

Determinants of Student Salaries in Professional Training Year

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Motivation

- Key changes in the UK higher education: increase in tuition fees and student debt.
- Against this backdrop, the industrial placement year is an important feature of several UK universities because:
 - industrial placements are often **remunerated**.
 - companies **offer graduate jobs** to placement students.
- This study focuses on placements offered to students of economics in a UK university, the University of Surrey.
- Aim: **identify key determinants of placement salaries utilising different sources of information.**
 - The sample's significant variation in placement salaries is an early promising indication of interesting outcomes.

What's next?

- Related literature
- Methodology
- Data
- Results
- Discussion
- Concluding remarks

Related literature

- Previous studies have found:
 - ① Positive effects of placement experience on employability outcomes (e.g. Knouse and Fontenot, 2008; Nunley et al., 2016; Silva et al., 2018) and skills (e.g. Knight and Yorke, 2004; Reddy and Moores, 2012).
 - ② Positive effects of degree performance on labour market outcomes (e.g. Di Pietro, 2017; Feng and Graetz, 2017).
- Wang and Crawford (2018) → academic performance is the *only* significant factor in securing a highly-paid placement.
 - Our study differs in focus, data, sample and methodology.
 - We present new and additional evidence on this topic.

Methodology

- Our model hypothesises the following natural log of salary (y) function for individual i

$$\ln(y_i) = \beta_0 + \mathbf{x}_i' \boldsymbol{\beta} + \epsilon_i, \quad (1)$$

where \mathbf{x}_i' is a set of individual demographic, academic, professional and labour characteristics and ϵ_i is an individual-level error term.

- We first estimate (1) by OLS. Next we employ a quantile regression model similar to (1), where quantile τ is given by

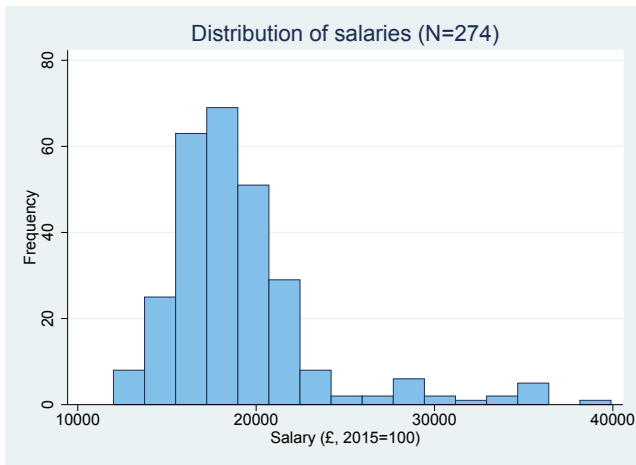
$$\tau = \Pr(y_i < q_i(\tau) | \mathbf{x}_i'). \quad (2)$$

- $q_i(\tau)$ is the model-based quantile.

Data: Sampling

- Three cohorts of placement students: 15/16; 16/17; 17/18.
 - 15/16: 104; 16/17: 119; 17/18: 64 → total of 287 students.
- University records: demographic characteristics; academic and job information.
- CV data: job experience, accomplishments, language.
- Due to some missing information (e.g. missing CVs or salaries) our final sample includes **274** placement students.

Data: Response variable (annual real salary)



Data: Explanatory variables

- Average first-year mark;
- Job experience: number of different jobs before placement;
- Job location (London = 1);
- Gender (= 1 if male), age;
- Fee status (= 1 if UK, = 0 if EU or overseas);
- Ethnicity (dummies for 'Asian' and 'Other');
- Programme (Business Economics BSc, Economics and Finance BSc and Economics and Mathematics BSc);
- Accomplishments (= 1 if made 'notable' achievement);
- Language (= 1 if more than one language is spoken);
- Industry type (dummies for 'Economic' and 'Technology' sectors).

Data: Descriptive statistics

Table 1: Sample descriptive statistics.

