WHO'S GOT A MATCH? THE DEVELOPMENT OF SKILLS AT UNIVERSITY AND THE RETURNS TO SKILLS AT WORK

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ABSTRACT

Futuretrack data are used to evaluate the future wage returns to skills acquisition while at university. A series of matching estimators and an inverse probability weighted regression adjustment (IPWRA) allow identification of the causal effect. It is found that graduates' use of skills at work is influenced by their having received training in these skills while at university, and that the wage returns to many of these skills is positive.

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Introduction

The rise in demand for higher education in many countries has been accompanied by moves towards cost sharing that have served to accentuate the need for investment in tertiary schooling to be remunerative. Hence skills relevant to the workplace, but often acquired as by-products of an academic education, have assumed increased importance. The skills agenda – typified, for example, by policy actions in Australia[1], the United States[2], United Kingdom[3], and more broadly in the European Union[4] – has highlighted the importance of explicitly developing such skills in students as they progress through higher education. The idea of competency-based education has a somewhat longer history, much influenced by input from several leading economists (Grubb et al., 1992; Marginson, 1994; Murnane and Levy, 1996).

Yet the evidence on the effectiveness of skills delivery in education is scanty. In this paper, we examine the impact that skills acquisition during higher education has on individuals' subsequent labour market performance. In so doing, we make use of an innovative data set that follows a cohort of students through from secondary education to the labour market, and which gathers detailed information about skills acquisition and use.

The remainder of the paper is structured as follows. The literature is briefly surveyed in the next section. Then the data used in the study is introduced and analysed. Conclusions are drawn in the final section of the paper.

Literature

While moves to ensure that higher education institutions deliver skills related to employability have been widespread, evaluation of these institutions' efforts in this regard has been more limited. The influential study by Arum and Roska (2011) suggests that the extent to which an undergraduate education imparts useful skills is often limited, at least in the first two years of their degree programmes.

An interesting recent study by Humburg and van der Velden (2015) uses data from a stated choice experiment conducted across nine European countries. Respondents were asked to select candidates for interview (on the basis of their curriculum vitae) and for hiring (with further information provided about their skills, as evaluated by an assessment centre, in areas including professional expertise, general academic skills, innovative skills, strategic and organisational skills, interpersonal skills and entrepreneurial skills). All of these skills were found significantly to influence the likelihood with which a candidate in the experiment would be hired. This study builds on earlier work, by Garcia-Aracil et al. (2004), who study data from the CHEERS survey[5] and examine the impact of various competencies on both income and job satisfaction. They find negative financial returns associated with skills related to

[1] http://bit.ly/2BLe2Rb
[2] http://bit.ly/2CMhqb0
[3] http://bit.ly/2BGgCaU
[4] http://bit.ly/2BtQOwf
[5] The CHEERS survey is an international project that involved an international survey of graduates five years after graduation. Details are at http://www.qtafi.de/cheers-european-graduate-survey.html.

physical activity and applying rules in a routine fashion Meanwhile, more creative skills – described as participative and methodological skills – and socio-emotional competencies (such as teamworking, reflective thinking, and integrity) are associated with positive income outcomes. Meanwhile, Salas-Velasco (2014) uses data from the REFLEX project[6] to assess the extent to which a range of skills (including communication, time management, performance under pressure etc.) are fostered by various pedagogical practices at university. He finds that assignment based assessment is effective in promoting many of the competencies deemed desirable in the workplace. The issue of how undergraduate education fosters skills development is further addressed by Jackson (2014), who analyses the determinants of students' self-reported strength in a variety of skills relevant to the workplace. She concludes that universities can help foster these skills by encouraging students to network and to undertake paid work during their studies.

The results discussed above correspond closely with more recent findings from the task-based analyses of Autor and Handel (2013) and Agasisti et al. (2018). In these studies, earnings are modelled as a function of both worker characteristics and measures of the extent to which abstract, routine and manual tasks are undertaken at work; both characteristics and tasks are found to contribute to the explanation of how earnings vary across individuals (and across jobs). Skills thus matter; but our understanding of the technology underpinning the production of these skills – and specifically on how higher education institutions can best develop these skills – is incomplete.

