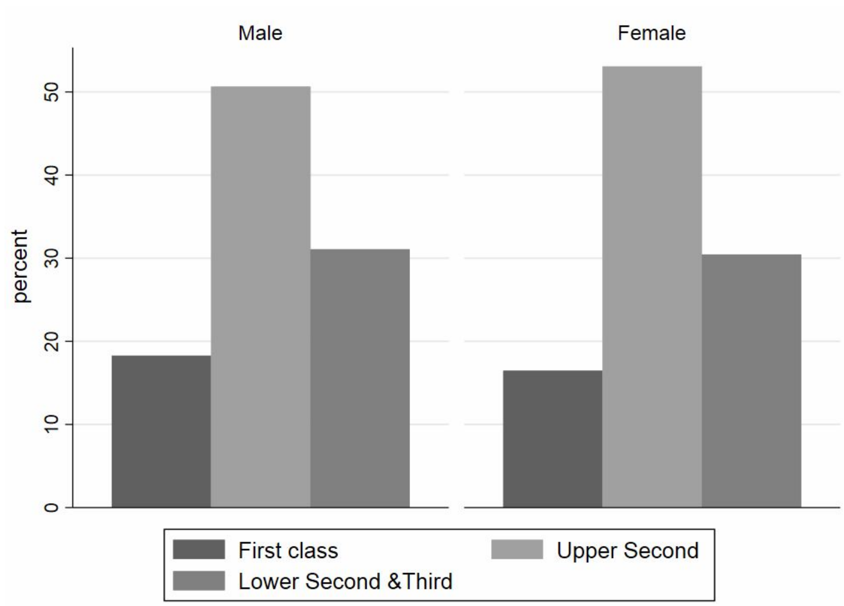


Figure 4: Degree class



3.2 Non-cognitive skills

LSYPE provides information on several aspects of the non-cognitive skills of respondents. A commonly used measure in this literature (not least because of its availability in recent datasets) is locus of control, first introduced by Rotter (1966), which aims to reflect how much control individuals believe they have over their lives. LSYPE asks cohort members in Wave 2, Wave 4, Wave 7 and Wave 8 a series of attitudinal questions that are meant to capture the concept of locus of control. The questions/statements remain the same across the LSYPE waves and Table 1 gives an overview. The individual can either strongly agree (SA), agree (A), disagree (D), or strongly disagree (SD) with each statement which in turn are coded from 1 to 4 [6].

For the main analysis in this paper we standardize the overall score of the locus of control variable taken just from Wave 2 (aged 14/15), because the response rate in Wave 4 was low, and waves 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. Summing the scores over the four statements in Wave 2 we construct an additive locus of control variable, with a minimum score of 4 and a maximum score of 16. On average, the wave 2 locus of control score is 11.98.

We further group attitudinal statements across the waves into the following topics: attitudes towards school, and questions that reflect self-esteem in Wave 4. The three attitudinal statements concerning feelings about school are seen in Table 2. We think that the questions asked about school-time reflect the pupil's own attitudes towards school and hence are an indication of the respondent's degree of conscientiousness or work ethic. For the directions of the statements to match up, we again invert the responses so that the higher the score on this scale the higher is work ethic in school and the more important school is to the individual. Table 3 provides an overview of questions on self-esteem, scores, and a derived additive variable that we generate from the four available statements, where a higher score on this scale implies higher self-esteem of the individual. As with locus of control and 'school importance', we standardize self-esteem for the main analysis.

[6] Statements 1, 2 and 4 were recoded so that a higher overall score indicates a greater **internal** locus of control – meaning the individual has greater confidence in the fact that he/she can influence his/her destiny, and vice versa for a person with a low score and therefore a more external locus of control

Table 1: 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

additive variable (min=4, max=16)	N	mean	sd
w2locus	3751	11.98	1.60

Table 2: 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	4751	10.33	1.35
school importance wave 2	4425	9.94	1.49
school importance wave 3	4393	10.07	1.46

Table 3: Statements on Self-Esteem

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	4379	13.02	2.69

Table 4: Income measures and non-cognitive skills by gender/degree

		hourly income (£)		weekly earnings (£)		hrs worked per week		Locus of Control		work ethics/ school importance		self-esteem	
		mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Male	No Degree	11.09	4.69	451.68	203.03	41.24	11.52	10.46	4.32	8.26	3.81	11.08	5.74
	Degree	12.80	6.76	509.72	213.94	40.79	9.18	10.75	4.31	8.98	3.60	11.89	4.90
Female	No Degree	10.30	10.94	349.18	158.05	35.74	9.65	10.38	4.19	8.66	3.72	10.34	5.49
	Degree	11.97	12.27	445.43	180.87	39.34	9.34	10.49	4.22	9.04	3.74	10.65	5.13

3.3 Outcome Variables

We are interested in the private financial returns to university degree attainment, and its sensitivity to the inclusion of non-cognitive controls. Earnings is the relevant dependent variable if the aim is to explore inequality and social mobility. On the other hand, the hourly wage is likely to be a better reflection of productivity. Thus, we use both the log weekly earnings and log hourly income from employment (at age 25) as outcomes. We compute the gross hourly wage, as the ratio of the gross weekly pay and hours worked per week. Administrative datasets usually provide only earnings data from tax records, so we compare estimates using log earnings (gross weekly pay). with those using log hourly earnings. Together, these two dependent variables allow us to explore the extent to which graduates earn more than non-graduates because they receive a higher wage, as well as because they may work longer hours per week.

Table 4 shows the mean of the hourly income, weekly earnings, and hours worked per week, as well as the mean of the locus of control, adolescent work ethic/school importance, and self-esteem score by gender and degree. The graduate hourly wage premium is very similar for both females and males (approx. £1.70 per hour). The graduate earnings premium is 28% for women (£96 per week), and 13% for men (£58). The weekly average hours differentials are 3.6 hours (10%) for females and -0.45 hours (-1%) for males. Table 4 also reports the average score for locus of control for both men and women. These are minimally larger for those with a degree compared to those without (6% of a SD for males and 3% for females). The same is true for the average score for school-importance/work ethic. Both men and women with a degree have a higher average score (19% of a SD for males and 10% for females) compared to individuals without a degree. The average score for self-esteem is also somewhat larger for graduates than non-graduates (14% of a SD for males and 6% of a SD for females).

3.4 Relationship between Income and Non-cognitive skills

As suggested above, earnings and wages are higher for graduates that non-graduates for both men and women. This section describes the relationship between the locus of control, work ethic and self-esteem with the mean of weekly gross income.

Figure 5 shows the mean of weekly gross pay at 25 for each possible overall locus of control score (at age 14/15) by gender and by subsequent degree status. In this, and subsequent figures, the bubble sizes reflect the cell sizes and the tails of the locus of control distribution were grouped due to very limited observation counts in the extremes. For graduates the relationship with locus of control is steeper for men than women. For non-graduates the relationship with locus of control is almost flat for both men and women. Thus, the college premium tends to be higher at the higher levels of locus of control (i.e. internal LoC) reflected in the (red) fitted line (using the weighted data).