Variable	Full sample				Quantiles (mean values)		
	Mean	S.D.	Min.	Max.	<Q10	Q25-Q75	>Q90
Salary (real)	19,027	4,222	12,000	39,894	14,315	18,927	29,165
First-year mark	70.58	7.25	51	88	66.51	70.97	73.01
Age	18.29	0.81	17	27	18.29	18.32	18.48
Gender (male)	0.69	0.46	0	1	0.61	0.73	0.7
Fee status (UK)	0.86	0.35	0	1	0.79	0.86	0.85
Ethnicity							
Asian	0.22	0.42	0	1	0.32	0.24	0.26
Other	0.15	0.36	0	1	0.18	0.13	0.19
Programme							
Business Economics BSc	0.1	0.3	0	1	0.25	0.07	0.11
Economics and Finance BSc	0.41	0.49	0	1	0.39	0.43	0.59
Economics and Mathematics BSc	0.05	0.21	0	1	0.04	0.05	0
Job location (London)	0.58	0.5	0	1	0.32	0.59	1
Job experience	2.78	1.36	0	8	2.71	2.82	3.37
Accomplishments	0.3	0.46	0	1	0.32	0.33	0.26
Language	0.39	0.49	0	1	0.21	0.46	0.41
Industry							
Economic sector	0.35	0.48	0	1	0.07	0.38	0.7
Technology sector	0.17	0.38	0	1	0.5	0.16	0.04
Observations			$N = 274$		28	141	27

Results: OLS

- We first estimate our model (1) by OLS.
- We start with the following basic model (M1):

$$\ln(y_i) = \beta_0 + \beta_1 \textit{year1mark} + \beta_2 \textit{jobexperience} + \epsilon_i.$$

- Then, we gradually add the rest of the control variables.
- Let's see the results...

Table 2: Model comparison of M1 to M12. Dependent variable: ln(salary)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
First-year mark	0.0068*** (0.0017)	0.0052*** (0.0016)	0.0052*** (0.0016)	0.0053*** (0.0016)	0.0053*** (0.0016)	0.0053*** (0.0016)	0.0058*** (0.0017)	0.0059*** (0.0017)	0.0047*** (0.0017)	0.0046*** (0.0017)	0.0064*** (0.0018)	0.0123*** (0.0039)
Job experience	0.0248*** (0.0091)	0.0159* (0.0085)	0.0161* (0.0086)	0.0161* (0.0086)	0.0162* (0.0087)	0.0161* (0.0088)	0.0140 (0.0088)	0.0144 (0.0088)	0.0147* (0.0085)	0.0153* (0.0086)	0.0151* (0.0085)	0.1683** (0.0845)
Job location (London)	0.1498*** (0.0191)	0.1498*** (0.0192)	0.1496*** (0.0192)	0.1496*** (0.0192)	0.1495*** (0.0193)	0.1441*** (0.0191)	0.1421*** (0.0190)	0.1124*** (0.0186)	0.1073*** (0.0194)	0.1067*** (0.0194)	0.1051*** (0.0190)	
Gender (Male)			0.0037 (0.0220)	0.0035 (0.0220)	0.0035 (0.0220)	0.0044 (0.0222)	-0.0222 (0.0234)	0.0048 (0.0232)	-0.0009 (0.0226)	0.0016 (0.0227)	-0.0018 (0.0221)	-0.0058 (0.0220)
Age			0.0128 (0.0128)	0.0127 (0.0128)	0.0127 (0.0128)	0.0126 (0.0130)	0.0142 (0.0119)	0.0133 (0.0125)	0.0137 (0.0111)	0.0135 (0.0111)	0.0153 (0.0104)	0.0177* (0.0103)
Fee status (UK)				-0.0012 (0.0351)	0.0020 (0.0379)	0.0131 (0.0370)	0.0320 (0.0381)	0.0324 (0.0371)	0.0328 (0.0370)	0.0306 (0.0370)	0.0306 (0.0372)	0.0307 (0.0369)
Ethnicity (Asian)						0.0032 (0.0273)	-0.0069 (0.0283)	-0.0215 (0.0300)	-0.0151 (0.0290)	-0.0131 (0.0292)	-0.0144 (0.0290)	-0.0158 (0.0288)
Programme (BE)							-0.0105 (0.0452)	-0.0134 (0.0457)	-0.0052 (0.0436)	-0.0031 (0.0436)	-0.0065 (0.0425)	-0.0074 (0.0428)
Programme (EF)							0.0428* (0.0240)	0.0456* (0.0244)	0.0460* (0.0242)	0.0426* (0.0243)	0.0426* (0.0239)	0.0414* (0.0235)
Programme (EM)							-0.0372 (0.0304)	-0.0354 (0.0321)	-0.0273 (0.0335)	-0.0256 (0.0326)	-0.0280 (0.0329)	-0.0299 (0.0322)
Accomplishments								-0.0023 (0.0218)	-0.0113 (0.0211)	-0.0125 (0.0212)	0.3848* (0.2311)	0.3264 (0.2214)
Language								0.0454 (0.0276)	0.0443* (0.0262)	0.0455* (0.0261)	0.0420 (0.0256)	0.0442* (0.0253)
Industry (Econ)									0.0864*** (0.0259)	0.0828*** (0.0262)	0.0794*** (0.0256)	0.0755*** (0.0251)
Industry (Tech)										-0.0252 (0.0229)	-0.0291 (0.0232)	-0.0364 (0.0231)
Mark × accomplish											-0.0057* (0.0033)	-0.0049 (0.0031)
Mark × job exp.												-0.0022* (0.0012)
Constant	9.2852*** (0.1208)	9.3385*** (0.1114)	9.3347*** (0.1128)	9.0945*** (0.2575)	9.0963*** (0.2596)	9.0889*** (0.2636)	9.0160*** (0.2452)	8.9959*** (0.2582)	9.0629*** (0.2261)	9.0786*** (0.2269)	8.9231*** (0.2224)	8.4647*** (0.3529)
N	274	274	274	274	274	274	274	274	274	274	274	274
F	12.3196	28.0873	21.2460	17.1984	14.5737	10.9212	8.6000	7.2367	7.0613	6.8042	6.6114	6.5357
p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R ²	0.0892	0.2287	0.2288	0.2316	0.2316	0.2318	0.2463	0.2556	0.2908	0.2927	0.3022	0.3120