Data and Analysis

The data used in this study come from the Futuretrack study. This is a longitudinal dataset collated by the Institute for Employment Research at the University of Warwick and funded by the Higher Education Careers Services Unit (HECSU) – an organisation, backed by Universities UK, that specialises in supporting the provision of careers advice in higher education. The study follows a cohort of students that applied to UK universities through the Universities and Colleges Admissions Service (UCAS) system in 2005-06. Data were collected in four sweeps - starting from their time in upper secondary school, twice during their university study, and once after they graduate from university and have entered the labour market. Until the Longitudinal Education Outcomes (LEO) administrative dataset recently became available, Futuretrack was the only source of data that followed students from before entry to after graduation from British universities. In contrast to LEO, Futuretrack includes a wealth of detailed information about the acquisition and subsequent utilisation of a range of skills. The fourth sweep of the survey contains detailed information about earnings, hours of work, industry, occupation (job title), region, and employer characteristics. Data on personal characteristics such as gender, ethnicity, health and parental occupation are also available. Previous studies that have made use of these data include Purcell and Elias (2013) and Behle et al. (2015). The Futuretrack microdata are available through the UK Data Service (https://discover.ukdataservice.ac.uk/).

[6] The REFLEX project, details of which are at http://www.reflexproject.org/, involved an international survey of higher education graduates across 15 countries. Respondents graduated in 2000 and were surveyed five years later. It was funded by the European Union's 6th Framework programme, and coordinated at Maastricht University.

Some 11 separate measures of skills and capabilities appear in the survey. These include: written communication; spoken communication; numerical analysis; critical evaluation; research; presentation; innovative thinking; enterprise; teamwork; individual work; and time management. Variables that indicate whether each of these skills is developed during undergraduate study and whether they are subsequently used in employment form the cornerstone of the analysis that follows. Some of the skills – notably numerical analysis, critical thinking, and research skills – may readily be identified as cognitive in nature, while others are non-cognitive.

The focus of the following analysis is on the impact of skills on the (log) wage.[7] Other variables used in the analysis, and on which observations are matched, are: educational attainment on entry to university (measured by the UCAS tariff[8]), subject of study (medicine, science/technology/engineering/mathematics, business and law, or other), class of degree awarded (first, upper second, lower second, other), gender, and ethnicity (white, other). Observations for which no data are available on educational attainment, subject studied, or wage are excluded from the analysis, leaving a sample size of some 3659.

The method of propensity score matching (Rubin, 1979; Rosenbaum and Rubin, 1983; Caliendo and Kopeinig, 2008; Stuart, 2010; Todd, 2010) allows the causal impact of a treatment – in this acquisition or use of specific skills – on an outcome variable – in this case earnings – to be evaluated by ensuring that treated individuals are compared only with untreated individuals who are, in respects other than treatment, similar. A probit estimator is used to obtain propensity scores, matching on a broad range of variables. These propensity scores measure the predicted probability with which each respondent is 'treated' by acquisition or use of each skill. Comparing treated and untreated respondents with similar propensity scores ensures a comparison of like with like, the random incidence of treatment being the only difference between each member of a set of respondents being compared with one another. Various methods can be used to select pairs. A common choice is to select (for each treated observation) the nearest (untreated) neighbour, with or without replacement. Alternatives include caliper matching (where a tolerance limit is imposed on the distance between pairs in a match), and methods where the comparator is a weighted average of observations rather than a single observation. The latter include kernel matching, where a weights (following, for example, the normal distribution) are applied to observations in the control group in preference to matching a treated observation with a single untreated respondent (Heckman et al., 1997).

In each of the analyses reported below, propensity score matching is undertaken using, as independent variables, information about respondents' ability, degree subject, degree result,

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[7] The log wage is calculated by dividing annual income by the product of 52 and weekly hours normally worked. Annual income is reported in the fourth sweep of the survey as income before tax deductions. This is a grouped variable, but with 15 groups it allows for quite precise evaluation of the hourly wage. Mid-points are used for the groups, with £85000 used for the top category.