Figure 6 looks at wage differences by type of HE institution conditional on having a degree. It makes a distinction between a degree obtained from an elite Russell Group university versus a degree obtained from a non-elite university. The relationship between earnings and locus of control, within graduates, is steeper for the elite than the non-elite HEIs, for both men and women. Thus, earnings differentials by HEI type, conditional on a degree, tend to be larger for those with high (i.e. internal) locus of control.

Similar relationships of weekly gross pay against self-esteem and against work ethic are illustrated in Figure 7 and Figure 8. While work ethic does shows positive relationships with weekly earnings, much of this is driven by hours of work variation (see Appendix Figure A1). The effect of self-esteem is flat, conditional on having a degree, but is positive for non-graduates.

Finally, we also explore the relationship between locus of control and degree class in Figure 9. In the UK, university degrees are classified into: first class; upper second; lower second (which we merge with students with the lesser classes because of their small cell sizes). Figure 9 stacks the LoC cells by degree class and shows that the higher one's locus of control the higher is one's degree class. The distribution of locus of control is close to normal for each degree class. Conditional on locus of control, the proportion of students who obtain each degree class remains broadly constant, although the proportion of firsts seems slightly skewed to the right.

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

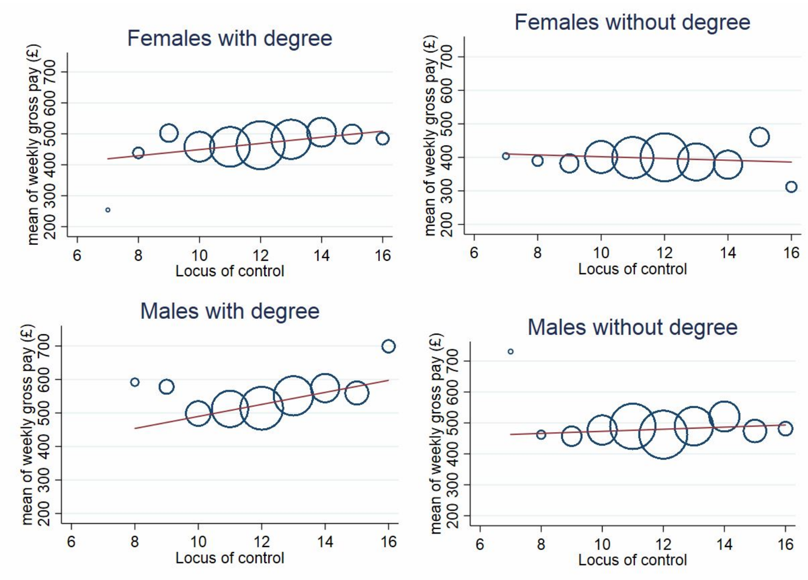


Figure 6: Mean of weekly gross pay (£) and Locus of Control (by gender and HEI type) conditional on having a degree

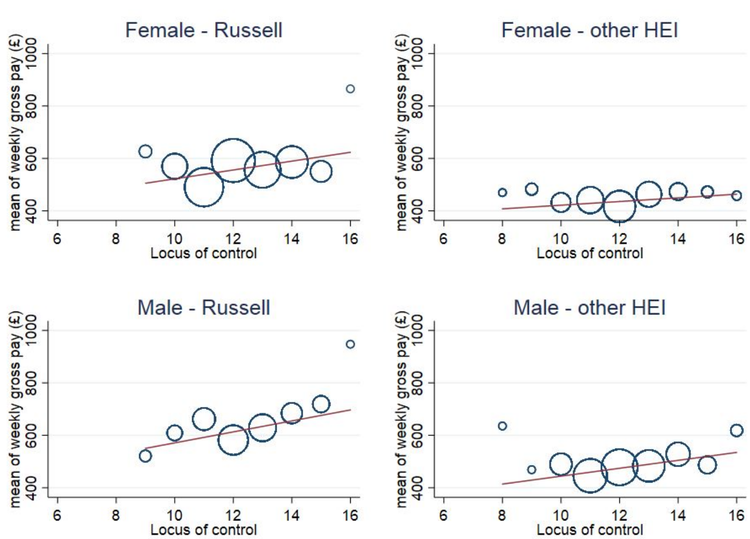


Figure 7: Mean of weekly gross pay (£) and Work Ethic (by degree attainment)

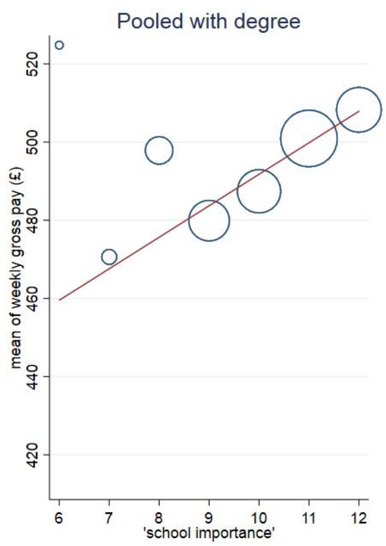


Figure 8: Mean of weekly gross pay (£) and Self-esteem (by degree attainment)

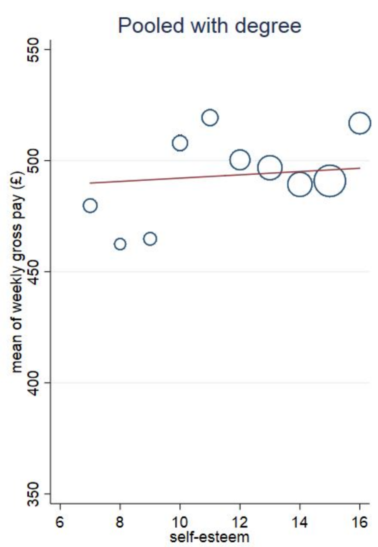
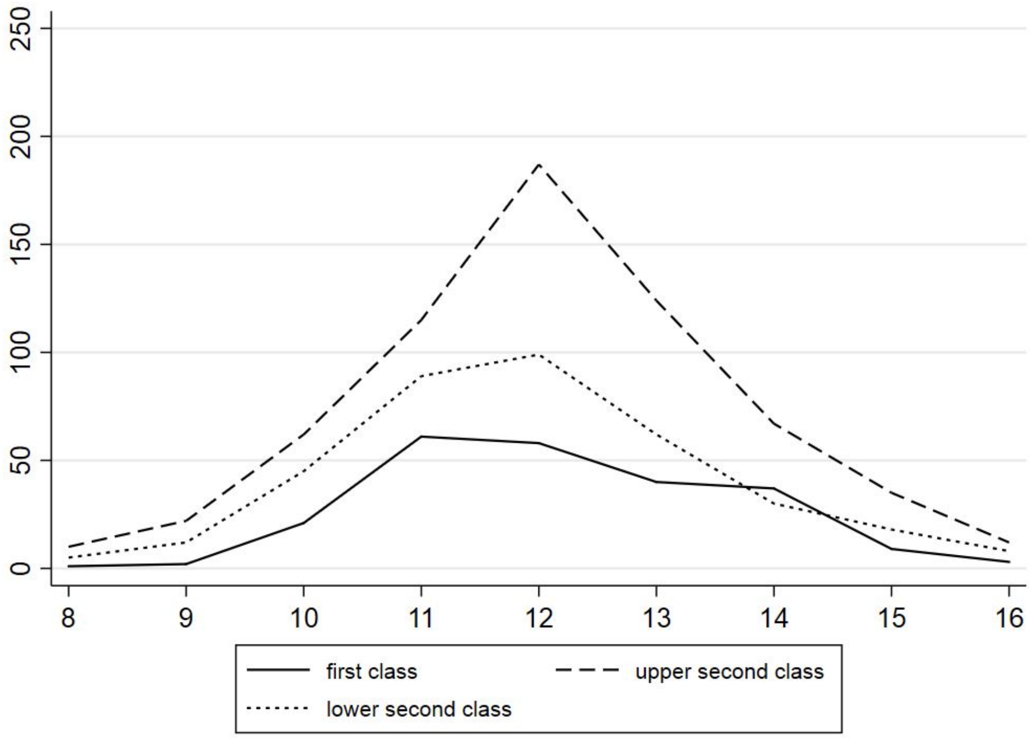