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

- Consistent and positive relationship between salaries and first-year academic performance.
- Likewise for job location (the ‘London effect’).
- Placement students in the ‘economic’ sector earn more.
- Weaker results include enrolment in the Econ. and Finance programme, job experience and language.
- No evidence of gender wage gap.
- Very weak or non-existent associations with: accomplishments, age, nationality and ethnicity.
- Lastly, interactions exhibit limited statistical significance.

Results: Quantile regression

- The next step of our analysis is based on Model 12.
- Quantile regression, using estimator of the covariance matrix suggested by Machado and Santos Silva (2013).
[Standard errors and t-statistics are asymptotically valid under heteroskedasticity and misspecification of the quantile regression function.]
- Our analysis will focus on:
 - ① comparison between mean versus median regression.
 - ② effect of covariates across quantiles of salaries distribution.
- Let's see the results...

Table 3: Model comparison of M12 OLS vs QR. Dependent variable: $\ln(\text{salary})$

	OLS	Q(0.1)	Q(0.25)	Q(0.5)	Q(0.75)	Q(0.9)
First-year mark	0.0123*** (0.0039)	0.0109 (0.0078)	0.0073* (0.0040)	0.0072** (0.0035)	0.0078 (0.0061)	0.0131** (0.0063)
Job experience	0.1683** (0.0845)	0.1934 (0.1564)	0.0957 (0.0908)	0.1107 (0.0737)	0.0414 (0.1442)	0.1517 (0.1250)
Job location (London)	0.1051*** (0.0190)	0.0699* (0.0366)	0.0654*** (0.0234)	0.0993*** (0.0214)	0.1400*** (0.0252)	0.1807*** (0.0300)
Gender (Male)	-0.0058 (0.0220)	-0.0068 (0.0410)	-0.0129 (0.0240)	-0.0106 (0.0225)	0.0264 (0.0341)	0.0485 (0.0368)
Age	0.0177* (0.0103)	0.0199 (0.0287)	0.0211 (0.0166)	0.0145 (0.0224)	0.0130* (0.0078)	0.0076 (0.0190)
Fee status (UK)	0.0307 (0.0369)	0.1068 (0.1131)	0.0175 (0.0325)	0.0202 (0.0276)	0.0354 (0.0452)	-0.0780* (0.0430)
Ethnicity (Asian)	-0.0158 (0.0288)	-0.0600 (0.0640)	-0.0213 (0.0274)	-0.0128 (0.0267)	0.0137 (0.0527)	0.0192 (0.0378)
Programme (BE)	-0.0074 (0.0428)	-0.0230 (0.0448)	-0.0332 (0.0406)	-0.0470 (0.0347)	-0.0542 (0.0481)	-0.0666 (0.0520)
Programme (EF)	0.0414* (0.0235)	0.0526 (0.0351)	0.0554** (0.0270)	0.0330 (0.0238)	0.0261 (0.0393)	0.0541 (0.0385)
Programme (EM)	-0.0299 (0.0322)	0.0329 (0.0485)	0.0031 (0.0344)	-0.0249 (0.0425)	-0.0705* (0.0404)	-0.0589* (0.0340)
Accomplishments	0.3264 (0.2214)	-0.0379 (0.3428)	0.1339 (0.2351)	0.0898 (0.1934)	0.5793 (0.4026)	0.6161** (0.2885)
Language	0.0442* (0.0253)	0.0579 (0.0422)	0.0584** (0.0284)	0.0355 (0.0236)	0.0004 (0.0295)	0.0516 (0.0441)
Industry (Econ)	0.0755*** (0.0251)	0.0611* (0.0330)	0.0326 (0.0254)	0.0332 (0.0242)	0.0621 (0.0575)	0.2090*** (0.0691)
Industry (Tech)	-0.0364 (0.0231)	0.0168 (0.0455)	-0.0378 (0.0329)	-0.0543** (0.0270)	-0.0218 (0.0345)	-0.0686** (0.0339)
Mark \times accomplish	-0.0049 (0.0031)	0.0006 (0.0047)	-0.0019 (0.0034)	-0.0016 (0.0028)	-0.0085 (0.0058)	-0.0097** (0.0041)
Mark \times job exp.	-0.0022* (0.0012)	-0.0026 (0.0021)	-0.0012 (0.0012)	-0.0015 (0.0010)	-0.0002 (0.0021)	-0.0017 (0.0018)
Constant	8.4647*** (0.3529)	8.3182*** (0.9297)	8.7171*** (0.4140)	8.9297*** (0.4248)	8.9009*** (0.4621)	8.7631*** (0.5875)
N	274	274	274	274	274	274
F	6.5357					
p	0.0000					
R ²	0.3120	0.2349	0.2736	0.2878	0.2763	0.2767