[8] The UCAS tariff awards points for qualifications earned in upper secondary education. For example, on the national Advanced level ('A level') qualifications, each A grade is worth 120 points, each B grade is worth 100 points, each C grade is worth 80 points, and so on.

gender, and ethnicity, plus all skill variables other than the one on which the matching exercise is performed.[9]

In Table 1, the focus is on respondents who state that their undergraduate course developed specific skills and capabilities 'a lot'. The coefficients reported in the table refer to the impact of this intervention on (log) hourly wages once in employment – the average treatment effect on the treated (ATT). As a robustness check, results from five different matching estimators are reported.[10] The table also reports results from the inverse probability weighted regression adjustment (IPWRA) method due to Wooldridge (2007). At conventional levels of significance, there is evidence that development of only two of these skills – spoken communication and numerical analysis - has a positive impact on subsequent earnings. There is weaker evidence of an effect of development in entrepreneurial skills and time management.

Table 2 examines corresponding wage effects for those respondents who report that specific skills are used 'a lot' in their current job. Many more of the ATT coefficients in this table are statistically significant. Indeed there is evidence to support a positive effect for: written communication; numerical analysis; critical evaluation; research skills; innovative thinking; teamworking; and time management. The attributes that attract a positive return thus include both cognitive and non-cognitive skills.

Taken together, the results reported in Tables 1 and 2 imply that, **while the *use* of skills in employment is rewarded through higher wages, with a few exceptions the *acquisition* of these skills is not**.[11] Clearly, then, a relevant question concerns how the acquisition of these skills enhances the likelihood of these skills subsequently being used. In Table 3, the ATT associated with each type of skill delivery on the (binary variable reporting) use of that specific skill in subsequent employment are reported. The controls in this matching exercise include all those used in the earlier analysis with the exception of the remaining skills variables. It is readily observed that delivery of training in each skill area while at university significantly raises the probability of using the corresponding skill in subsequent employment.[12] Through this effect, such training therefore indirectly raises remuneration. If one imagines a triangle, the corners of which represent skill acquisition, skill use, and the returns to skill, then acquisition influences use which in turn influences returns, but there is no direct link between acquisition and returns.

[9] Ability is measured by the 'tariff', which is a score based on respondents' performance in national examinations used as entry criteria to university. Various types of qualification are included in the tariff, the best known being the General Certificate of Education Advanced Level (A level) qualification. Each A grade at A level contributes 120 points to the tariff; each B grade is 100 points, each C grade is worth 80 points and so on. The mean tariff for our sample of 3659 respondents is 392.6. Degree subject is measured as four binary variables indicating participation in: medicine; science, technology, engineering and mathematics; business and law; and (the omitted category) all other subjects. The class of degree awarded is represented by binary variables indicating first class honours, upper second class, lower second class, or (the omitted category) all other classifications. Gender and ethnicity are represented by binary variables for males and for whites.

[10] Other estimators (not reported here) sampled neighbours with replacement and/or ensured common support by trimming; the results are qualitatively similar and those reported here are selected to be representative.

[11] We note in passing that this provides further evidence relevant to the human capital versus signalling/screening debate (Johnes, 1998).

[12] There is one exception: the IPWRA estimate on spoken communication.

As a further robustness check, the exercises reported above have been repeated, this time including further variables in the matching function. These additional variables concern the nature of employment secured after graduation and include an industry dummy (identifying graduates working in the service industries) and variables indicating whether the graduate's employer is small (employing fewer than 50 workers), medium (20-249 workers) or large. The full set of results is reported in the appendix, but we note here that these results are very similar to those reported for the simpler specifications in Tables 1-3.

Conclusion

Increased focus on the skills agenda has been a feature of higher education as the sector has transited from boutique through elite and on to mass provision (Garnett-Jones and Turpin, 2012). Yet evaluation of the effectiveness of higher education institutions in delivering skills to their students that are of subsequent benefit in the labour market has been limited. In this paper, evidence is provided that suggests that such provision raises the likelihood with which students progress to employment in which the practice of these skills is a requisite of the job, and that these skills, *where used*, in many cases raise earnings.