Figure 9: Degree classification across Locus of control



4 Methodology

To assess the effect of non-cognitive skills on wages at age 25 we augment a standard wage equation with measures of non-cognitive skills and we specify the following linear model:

$$y = \alpha + \mathbf{D}'\beta + \mathbf{NC}'\gamma + \mathbf{X}'\delta + \epsilon$$

where y is the outcome variable (either log hourly wage or log weekly earnings) of the individual; D indicates either a binary treatment control for having a degree, or the vector of multiple treatments of degree classes, with no degree as the control group in both cases; NC is a vector of non-cognitive skills (as discussed in Section 2); and X is a vector of individuals' characteristics (controls for gender, ethnicity, and region). Our sample size does not provide the power to estimate separately by the elements of **D**.

We begin by estimating the equation using Ordinary Least Squares for single treatment models and Inverse Probability Weighted Regression Adjustment (IPWRA) estimation in the case of multiple treatment effects. Both methods rely on the conditional independence assumption and IPWRA weights the data to give greater weight to individuals who have similar characteristics but receive different treatments.

The model is estimated for a sample of those in paid employment at age 25. The non-cognitive skills included in the main analysis are: standardized scores of the locus of control (measured at age 14/15 - a year before GCSEs), work ethic, and self-esteem (as discussed in Section 2) [7]. We also vary the definition of non-cognitive skills (whose results are also presented in section 5). Rather than using the definition of each NC skill based on the addition of scores for several questions, we instead also obtain standardized measures through principle component analysis. [8]

We estimate single treatment models (degree or no degree) and multiple treatment models (elite institution degree, other HEI degree, or none; and STEM degree, Social Science degree, Arts & Humanities degree, or none; and their interactions), and degree classes interacted with NC skills.

To model the probability of being in the treatment groups in IPWRA we control for the main and second parent's education, and the individual's gender, ethnicity, and current region. We present estimates that control for non-cognitive skills alongside estimates of a conventional model that does not include them.[9]

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[7] Non-cognitive skills used in the analysis are recorded at age 14-16, long prior to the degree treatment, to reduce the possible correlation with the anticipation of attending university. We base this presumption on the argument that non-cognitive skills are likely to undergo only modest changes on average between 16 and 18 (Caliendo et al., 2015)

[8] We further include 'missing-dummies' in the OLS specification with the aim of retaining sample size. We control for missingness in the case of HEI type and for missing observations across the non-cognitive skills mentioned previously. We acknowledge that including these dummies may give biased estimates if the observations are not missing at random. We have also estimated all specifications without these dummies, as well as dropped those observations by missingness, and we find that the wage and earnings premia estimates are not significantly affected. Not controlling for missing NC skills, negligibly affects NC skill estimates, and affects the degree estimate by inflating it by 0.5 percentage points. Not controlling for degree-missingness but controlling for NC skills-missingness, increases the degree-estimate by 0.5 percentage points as well and reduces the LOC-estimate by 1 percentage point. Not controlling for neither degree-missingess nor NC skills-missingess has similarly small effects. We also drop the observations affected by missingness. Results are available upon request.

[9] We also estimate using Propensity Score Matching (PSM) using the Stata code *teffects psmatch*. The results obtained are presented in Tables B1 and B2 of Appendix B as they are very similar to the results obtained with IPWRA below, but they provide less detail than here.

4.1 Inverse Probability Weighted Regression Adjustment

Inverse Probability Weighted Regression Adjustment (IPWRA) is an alternative bias-reducing method. IPWRA, akin to PSM, accounts for the nonrandom treatment assignment using a multinomial logit first stage - but it does so by *weighting* the control and treatment groups to make them more comparable. That is, in contrast to PSM, the IPWRA method fits the conditional model for the outcome by weighting observations instead of matching them.

IPWRA is characterized by the double-robust property, meaning that if either treatment model or outcome model are misspecified (but not both) the estimates of the treatment effects will nevertheless be consistent. The outcome is modelled by controlling for non-cognitive skills, gender, region, and the treatment is modelled by controlling for non-cognitive skills, parents' education, gender, and region. To compare how much the treatment effect is affected by the inclusion of non-cognitive skills we estimate with and without non-cognitive skills when modelling treatments and outcomes in separate equations. The main reason for employing IPWRA here is that it allows for multiple treatments. This allows, for example, elite university degrees and those from non-elite institutions to be treated as two different treatments, relative to the no-degree control individuals. The different majors are treated as three treatments (STEM, Social Sciences, Arts & Humanities). Combining these treatments it allows us to estimate the effects of the six interactions between the two treatment types (Elite and STEM, for example). We estimate IPWRA using the Stata code *teffects ipwra*.

4.2 Sensitivity to selection bias

One of the aims of this study is to analyze whether previous estimates of returns to higher education are reliable, despite not being able to observe non-cognitive skills. So we compare estimates that control for these with those that do not. Nonetheless, we also want to formally test whether controlling for non-cognitive skills makes specifications less sensitive to selection bias. OLS and IPWRA both depend on no selection on unobservables, and we follow Oster (2016) who, building on Altonji et al. (2005), has developed a novel method for assessing bias arising from unobservables. The method aims to calculate the lower bound of the treatment effect using information from coefficient movements *and* movements in R-squared when adding further controls to the specification. It allows us to not only to explore the lower bound of the estimates, assuming that there are still unobserved (non-cognitive) factors which may affect the outcome variables, but also allows us to compare these lower bounds before and after the inclusion of non-cognitive controls. The method also calculates the proportional degree of selection between observables and unobservables which would be required to confound the observed treatment effects - that is, drive their effects to zero. This latter provides a sense check on the reasonableness of the no selection on unobservables assumption.

5 Results

The following section presents the estimation results for the returns to higher education, with and without including non-cognitive controls. We present the results for hourly wages first, followed by the results for weekly earnings; we then provide robustness checks using alternative non-cognitive skill definitions. Finally, we include the returns to different degree classifications.

