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The impact of work placements on graduate earnings

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ABSTRACT
This study investigates whether the completion of an optional 'sandwich' work placement enhances graduate starting salaries. We use a variety of multivariate regression techniques to investigate this issue and find that the graduate starting salaries of students who took professional work placements were significantly higher by £1686 ($2105) compared to non-placement students. We make a methodological contribution to the literature by controlling for self-selection bias. That is, our analysis takes into consideration that certain students self-select in to work placements and that they would have had higher starting salaries regardless of whether choosing to take a work placement. Additional insights showed that placements may be detrimental in terms of alleviating class and gender pay inequality but may have helped to reduce ethnic pay inequality. Our results have important implications for graduate employability and its impact on wider society.

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Graduate earnings; employability; work placement; self-selection; pay inequality

1. Introduction

In the competitive global higher education system, graduate employability has become a leading metric in which to judge higher education institutions (see Bennett 2019; Healy, Brown, and Ho 2022a; Healy, Hammer, and McIlveen 2022b). Graduate employment rates are now a core component of university rankings (Christie 2017) and the quality of undergraduate and postgraduate programmes are being judged on the labour market outcomes that they generate (Mason, Williams, and Cranmer 2009; Mavromaras et al. 2013; McGuinness 2003). In the United Kingdom, for example, Universities are frequently exposed to political pressure and there has become a greater expectation that a university education should provide work-integrated learning in order to achieve superior outcomes. According to the UN, the world's population is projected to reach 10.4 billion people by 2100 and this will no doubt create a significant expansion in higher education across the world and result in a fiercely competitive labour market for graduates. In order to prepare for a rapidly changing world, higher education institutions will need to provide skills to allow graduates to excel in this exciting and innovative environment that will include the new technologies of the 4th industrial revolution such as artificial intelligence, advanced robotics, smart technology, and the internet of things.

One of the key mechanisms in which Universities may enable graduates to transition into this new competitive environment, is the use of professional work placements that are integrated into the curriculum. Across the world, a number of institutions have emerged as specialists in this area and not only offer programmes that one would expect to encompass a work component, such as teaching and nursing, but also offer the opportunity across programmes that typically might not be expected to have a work component, such as the social sciences. It is often argued that

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professional work placements improve employability after graduation and allow students to obtain workplace skills that traditional degree courses do not accommodate (Inceoglu et al. 2019). But does taking a work placement enable students to generate higher earnings after graduation compared to those students who do not go on a work placement? Economists are typically in agreement that there is a direct link between the growth in labour productivity and the growth in real wages (see Meager and Speckesser 2011). Hence, evidence of higher wages for placement students (compared to non-placement students) is indicative of higher productivity and a barometer in which the university can be judged in terms of its impact to wider society.

This paper fills an important gap in the literature by using a large student database to provide estimates of the impact of work placements on graduate starting salaries. We utilise multivariate regression and propensity score matching techniques to investigate the impact of placements on graduate starting salaries for a sample of students from Aston University in the United Kingdom. During our sample timeframe, a subset of undergraduate students at Aston University were given a choice as to whether to undertake a yearlong work placement or not. Having a choice, is a fundamental factor that influences our research design as it should control for such a possibility (self-selection) in order to identify the causal impact of undertaking a placement on graduate earnings.

At present, there is a lack of research devoted to assessing the impact of placements on graduate employability. Furthermore, research on graduate earnings is almost completely absent in the literature. There are some early studies that have explored the impact of placements on graduate earnings, but typically, they use bivariate descriptive statistics (see Blackwell et al. 2000; Reddy and Moores 2006; Wilton 2012). Furthermore, they do not take into consideration self-selection issues that may result in biased estimates. Self-selection arises when individuals have a choice to enter into or participate in, a programme (treatment) or not – in this case, the choice to undergo a 'sandwich' work placement. This creates problems to statistically evaluate the effect of the programme (treatment) on a specific outcome. For example, in our context, a finding that placements (treatment) enhance graduate earnings (outcome). Using bivariate statistics from a sample of students that are not chosen at random (self-selection), could be miss-leading because it might be the case that a student would have had higher earnings regardless of whether the student chose to do a placement or not. What this amounts to saying, is that 'high calibre' students may self-select and choose to do a professional placement and, at the same time, perhaps due to the cascading effect of privilege and a lack of cultural capital, some students may opt out of the professional work placement. Hence, researchers may mistakenly attribute a positive effect of a professional placement year on future graduate earnings when the real cause of the outcome is other confounding factors such as socio-economic status.