That said, tuition in certain skills is more successful than that in others. The ubiquity of negative signs on the ATT associated with presentation skills is surprising, but may be a feature of a higher education regime in which student numbers have vastly grown. Thus a challenge for higher education institutions in practice, and for those undertaking the research in pedagogy that underpins this practice, is to establish how such skills can effectively be delivered in a mass system.

Table 1: Impact on log wage of skills delivery at university, various matching estimators

written	-0.043	-0.038	-0.038	-0.042	-0.051	-0.062
communication	(2.44)	(1.45)	(1.40)	(1.71)	(2.66)	(2.72)
spoken	0.029	0.066	0.066	0.065	0.068	0.025
communication	(1.84)	(2.70)	(3.22)	(2.57)	(3.16)	(1.10)
numerical	0.116	0.112	0.112	0.112	0.116	0.077
analysis	(5.14)	(4.06)	(3.56)	(4.57)	(5.50)	(3.61)
critical	0.006	-0.004	-0.004	-0.002	0.018	-0.010
evaluation	(0.34)	(0.11)	(0.13)	(0.06)	(0.68)	(0.41)
research skills	-0.015	-0.033	-0.033	-0.038	-0.044	-0.037
	(0.67)	(1.12)	(1.17)	(1.40)	(1.86)	(1.71)
presentation	-0.031	-0.029	-0.029	-0.027	-0.032	-0.052
skills	(2.12)	(1.10)	(1.12)	(0.91)	(1.37)	(1.85)
innovative	0.012	0.014	0.014	0.020	0.015	0.013
thinking	(0.67)	(0.50)	(0.40)	(0.58)	(0.68)	(0.60)
entrepreneurial	0.043	0.066	0.066	0.066	0.061	0.169
skills	(1.18)	(1.73)	(1.79)	(1.48)	(1.85)	(3.71)
teamwork	0.030	0.011	0.011	0.010	0.017	-0.020
	(1.38)	(0.60)	(0.54)	(0.37)	(0.86)	(1.05)
ability to work	0.004	0.017	0.017	0.011	0.024	0.002
individually	(0.19)	(0.49)	(0.39)	(0.24)	(0.73)	(0.08)
time	0.004	0.034	0.034	0.025	0.030	0.000
management	(0.19)	(1.24)	(1.58)	(0.97)	(1.31)	(0.00)

Note: z values in parentheses. The matching estimators used are: nearest neighbour without replacement; radius caliper (set at 0.1) without replacement; radius caliper (set at 0.1) with 5 neighbours without replacement; a normal kernel with bandwidth set at 0.05; a normal kernel with 5 neighbours and bandwidth set at 0.15. The final column reports results from the IPWRA estimator.

Table 2: Impact on log wage of skill use at work, various matching estimators

written	0.210	0.086	0.086	0.086	0.132	0.120
communication	(10.73)	(3.71)	(4.31)	(3.60)	(6.95)	(5.89)
spoken	-0.049	-0.010	-0.010	-0.011	-0.010	-0.009
communication	(1.80)	(0.32)	(0.29)	(0.39)	(0.38)	(0.28)
numerical	0.078	0.037	0.037	0.033	0.070	0.046
analysis	(3.68)	(1.56)	(1.96)	(1.45)	(3.74)	(2.27)
critical	0.147	0.077	0.077	0.080	0.099	0.131
evaluation	(7.95)	(3.75)	(3.00)	(3.84)	(4.58)	(5.92)
research skills	0.040	0.049	0.049	0.053	0.057	0.071
	(1.71)	(2.00)	(2.15)	(1.97)	(3.00)	(2.34)
presentation	-0.028	-0.019	-0.019	-0.019	-0.010	0.021
skills	(1.25)	(1.03)	(0.78)	(0.79)	(0.51)	(0.89)
innovative	0.033	-0.011	-0.011	-0.009	0.011	0.038
thinking	(2.28)	(0.51)	(0.45)	(0.44)	(0.70)	(1.63)
entrepreneurial	-0.088	-0.091	-0.091	-0.093	-0.054	-0.080
skills	(2.53)	(2.75)	(2.55)	(2.86)	(1.55)	(1.55)
teamwork	0.038	0.057	0.057	0.052	0.065	0.020
	(1.66)	(2.24)	(2.28)	(2.14)	(2.76)	(0.82)
ability to work	0.006	-0.037	-0.037	-0.045	-0.028	-0.062
individually	(0.22)	(1.37)	(1.30)	(1.41)	(0.83)	(2.11)
time	0.174	0.118	0.118	0.083	0.150	0.041
management	(5.04)	(2.15)	(2.29)	(1.42)	(3.83)	(0.98)

Note: See notes to Table 1.