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

- OLS tends to overestimate the effect of the covariates in comparison with $Q(0.5)$.
- The effects of first-year academic performance and job location are the highest at the top quantile.
- Strong association of economic sector and placement earnings at the top quantile.
- The accomplishments' coefficient is large and statistically significant at the top quantile.
- Enrolments in different programmes show non-existent or weak associations with placement earnings.
- Language is significant once and only one interaction is significant at the top quantile.
- Similar results to OLS for gender, age, nationality and ethnicity; job experience is never statistically significant.

Discussion

- **Academic performance, job location and industry type** being robust predictors of placement salaries.
- Academic performance not only increases the chances of securing a placement (Arsenis and Flores, 2019), but also its returns.
- The positive effects of London and the economic sector on earnings are intuitive and are in line with official statistics (ONS, 2018).
- Job experience is not a strong predictor of earnings; employers offer training and several have rigorous hiring processes.

- Interesting results at the top quantile, $Q(0.9)$:

Almost twice the size of the first-year mark coefficient than at the median.

- Indeed, 78% of students with top salaries achieved a first-class mark in the first year of their studies.
- An intuitive result: top employers recruit the most academically competent students.

Also, accomplishments appear to matter at this part of the distribution.

- Employers scrutinise candidates assessing not only academic skills but extracurricular competencies too.

Accomplishments matter, but possibly not as much as academic performance.

- The coeff. of interaction term is *negative*: students with accomplishments had significantly lower average grades.

- **We find no evidence of earnings differences between genders.**
 - This is consistent with findings on entry to the labour market (Manning and Swaffield, 2008).
 - But later on discrepancies emerge in favour of men (e.g. Chevalier, 2011; Albrecht et al., 2018).
- **This outcome is true even at the top of the earnings distribution.**
 - In contrast to previous studies, we find no earnings gender gap at the highest-paid jobs.
 - We find similar earnings differentials both at the bottom (10th perc.) and top (90th perc.) of the distribution.
 - Also, the proportion of males/females are similar at the distribution extremes; females at about 35%.

Concluding remarks

- This study is a one of the first attempts to explore *placement* labour market outcomes.

Key empirical findings:

- ➊ The average first-year mark is a strong predictor of placement earnings.
- ➋ In addition, job location and type of industry are important determinants of placement salaries.
- ➌ Highly-paid placements are also associated with candidates' accomplishments.
- ➍ Other demographic factors (e.g. gender and nationality) and past job experience do not have much (or any) explanatory power.

Implications

- Clearly, early degree performance is important, but, typically, no weight is attached to it.
- There is a discussion on the ‘value’ offered by UK universities and students’ expectations increase.
- This study adds one more argument to this discourse suggesting reforms in higher education.
- Counting first-year performance will encourage students to increase their efforts improving academic results.
- Employers will also be better informed of the graduates’ abilities utilising a more effective indicator of academic performance.