5.1 Wages

We present wage results for pooled males and females, as well as wages by males and females separately. These are obtained by OLS in Table 5 (pooled male and female), Table 6 (male), and Table 7 (female). We present the average returns to a degree, as well as returns by institution (the elite Russell Group universities vs other HEI), subject (STEM, Social Sciences, Arts and Humanities). We also estimate returns by subject type AND institution type. The results of our four specifications are presented in four blocks, each with two columns: column (1) refers to the baseline regression without non-cognitive skills and column (2) controls for non-cognitive skills.

In Table 5 we see that the average return to a degree is 11.3% in the baseline regression. Controlling for locus of control, work ethic and self-esteem the returns reduce to 10.6% - a statistically insignificant difference of less than one percentage point. The F-test of joint insignificance for the included NC skills is rejected, but only locus of control is individually statistically significant. A one standard deviation change in locus of control increases an individual's wages by 3.3%. The female differential varies from between -6 .4 and -7.7 % across specifications in Table 5.

The return to a Russell Group degree, relative to none, is 20% which is more than three times as large as the wage premium for graduates of non-elite HE institutions, at 5.6%, in both cases taking account of NC skills. The difference in estimates controlling for NC skills and not is again statistically insignificant and relatively modest at close to 1%.

We further decompose average degree returns by subject areas such as STEM, Social Science, and Arts and Humanities, in the third block, and lastly look at the returns to studying these subjects at either Russell or other HE institutions in the final block. The average returns to STEM and Social Science subjects seem to be the same when we do not control for NC skills at 14.4%. They fall to 13.5% after accounting for NC skills. The estimates for an Arts and Humanities degree are only 2% , and 1.1% without NC skills, and they are not statistically significantly different from non-graduate controls. The returns to obtaining a degree from an elite university are unsurprisingly larger regardless of subject studied. Controlling for non-cognitive skills, a STEM subject at an elite university has a return of 24.4%; the Social Science return is 21.1%; and the Arts and Humanities return is 12.8%. Again the difference between these estimates and those estimates that do not take NC skills into account are modest at 1-2 percentage points. The biggest effect of institution type is for Arts and Humanities where the return in an elite institution is close to 13% compared to -3% for the non-elite case. Locus of control is the only NC skill that is statistically significant and its effect remains around 3% irrespective of specification.

Our headline estimate of the average wage premium to a university degree is around 10%. This is lower than typical estimates obtained from data containing individuals from across the life-cycle - reflecting the very early stage of the lifecycle of LSYPE. Recent UK estimates obtained from administrative data at a similar age are in the same ballpark as here(Belfield et al., 2018b). Indeed, the extent of heterogeneity in returns by subject *and* institution that are the dominant feature of Belfield et al. (2018a) and Belfield et al. (2018b) are also reflected here, to the extent that LSYPE allows.

Table 6 and Table 7 present results for the same specifications as Table 5 but now allows for differences in wage premia between males and females. Overall, there is very little difference between any estimate in Column (1) and corresponding estimates in Column (2) - the effect of NC skills is broadly similar for males and females. Controlling for non-cognitive skills reduces the estimate to the returns to a degree only modestly by 1-2 percentage points. The headline estimates for wage premia, in the first block of estimates, are uniformly higher for females, although the differential is never statistically significant. For example, the average wage premium is close to 10% for males and 13% for females. In the second block of estimates we explore institutional type differences. The elite HEI differential is close to 20% for men, and 22% for women. The wage premia associated with a non-elite HEI degree is, however, much smaller for men at around 3%, compared to close to 10% for women.

Table 5: Wage returns to a degree (OLS - pooled male and female)

	Overall		by Institution		by Subject		by Subject x Institution	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.113***	0.106***						
	(0.016)	(0.017)						
Russell Group			0.212***	0.200***				
			(0.026)	(0.026)				
Other HEI			0.062***	0.056**				
			(0.019)	(0.019)				
STEM					0.144***	0.135***		
					(0.022)	(0.022)		
Social Sciences					0.144***	0.136***		
					(0.026)	(0.026)		
Arts&Humanities					0.020	0.011		
					(0.024)	(0.024)		
STEM*Russell							0.254***	0.244***
							(0.038)	(0.038)
STEM*Other							0.103***	0.095***
							(0.024)	(0.025)
SocSc*Russell							0.228***	0.211***
							(0.044)	(0.044)
SocSc*Other							0.110***	0.107***
							(0.030)	(0.030)
A&H*Russell							0.141***	0.128**
							(0.042)	(0.042)
A&H*Other							-0.027	-0.032
							(0.026)	(0.027)
Female	-0.077***	-0.075***	-0.068***	-0.068***	-0.066***	-0.066***	-0.064***	-0.064***
	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)
Locus of control		0.033***		0.030***		0.030***		0.029***
		(0.008)		(0.008)		(0.008)		(0.008)
Work ethic		0.013		0.014		0.017		0.014
		(0.008)		(0.009)		(0.009)		(0.009)
Self-esteem		-0.004		-0.006		-0.007		-0.007
		(0.011)		(0.012)		(0.012)		(0.012)
F-test of NC coeffs		F(3, 4064)=8.29		F(3, 3515)=6.30		F(3, 3516)=7.02		F(3, 3504)=6.17
		p <.001		p <.001		p <.001		p <.001
R-sqr	0.073	0.082	0.074	0.082	0.072	0.081	0.079	0.088
N	4077	4077	3529	3529	3531	3531	3522	3522

Note: The dependent variable is log of gross hourly wage. Specification (1) does not control for non-cognitive skills, while specification (2) does. All specifications include the following additional controls: gender, ethnicity as well as regional dummies. All observations are weighted by the most recent LSYPE sample weights.

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

Table 6: Wage returns to a degree (OLS - male)

	Overall		by Institution		by Subject		by Subject x Institution	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.101***	0.094***						
	(0.024)	(0.025)						
Russell Group			0.200***	0.187***				
			(0.038)	(0.038)				
Other HEI			0.030	0.025				
			(0.028)	(0.028)				
STEM					0.094**	0.083*		
					(0.034)	(0.034)		
Social Sciences					0.141***	0.131***		
					(0.038)	(0.038)		
Arts&Humanities					-0.010	-0.013		
					(0.038)	(0.040)		
STEM*Russell							0.198**	0.188**
							(0.061)	(0.062)
STEM*Other							0.059	0.049
							(0.037)	(0.037)
SocSc*Russell							0.223***	0.203***
							(0.057)	(0.054)
SocSc*Other							0.095*	0.093*
							(0.046)	(0.046)
A&H*Russell							0.160*	0.153*
							(0.068)	(0.069)
A&H*Other							-0.098*	-0.096*
							(0.041)	(0.044)
Locus of control		0.034**		0.033**		0.033**		0.032**
		(0.012)		(0.012)		(0.012)		(0.012)
Work ethic		0.006		0.007		0.011		0.007
		(0.013)		(0.014)		(0.014)		(0.014)
Self-esteem		0.001		-0.004		-0.004		-0.004
		(0.022)		(0.024)		(0.024)		(0.024)
F-test of NC coeffs		F(3, 1837)=4.18		F(3, 1588)=3.46		F(3, 1588)=3.64		F(3, 1582)=3.26
		p <.01		p <.05		p <.0 . 5		p <.05
R-sqr	0.071	0.081	0.072	0.083	0.068	0.080	0.078	0.088
N	1849	1849	1601	1601	1602	1602	1599	1599

Note: The dependent variable is log of gross hourly wage. Specification (1) does not control for non-cognitive skills, while specification (2) does. All specifications include the following additional controls: gender, ethnicity as well as regional dummies. Further control for missing values in the sample for degree-observations as well as non-cognitive skill observation are also included (see Section 4). All observations are weighted by the most recent LSYPE sample weights.