Table 3: Impact of skills delivery at university on corresponding skill use at work

written	0.090	0.120	0.120	0.121	0.117	0.087
communication	(5.04)	(6.98)	(6.66)	(6.96)	(5.26)	(4.58)
spoken	0.093	0.084	0.084	0.083	0.097	0.014
communication	(7.82)	(7.75)	(6.66)	(6.83)	(7.79)	(0.89)
numerical	0.308	0.293	0.293	0.289	0.295	0.257
analysis	(15.64)	(14.34)	(18.47)	(16.71)	(15.04)	(13.17)
critical	0.176	0.150	0.150	0.152	0.156	0.116
evaluation	(7.10)	(8.04)	(8.19)	(9.13)	(10.10)	(5.47)
research skills	0.142	0.131	0.131	0.132	0.133	0.128
	(6.87)	(7.75)	(9.12)	(9.04)	(8.31)	(7.45)
presentation	0.133	0.130	0.130	0.131	0.128	0.110
skills	(8.29)	(8.86)	(8.82)	(8.40)	(9.53)	(5.96)
innovative	0.221	0.221	0.221	0.220	0.225	0.116
thinking	(13.40)	(16.19)	(13.50)	(15.32)	(14.68)	(6.14)
entrepreneurial	0.215	0.228	0.228	0.229	0.229	0.125
skills	(9.19)	(8.46)	(8.05)	(9.33)	(8.66)	(3.85)
teamwork	0.143	0.123	0.123	0.121	0.142	0.081
	(8.87)	(8.64)	(10.57)	(8.17)	(10.26)	(3.99)
ability to work	0.127	0.153	0.153	0.154	0.152	0.090
individually	(6.99)	(8.69)	(9.82)	(10.88)	(9.17)	(3.38)
time	0.113	0.107	0.107	0.108	0.112	0.056
management	(6.63)	(7.83)	(8.56)	(7.30)	(8.89)	(3.76)

Note: See notes to Table 1.

References

Arum, Richard and Josipa Roska (2011) Academically Adrift: Limited Learning on College Campuses, Chicago: University of Chicago Press.

Autor, David and Michael Handel (2013) Putting tasks to the test: human capital, job tasks and wages, Journal of Labor Economics, 31, S59-S96.

Agasisti, Tommaso, Geraint Johnes and Marco Paccagnella (2018) Tasks, occupations and wages in OECD countries, mimeo.

Behle, Heike, Gabriel Atfield, Peter Elias, Lynn Gambin, Anne Green, Terence Hogarth, Kate Purcell, Charikleia Tzanakou and Christopher Warhurst (2015) Reassessing the employment outcomes of higher education, in Case, Jennifer and Jeroen Huisman (eds) Researching higher education: international perspectives on theory, policy and practice, London: Routledge.

Caliendo, Marco and Sabine Kopeinig (2008) Some practical guidance for the implementation of propensity score matching, Journal of Economic Surveys, 22, 31-72.

Garcia-Aracil, Adela, Jose-Gines Mora and Luis Villa (2004) The rewards of human capital competencies for young European higher education graduates, Tertiary Education and Management, 10, 287-305.

Garnett-Jones, Sam and Tim Turpin (2012) Globalisation and the changing functions of Australian universities, Science Technology and Society, 17, 233-274.

Grubb, Norton, Torry Dickinson, Lorraine Giordano and Gail Kaplan (1992) Betwixt and between: education, skills and employment in sub-baccalaureate labor markets, Berkeley: National Center for Research in Vocational Education.

Heckman, James, Hidehiko Ichimura and Petra Todd (1997) Matching as an econometric evaluation estimator: evidence from evaluating a job training program, Review of Economic Studies, 64, 605-654.

Humburg, Martin and Rolf van der Velden (2015) Skills and the graduate recruitment process: evidence from two discrete choice experiments, Economics of Education Review, 49, 24-41.

Jackson, Denise (2014) Testing a model of undergraduate competence in employability skills and its implications for stakeholders, Journal of Education and Work, 27, 220-242.

Johnes, Geraint (1998) Human capital versus sorting: new data and a new test, Applied Economics Letters, 5, 665-667.

Marginson, Simon (1994) The problem of transferable skills, Melbourne Studies in Education, 35, 4-28.

Murnane, Richard and Frank Levy (1996) Teaching the new basic skills: principles for educating children to thrive in a changing economy, New York: Free Press.

Purcell, Kate and Peter Elias (2013) Classifying graduate occupations for the knowledge society, London: HECSU, https://www2.warwick.ac.uk/fac/soc/ier/futuretrack/findings/elias_purcell_soche_final.pdf

Rosenbaum, Paul R. and Donald B. Rubin (1983) The central role of the propensity score in observational studies for causal effects, Biometrika, 70, 49-55.

Rubin, Donald B. (1979) Using multivariate matched sampling and regression adjustment to control bias in observational studies, Journal of the American Statistical Association, 74, 318-328.

Salas-Velasco, Manuel (2014) Do higher education institutions make a difference in competence development? A model of competence production at university, Higher Education, 68, 503-523.

Stuart, Elizabeth (2010) Matching methods for causal inference: a review and a look forward, Statistical Science, 25, 1-21.

Todd, Petra (2010) Matching estimators, in Steven Durlauf and Lawrence Blume (eds) Microeconometrics: the New Palgrave Economics Collection, London: Palgrave Macmillan.

Wooldridge, Jeffrey (2007) Inverse probability weighted estimation for general missing data problems, Journal of Econometrics, 141, 1281-1301.

Appendix

Table A1: Impact on log wage of skills delivery at university, various matching estimators, sector and firm size included in set of variables on which respondents are matched

written	-0.044	-0.036	-0.036	-0.040	-0.050	-0.063
communication	(2.61)	(1.41)	(1.34)	(1.66)	(2.58)	(2.78)
spoken	0.027	0.067	0.067	0.066	0.068	0.027
communication	(1.63)	(2.77)	(3.30)	(2.63)	(3.09)	(1.25)
numerical	1.116	0.103	0.103	0.103	0.108	0.067
analysis	(5.40)	(3.69)	(3.45)	(4.25)	(5.26)	(3.23)
critical	0.006	-0.007	-0.007	-0.004	0.016	-0.013
evaluation	(0.30)	(0.21)	(0.24)	(0.12)	(0.63)	(0.55)
research skills	-0.016	-0.036	-0.036	-0.051	-0.044	-0.039
	(0.71)	(1.19)	(1.28)	(1.51)	(1.84)	(1.88)
presentation	-0.026	-0.023	-0.023	-0.026	-0.030	-0.050
skills	(1.76)	(0.91)	(0.93)	(0.86)	(1.27)	(1.86)
innovative	0.010	0.015	0.015	0.022	0.016	0.014
thinking	(0.58)	(0.52)	(0.43)	(0.64)	(0.74)	(0.67)
entrepreneurial	0.052	0.060	0.060	0.057	0.058	0.184
skills	(1.32)	(1.66)	(1.70)	(1.30)	(1.74)	(3.42)
teamwork	0.033	0.013	0.013	0.012	0.017	-0.019
	(1.57)	(0.71)	(0.60)	(0.48)	(0.83)	(0.99)
ability to work	0.007	0.019	0.019	0.014	0.026	0.005
individually	(0.34)	(0.57)	(0.45)	(0.31)	(0.81)	(0.17)
time	0.002	0.032	0.032	0.023	0.030	-0.004
management	(0.10)	(1.22)	(1.51)	(0.90)	(1.29)	(0.17)

Note: See notes to Table 1.