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

In the third blocks of Tables 6 and Table 7, the wage premium for a STEM subject are twice as large for females than for males - at 20% for women and 9% for men. We also note bigger differences in returns between male and female STEM graduates from elite universities as compared to the non-elite institutions. While there are some important gender differences in graduate wage premia, the gender differences in returns to NC skills are small. Locus of control remains to be the only statistically significant NC skill for both genders, with the exception of work ethic for females when we look at the specification by institution and subjects respectively. A one standard deviation change in locus of control (more internal locus of control) has a return of around 3% on top of the returns to a degree for both males and females. For females a one standard deviation change in work ethic importance increases wages by around 2%.

Since gender is not our focus here, and since the differences in results are small relative to what they have in common, we continue to present results using the pooled data only. Table 8 presents results for the Oster sensitivity to selection bias test (Oster, 2016) using the pooled data and the log wage rate as the dependent variable. Columns (1) and (4) are drawn from the first block of Table 5 to remind ourselves that controlling for NC skills barely reduces the wage premium. Comparing columns (3) and (6) we see that controlling for NC skills increases the selection on unobservables which would confound the observed treatment effect only fractionally. It follows that the bias in the estimates for the wage premium is not greatly affected by controlling for non-cognitive skills. We conclude that controlling for non-cognitive skills does not significantly decrease selection, thus the omission of these skills in many other studies does not appear to be a cause for concern.

However, there is a case for thinking that IPWRA estimates are more robust to selection than OLS. Table 9 presents the IPWRA results for the pooled sample, comparable with the OLS estimates in Table 5. The headline estimates from Table 9 are, indeed, smaller than corresponding OLS results (by about 4%) but the pattern of results from the IPWRA analysis is very similar to before. The difference in estimates between specifications which control for NC skills and not remains modest at around 1 percentage point. The estimated wage premia fall across the board - driving the Arts & Humanities treatment effect to become insignificantly different from zero, when it had been about 6% and significant. The same is true for the Arts & Humanities estimate for the non-elite graduates - it is significantly large and negative.

Table 7: Wage returns to a degree (OLS - female)

	Overall		by Institution		by Subject		by Subject x Institution	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.130***	0.121***						
	(0.022)	(0.022)						
Russell			0.229***	0.213***				
			(0.036)	(0.036)				
Other HEI			0.098***	0.091***				
			(0.025)	(0.025)				
STEM					0.204***	0.193***		
					(0.027)	(0.027)		
Social Sciences					0.152***	0.146***		
					(0.036)	(0.036)		
Arts&Humanities					0.054	0.041		
					(0.031)	(0.032)		
STEM*Russell							0.315***	0.301***
							(0.044)	(0.044)
STEM*Other							0.161***	0.152***
							(0.029)	(0.029)
SocSc*Russell							0.226**	0.214**
							(0.071)	(0.072)
SocSc*Other							0.132***	0.128***
							(0.039)	(0.039)
A&H*Russell							0.135**	0.116*
							(0.052)	(0.052)
A&H*Other							0.029	0.019
							(0.034)	(0.034)
Locus of control		0.032***		0.027**		0.028**		0.027**
		(0.009)		(0.010)		(0.010)		(0.010)
Work ethic		0.020		0.022*		0.023*		0.021
		(0.010)		(0.011)		(0.011)		(0.011)
Self-esteem		-0.008		-0.008		-0.009		-0.009
		(0.010)		(0.011)		(0.011)		(0.011)
F-test of NC coeffs		F(3, 2216)=6.45		F(3, 1915)=4.88		F(3, 1915)=5.55		F(3, 1906)=4.95
		p <.001		p <.01		p <.001		p <.01
R-sqr	0.066	0.077	0.072	0.082	0.075	0.085	0.082	0.091
N	2228	2228	1928	1928	1929	1929	1923	1923

Note: The dependent variable is log of gross hourly wage. Specification (1) does not control for non-cognitive skills, while specification (2) does. All specifications include the following additional controls: gender, ethnicity as well as regional dummies. Further control for missing values in the sample for degree-observations as well as non-cognitive skill observation are also included (see Section 4). All observations are weighted by the most recent LSYPE sample weights.

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

Table 8: Wage premium sensitivity to selection bias

	(1) OLS	(2) bias adj. β with δ=1	(3) δ^0 for β=0	(4) OLS with NC	(5) bias adj. β with δ=1	(6) δ^0 for β=0
Degree	0.113***	0.078*	1.787*	0.106***	0.073*	1.899
	(0.016)	(0.036)	(0.764)	(0.017)	(0.029)	(0.981)
R-sqr	0.073			0.082		
N	4,077			4,077		

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

Note: The dependent variable is log gross hourly wage. Specifications (1) and (4) include gender, ethnicity, and regional dummies. All observations are weighted by LSYPE sample weights. (2) and (5) shows the bias adjusted β with δ fixed at 1 (obtained with Stata command *psacalc* provided by Oster (2016) to test the coefficient stability of specification (1) and (4). Columns (3) and (6) shows how much proportional selection in unobservables will fully confound the estimate for β, where we fix R_{max}=1.3$\tilde{R}$ for reasons outlined in Oster (2016).

5.2 Earnings

All of the developing literature that uses administrative data provide estimates of earnings, not wage rate, premia. For some purposes, at least, we are interested in the wage rate premium. In Table 10 we tabulate the returns to a degree in terms of weekly earnings to complement the wage rate estimates in Table 5. As before, we look at overall returns, returns by institution type, by subject group, and by subject group AND type of institution. Overall the graduate earnings premium, without controlling for NC skills, is 18.2%, while controlling for NC skills this reduces to 16.4%. These estimated earnings premia are significantly higher than the wage premia of Table 4, reflecting a large (around 6%) positive impact on hours (of over 2 hours, on average). These effects are higher than was the case for wages, which leads us to conclude that graduates also work more hours in addition to receiving a higher wage than non-graduates [10]. The effect of a standard deviation change in locus of control is now larger at 4.7%, and contrary to

[10]There appears to be little research on how weeks worked per annum, or the entitlement to paid vacation days, vary by education. Bryan (2006) appears to be the only study for the UK that bears on this. This uses the Labour Force Survey (similar to the US CPS) and estimated reduced form effects of degree premia of around 0.9 hours per week and of one additional day of annual vacation. Since these results also control for a wide range of bad controls it seems likely that they will be considerable underestimates.

Table 9: Wage returns to a degree (IPWRA - pooled)

	Overall		by Institution		by Subject		by Subject x Institution	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.085***	0.075**						
	(0.024)	(0.023)						
Russell Group			0.162***	0.148***				
			(0.042)	(0.039)				
Other HEI			0.028	0.013				
			(0.035)	(0.032)				
STEM					0.106***	0.095***		
					(0.028)	(0.027)		
Social Sciences					0.102**	0.096**		
					(0.034)	(0.034)		
Arts&Humanities					-0.033	-0.045		
					(0.035)	(0.035)		
STEM*Russell							0.169***	0.159***
							(0.049)	(0.047)
STEM*Other							0.081*	0.071*
							(0.037)	(0.035)
SocSc*Russell							0.205**	0.178*
							(0.073)	(0.073)
SocSc*Other							0.058	0.0.039
							(0.047)	(0.048)
A&H*Russell							0.032	0.018
							(0.059)	(0.050)
A&H*Other							-0.095*	-0.096*
							(0.048)	(0.038)
N	2254	2254	1940	1940	1944	1944	1923	1923

Note: The dependent variable is log of gross hourly wage. Specification (1) does not control for non-cognitive skills, while specification (2) does. All specifications include the following additional controls: gender, ethnicity as well as regional dummies. All observations are weighted by the most recent LSYPE sample weights.

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

the wage specifications work ethic is statistically significant too, with an effect of 4.5%. Graphing the distribution of weekly hours worked by work ethic supports the positive effect observed (see Appendix A).

Controlling for NC skills, a Russell graduate earns 33.7% more than a non-graduate, much higher than the corresponding wage effect of 20%, while a graduate from a non-elite HE institution earns just 9.3% more in weekly earnings, also higher than the wage premium of 5.6%. The corresponding estimates without NC skill controls are 37% and 10.6% respectively. The average returns to a STEM and Social Science degree are 24.1% and 21.8% respectively without NC skill control and controlling for them decreases these estimate by around 2%. Arts & Humanities provide an earnings premium of 6% and 8.1%, with and without NC skills, although the former is not significantly different from zero.

Earnings premia are once again higher for each subject group at Russell universities. Controlling for NC skills, STEM at an elite university has an earnings premium of 35.6%, while it is only 17.1% at non-elite institutions. These estimates are slightly higher when not controlling for NC skills, at 38.2% and 18.7% respectively. Social Sciences obtained from a Russell university show the highest earnings premium at 37.2% with NC skills and 41.1% without. It should also be noted that while Arts & Humanities at a non-elite institution, although not statistically significant, have a small negative return at -1.6% (controlling for NC skills) obtaining an Arts & Humanities degree, from an elite university, gives a relatively high premium of 27.8% in terms of weekly earnings, compared to the 13% wage premium.

Locus of control is statistically significant in all specifications and shows an effect of around 4.5% per standard deviation. Contrary to the wage specifications, work ethic is highly statistically significant in all earnings specifications, with a similar return. This is consistent with high work ethic graduates working longer hours.

Similarly to Table 8 in the case of wages, Table 11 presents results for the Oster sensitivity to selection bias test, here for the earnings estimates. Specifications with and without non-cognitive controls result in a lower bound of the earnings premium that is approx. 5 percentage points lower than the OLS estimate. Comparing columns (3) and (6), including more controls gives us a coefficient of proportionality between unobservables and observables that is smaller, meaning the relative degree of importance between unobservables and observables in explaining the outcome has reduced, compared to a specification that does not control for non-cognitive skills. It seems that in terms of earnings, the two statistically significant non-cognitive skills locus of control and work ethic do improve on the specification and reduce bias.

We have also looked at the returns of higher education using other definitions of non-cognitive skills. We have applied principal component analysis to all the non-cognitive skill statements discussed in Section 3.2 (and originally used in the main analysis) and obtained 3 factors that can be broadly summarized into locus of control, work ethic, and self-esteem (only the latter is the same as the previous definition because the statement "How well you get on in this world is mostly a matter of luck" is now attributed to the second factor instead of locus of control. Table B3 shows the specifications using these non-cognitive skills. It becomes apparent that only work ethic is statistically significant and of quantitative importance, with a return of 2.5%. The robustness of the estimate of the returns to a degree is similar to the previous specifications. The estimates are at most reduced by 2 percentage points.

5.3 Returns to Degree Classifications: Wages and Earnings

Figure 4 showed that the average (across males and females) percentage of graduates that obtained a First classification was 18%, while the percentage obtaining an Upper Second classification was 52%, and 30% received a lower degree classification. Most of this cohort will have graduated from university around 2012 and these figures are close to the national averages at the time (although there has been a great deal of "grade inflation" around this period).

Although undergraduate students are relatively homogeneous within courses (i.e a particular major at a particular institution), because courses select largely by prior test scores, the degree class outcomes vary greatly across individuals within a course. We surmise that the NC skills that students on a course have are the important unobservable, to the course admission authority, that drives academic success conditional on being admitted. LSYPE records the degree class of each individual graduate. We treat NC skills as exogenous, conditional on course, and estimate the wage and earnings premia to different degree classes, including NC skills in the specification and not.

Our prior is that employers of graduates at such an early age have had little opportunity to establish and reward NC skills so degree class acts as a signal to employers. Thus, we expect that NC skills conditional on degree class will not greatly affect wages and that degree class, at least in the short run, acts as a sufficient statistic for NC skills. Indeed, one role that a degree might play is to signal skills to the potential employers of newly minted graduates, and being able to credibly communicate NC skills through degree class might be a reliable way for good graduates to do so.

Table 10: Earnings returns to a degree (OLS - pooled)

	Overall		by Institution		by Subject		by Subject x Institution	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.182***	0.164***						
	(0.022)	(0.022)						
Russell Group			0.370***	0.337***				
			(0.033)	(0.033)				
Other HEI			0.106***	0.093**				
			(0.026)	(0.026)				
STEM					0.241***	0.221***		
					(0.030)	(0.030)		
Social Sciences					0.218***	0.200***		
					(0.035)	(0.034)		
Arts&Humanities					0.081*	0.060		
					(0.033)	(0.033)		
STEM*Russell							0.382***	0.356***
							(0.055)	(0.056)
STEM*Other							0.187***	0.171***
							(0.032)	(0.032)
SocSc*Russell							0.411***	0.372***
							(0.049)	(0.049)
SocSc*Other							0.140***	0.133***
							(0.040)	(0.040)
A&H*Russell							0.309***	0.278***
							(0.045)	(0.045)
A&H*Other							-0.003	-0.016
							(0.038)	(0.038)
Female	-0.237***	-0.231***	-0.237***	-0.233***	-0.233***	-0.230***	-0.229***	-0.226***
	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Locus of control		0.047***		0.044***		0.046***		0.044***
		(0.010)		(0.011)		(0.011)		(0.011)
Work ethic		0.045***		0.045***		0.047***		0.042***
		(0.012)		(0.013)		(0.012)		(0.012)
Self-esteem		0.010		0.010		0.008		0.008
		(0.010)		(0.011)		(0.011)		(0.011)
F-test of NC coeffs		F(3, 4160)=16.25		F(3, 3602)=13.59		F(3, 3603)=14.97		F(3, 3591)=13.12
		p <.001		p <.001		p <.001		p <.001
R-sqr	0.125	0.143	0.134	0.152	0.127	0.146	0.139	0.156
N	4173	4173	3616	3616	3618	3618	3609	3609

Note: The dependent variable is log of gross weekly earnings. Specification (1) does not control for non-cognitive skills, while specification (2) does. All specifications include the following additional controls: gender, ethnicity as well as regional dummies. Further control for missing values in the sample for degree-observations as well as non-cognitive skill observation are also included (see Section 4). All observations are weighted by the most recent LSYPE sample weights.