Table A2: Impact on log wage of skill use at work, various matching estimators estimators, sector and firm size included in set of variables on which respondents are matched

written	0.200	0.079	0.079	0.075	0.121	0.108
communication	(9.50)	(4.15)	(3.44)	(3.36)	(5.31)	(5.40)
spoken	-0.058	-0.011	-0.011	-0.016	-0.012	-0.018
communication	(1.97)	(0.32)	(0.31)	(0.55)	(0.46)	(0.62)
numerical	0.082	0.034	0.034	0.031	0.067	0.043
analysis	(3.86)	(1.88)	(1.84)	(1.58)	(3.46)	(2.13)
critical	0.140	0.064	0.064	0.067	0.088	0.115
evaluation	(7.45)	(2.67)	(2.96)	(2.67)	(5.41)	(5.30)
research skills	0.037	0.046	0.046	0.050	0.055	0.069
	(1.76)	(1.89)	(1.77)	(1.98)	(2.62)	(2.29)
presentation	-0.027	-0.013	-0.013	-0.034	-0.006	0.024
skills	(1.27)	(0.61)	(0.56)	(0.63)	(0.27)	(1.02)
innovative	0.037	-0.003	-0.003	0.002	0.020	0.048
thinking	(2.07)	(0.10)	(0.10)	(0.07)	(1.10)	(2.09)
entrepreneurial	-0.087	-0.035	-0.035	-0.037	-0.043	-0.036
skills	(1.90)	(0.83)	(0.93)	(0.98)	(1.42)	(0.77)
teamwork	0.012	0.040	0.040	0.032	0.058	0.003
	(0.50)	(1.69)	(1.56)	(1.25)	(2.62)	(0.13)
ability to work	0.011	-0.028	-0.028	-0.033	-0.023	-0.052
individually	(0.42)	(1.04)	(0.90)	(1.22)	(0.85)	(1.70)
time	0.150	0.125	0.125	0.079	0.145	0.049
management	(4.12)	(2.44)	(3.04)	(1.26)	(3.97)	(1.25)

Note: See notes to Table 1.

Table A3 Impact of skills delivery at university on corresponding skill use at work estimators, sector and firm size included in set of variables on which respondents are matched

written	0.090	0.121	0.121	0.123	0.118	0.087
communication	(3.95)	(6.16)	(6.31)	(6.38)	(7.30)	(4.56)
spoken	0.090	0.085	0.085	0.084	0.098	0.015
communication	(7.54)	(7.65)	(7.93)	(7.50)	(8.78)	(0.92)
numerical	0.304	0.284	0.284	0.281	0.293	0.249
analysis	(16.99)	(12.51)	(13.99)	(11.74)	(16.46)	(12.98)
critical	0.166	0.149	0.149	0.151	0.155	0.109
evaluation	(8.18)	(8.82)	(9.18)	(7.81)	(8.66)	(5.17)
research skills	0.139	0.131	0.131	0.132	0.132	0.131
	(6.26)	(8.57)	(10.28)	(7.73)	(9.06)	(7.79)
presentation	0.130	0.135	0.135	0.137	0.129	0.115
skills	(7.94)	(9.47)	(9.06)	(8.84)	(8.96)	(6.31)
innovative	0.225	0.220	0.220	0.219	0.225	0.114
thinking	(14.50)	(14.56)	(13.63)	(12.20)	(11.49)	(6.03)
entrepreneurial	0.237	0.228	0.228	0.227	0.229	0.123
skills	(6.91)	(8.91)	(7.59)	(9.59)	(8.35)	(3.86)
teamwork	0.149	0.125	0.125	0.124	0.142	0.083
	(10.49)	(7.53)	(9.23)	(8.03)	(10.31)	(4.09)
ability to work	0.127	0.153	0.153	0.154	0.152	0.086
individually	(6.68)	(8.97)	(6.99)	(8.24)	(9.01)	(3.36)
time	0.109	0.107	0.107	0.107	0.112	0.055
management	(7.31)	(8.33)	(8.11)	(6.97)	(8.58)	(3.75)

Note: See notes to Table 1.