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

Table 11: Earnings premium sensitivity to selection bias

	(1) OLS	(2) bias adj. β with δ=1	(3) δ^0 for β=0	(4) OLS with NC	(5) bias adj. β with δ=1	(6) δ^0 for β=0
Degree	0.182***	0.135***	2.028**	0.164***	0.106**	1.863**
	(0.022)	(0.039)	(0.645)	(0.022)	(0.035)	(0.651)
R-sqr	0.125			0.143		
N	4,173			4,173		

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

Note: The dependent variable is the log of gross weekly earnings. Specifications (1) and (4) include gender, ethnicity, and regional dummies. All observations are weighted by LSYPE sample weights. (2) and (5) shows the bias adjusted β with δ fixed at 1 (obtained with Stata command *psacalc* provided by Oster (2016) to test the coefficient stability of specification (1) and (4). Columns (3) and (6) shows how much proportional selection in unobservables will fully confound the estimate for β, where we fix $R_{max}=1.3\tilde{R}$ for reasons outlined in Oster (2016).

Table 12 shows the estimated degree class effects on wages and earnings [11]. Focusing on columns 1-4 for the OLS wage premia in Table 12 we see that NC skills no longer have significant effects. Previously, in Table 5, LoC had an effect of 3.3% compared to an insignificant effect of 1.3% in Table 12. Graduates with a first class degree earn 15.9% more than non-graduates, estimated by OLS, which is not significantly greater than the 13% premium for an upper second class degree. However, the return to a lower-second or third class degree is just 1% which is not significantly different from the counterfactual non-graduate wage. The suggestion is that around *one third* of students experience no significant financial gain from university. When we contrasted Table 5 OLS estimates with Table 9 we found lower wage premia across comparable specifications. Similarly, here, in Table 12 we also find lower degree class estimates using IPWRA compared to OLS and the effects of lower second and third class are now negative, albeit insignificantly so. The NC skills remain individually insignificant.

Looking at degree class earnings premia, in Table 12 columns 5-8, we find IPWRA generate lower estimates of degree class earnings premia, as before for wages. Work ethic remains significant in the OLS specification and suggests a one SD rise would raise hours by approximately 4. LoC remains significant in the IPWRA specification for first class but not otherwise.

[11] Tables 5 and 10 include NC skills, but estimation of the degree class effect on wages without controlling for NC-skills, results in estimates that are on average 1% higher (in line

Table 12: Wage and Earnings returns to degree classification

	Wage returns				Earnings returns			
	OLS		IPWRA		OLS		IPWRA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1st	0.159***	0.122***			0.238***	0.200***		
	(0.031)	(0.034)			(0.043)	(0.046)		
2.1	0.130***		0.093***		0.199***		0.131***	
	(0.021)		(0.028)		(0.027)		(0.034)	
$\leq$ 2.2	0.010			-0.017	0.048			-0.020
	(0.025)			(0.031)	(0.036)			(0.046)
Female	-0.089***	0.018	-0.085*	-0.106*	-0.233***	-0.061	-0.127*	-0.102
	(0.018)	(0.060)	(0.040)	(0.052)	(0.025)	(0.091)	(0.051)	(0.080)
Locus of control	0.013	0.037	0.022	-0.040	0.024	0.066*	0.047	-0.046
	(0.009)	(0.030)	(0.022)	(0.027)	(0.014)	(0.038)	(0.029)	(0.042)
Work Ethic	0.016	-0.011	-0.001	0.025	0.056**	0.027	0.026	-0.011
	(0.012)	(0.038)	(0.031)	(0.030)	(0.018)	(0.043)	(0.031)	(0.050)
Self Esteem	0.015	0.026	0.025	0.005	0.021	-0.026	0.029	0.045
	(0.010)	(0.026)	(0.020)	(0.023)	(0.015)	(0.038)	(0.029)	(0.034)
R-sqr	0.085	-	-	-	0.136	-	-	-
N	2173	1408	1408	1408	2225	1438	1438	1438

Note: The dependent variable is log of gross hourly wage. 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 observation (see Section 4). 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 Discussion and Conclusion

The aim of the study has been to explore the robustness of estimates of the financial return to Higher Education to the inclusion of non-cognitive skills such as locus of control, conscientiousness (here in the form of adolescent work ethic) and self-esteem. We use OLS estimation as well as Inverse Probability Weighted Regression Adjustment. We 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) until the most recent wave (8) at age 25. This wave contains not only updated information on the individual's life but also includes, for the first time, labor market outcomes such as wages, earnings, hours, and employment status.

We have shown, surprisingly, that controlling for non-cognitive skills makes no difference to our estimates of the return to a degree. Moreover, this remains true when we disaggregate degree by subject groups, by elite vs non-elite HEIs, and both. We lastly also looked at the premia associated with the different degree classifications. We find much larger graduate earnings premia than graduate wage premia - consistent with the idea that graduates

with earlier results).

may want to use their greater human capital more intensively. This is also reflected with work ethic being a more important determinant of earnings than it is of wages.

Across both estimation methods used (OLS and IPWRA) the results do not suggest that previously estimated graduate earnings premia have been significantly overestimated because of the omission of NC skills. Indeed, controlling for non-cognitive skills changed the estimates only modestly. The estimates for the returns to higher education, at this age, are in line with the previous literature averaging at around 10%. IPWRA estimates are generally consistently slightly lower than OLS estimates. In fact, our IPWRA estimates are close to the Oster bounds, which might suggest that this weighting method does contribute to reducing ability bias. Non-cognitive skills reduce the estimate for the graduate premia by 2% on average. The non-cognitive skill that stands out as being the only statistically significant one, for almost all specifications, was locus of control in the case of wages, and work ethic in the case of earnings. These appear to be quantitatively important since a 1 standard deviation change in each of the two NC skills could have approximately the same effect on earnings as a third of the effect that a degree has. However, it does not appear that the effect of NC skills on premia is significantly different between graduates and non-graduates. It appears that not controlling for locus of control does not affect the returns to a degree. Furthermore, when analysing the returns to degree class the predictive power of including NC skills is lost. It seems that degree class captures the relevant NC skills to a large extent already.

There are many extensions it would be interesting to explore, including more comprehensive analyses by gender. While it is not unusual to exploit outcomes at age 25, one should bear in mind that these individuals are still relatively early in their career path and some have just finished university while others, who did not pursue Higher Education would have more work experience. In particular, the effects of NC skills may only become apparent later, after more work experience has been accumulated. So far we show the effects of these NC skills are important, but its not yet clear whether they fade or not in later life. Thus, it would be interesting to study this further with the release of LSYPE at age 32.

It would also be interesting, were a larger sample be available, to follow the Heckman, Stixrud, and Urzua (2006) methodology and estimate a latent factor model on this data. In 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.

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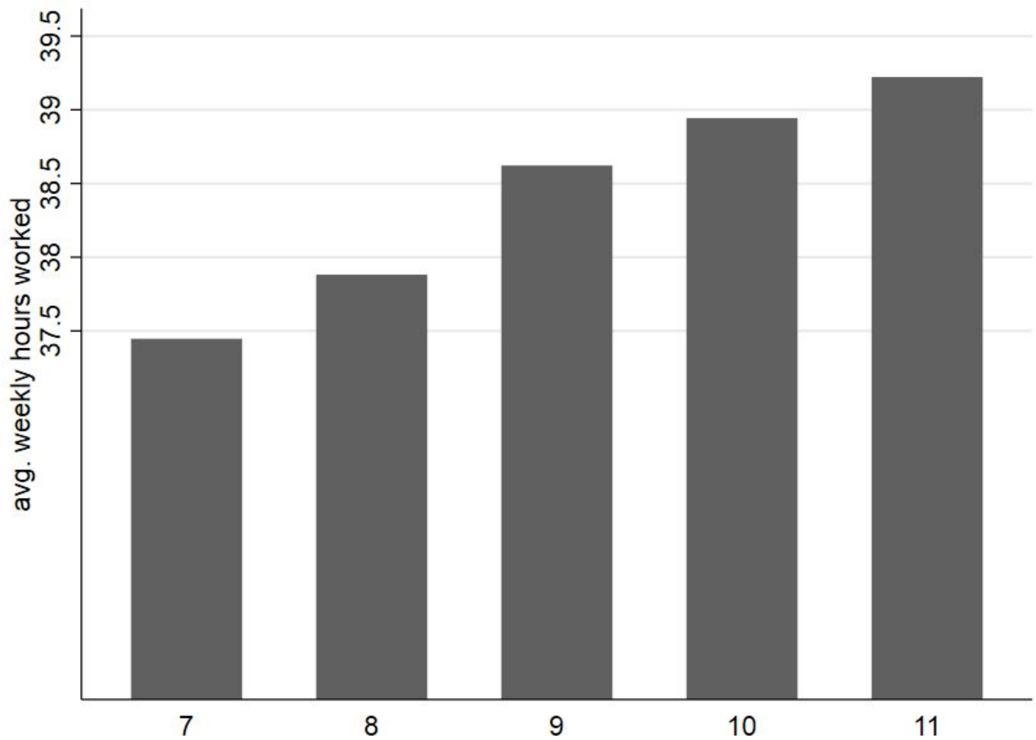
Appendices

A Additional graphs

Figure A1: Hours worked per week by Work Ethic



B Propensity Score Matching

Table B1: Wage returns to having obtained a degree - OLS & PSM (standardized NC skills)

	OLS						PSM					
	Pooled		Men		Women		Pooled		Men		Women	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.104***	0.095***	0.089***	0.082**	0.124***	0.111***	0.082***	0.052	0.089*	0.106*	0.085**	0.029
	(0.019)	(0.019)	(0.027)	(0.027)	(0.026)	(0.026)	(0.024)	(0.037)	(0.040)	(0.042)	(0.033)	(0.064)
Locus of control		0.033***		0.036**		0.030**		✓		✓		✓
		(0.008)		(0.013)		(0.010)						
Work Ethic		0.016		0.007		0.023*		✓		✓		✓
		(0.009)		(0.014)		(0.011)						
Self-Esteem		-0.007		-0.001		-0.011		✓		✓		✓
		(0.012)		(0.023)		(0.010)						
R-sqr	0.072	0.081	0.073	0.082	0.059	0.071	-	-	-	-	-	-
N	3301	3301	1506	1506	1795	1795	1547	1547	718	718	829	829

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. 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 B2: Wage returns to having obtained a degree - OLS & PSM (standardized NC skills) controlling for missings

	OLS						PSM					
	Pooled		Men		Women		Pooled		Men		Women	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.113***	0.106***	0.101***	0.094***	0.130***	0.121***	0.099***	0.061*	0.113***	0.103*	0.087**	0.048
	(0.016)	(0.017)	(0.024)	(0.025)	(0.022)	(0.022)	(0.021)	(0.028)	(0.030)	(0.044)	(0.029)	(0.042)
Locus of control		0.033***		0.034**		0.032***		✓		✓		✓
		(0.008)		(0.012)		(0.009)						
Work Ethic		0.013		0.006		0.020		✓		✓		✓
		(0.008)		(0.013)		(0.010)						
Self-Esteem		-0.004		-0.001		-0.008		✓		✓		✓
		(0.011)		(0.022)		(0.010)						
R-sqr	0.073	0.082	0.071	0.081	0.066	0.077	-	-	-	-	-	-
N	4077	4077	1849	1849	2228	2228	1794	1794	823	823	971	971

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, as well as controls for missing-NC-skill-observations. 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 B3: Wage returns to a degree - PCA (OLS)

	Overall		by Institution		by Subject		by Subject x Institution	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Degree	0.104***	0.092***						
	(0.019)	(0.019)						
Russell			0.198***	0.179***				
			(0.030)	(0.030)				
other HEI			0.049*	0.040				
			(0.021)	(0.021)				
STEM					0.133***	0.120***		
					(0.025)	(0.025)		
Social Sciences					0.132***	0.122***		
					(0.030)	(0.030)		
Arts&Humanities					0.004	-0.011		
					(0.026)	(0.027)		
STEM*Russell							0.229***	0.214***
							(0.043)	(0.044)
STEM*Other							0.098***	0.088***
							(0.027)	(0.27)
SocSc*Russell							0.238***	0.222***
							(0.050)	(0.049)
SocSc*Other							0.089**	0.082*
							(0.034)	(0.034)
A&H*Russell							0.117**	0.094*
							(0.045)	(0.045)
A&H*Other							-0.040	-0.050
							(0.029)	(0.029)
Locus		0.006		0.005		0.005		0.004
		(0.007)		(0.007)		(0.007)		(0.007)
Work ethic		0.025***		0.024***		0.026***		0.024***
		(0.007)		(0.007)		(0.007)		(0.007)
Self-esteem		-0.004		-0.005		-0.006		-0.006
		(0.007)		(0.008)		(0.008)		(0.008)
R-sqr	0.072	0.079	0.070	0.077	0.069	0.77	0.076	0.083
N	3301	3301	2860	2860	2865	2865	2856	2856

Note: The dependent variable is log of gross hourly wage. Specification (1) does not control for non-cognitive skills, while specification (2) does. All specifications include the following additional controls: gender, ethnicity as well as regional dummies. Further control for missing values in the sample for degree-observations are also included (see Section 4). All observations are weighted by the most recent LSYPE sample weights.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$