Hence, in this paper, we use propensity score matching as a technique to allow us to control for the self-selection problem. Propensity Score Matching is a statistical technique used to estimate the causal effect of a treatment (i.e. the decision to go on placement) on an outcome variable, in this case graduate earnings. It has been applied before in related literature when analysing the impact of work placements on academic achievement (see Jones, Green, and Higson 2017). Therefore, our research makes a strong methodological contribution to the placement's literature and forms one of this paper's main contributions. Hence, we devote significant attention to the method in our discussion below.

Our second key contribution shows that graduate starting salaries were on average £1686 ($2105)[1] higher for students who undertook work placements compared to those students that choose not to go on placement. This is an important finding as it is the literature's first estimate of the impact of work placements on graduate earnings after controlling for self-selection. Our third key contribution shows that there was heterogeneity in terms of the placement effect, such that we found some evidence that placements enhance class and gender pay inequality but at the same time may mitigate ethnic pay inequality. These results have important implications for higher education institutions that may currently run academic programmes with work-integrated learning and for institutions that may wish to introduce work placements into their curriculum. It also has wider implications for higher education and the economy more broadly as it may indicate that graduates who undertake work placements have a higher degree of productivity compared to their non-placement contemporaries. Indeed, our findings have important insights for the design of new degree programmes that integrate a work element, such as degree apprenticeships that have recently become more popular in the United Kingdom.

The remainder of this paper is set out as follows. In the next section, we discuss succinctly the nascent literature that looks at the impact of work placements in higher education and in particular focus on existing studies that look specifically at the impact of placements on graduate earnings. We then go on to discuss in detail the empirical methodology that controls for self-selection and outline our research design. Following this, we discuss the data and then go on to report our empirical results. Finally, we conclude and discuss the importance of our findings, given the growing importance of employability in higher education and its impact upon society.

2. Literature review

The extant research on the effects of sandwich degrees in higher education has focused much more on the impact they have on student performance in terms of degree classification or final year marks. Indeed, the literature provides inconclusive results for this domain, but the weight of evidence is more suggestive that placements improve student performance. Gomez, Lush, and Clements (2004) utilise multivariate regression analysis and find a final year placement effect of around 4%. Similar estimates are reported by Surridge (2008) for a cohort of accounting and finance students with a placement effect of around 3.6%. Moreover, Mandilaras (2004) found that a placement year improved the likelihood of obtaining an upper second-class degree by around 30 percentage points. Further studies by Mansfield (2011), Green (2011) and Crawford and Wang (2016) also find evidence of a significant impact on academic performance with the latter also finding evidence for international students. In the main however, although these studies do anecdotally remark on the issue of self-selection, (Crawford and Wang 2016; Green 2011) they generally do not specifically control for it. Exceptions to this include Driffield, Foster, and Higson (2011) and Jones, Green, and Higson (2017) who find a positive impact of work placement on performance after controlling for it. One might conjecture therefore, that the positive placement effect on student performance feeds through into better employment outcomes and higher starting salaries for graduates. However, at present, there is limited evidence in the literature to shed light on this predication.

In terms of the direct link between the impact of choosing to undertake a work placement on graduate earnings, there is a paucity of research. According to the Higher Education Statistics Agency (HESA) in the UK, data for 2009/10 showed that the average salary of students who have undertaken a work placement is 8% higher than those students who chose not to do a work placement 6 months after graduation. However, other than this non-peer reviewed finding, only a few recent studies have looked at the impact of placements or work experience on employability i.e. whether graduates who have undertaken work placements have secured employment after graduation or whether there is a premium associated with doing a work placement. Blackwell et al. (2000) incorporate four empirical studies of work experience in higher education and find that it contributes to a more positive view of the learning experience and that it leads to higher employment and possibly higher wages. But there is no tangible evidence from this research because the results rely on responses to various surveys. Reddy and Moores (2006) utilise a small sample of psychology students and find some evidence that indicates that pay is slightly higher for students who have undertaken a degree with a placement year. Furthermore, they also find that placement students are also more likely to be in, or on their way to, their chosen careers. Wilton (2012) finds that for women who undertook a work placement, their earnings were 5% higher (four years after graduation) than their non-work placement peers and that the figure for men was slightly less at 4%. But this evidence is based on simple t-tests, it therefore lacks the rigour of a thorough multivariate analysis and does not control for self-selection. Lastly, Smith et al. (2018) report a positive earnings differential between placement and non-placement students for a cohort of computer science graduates but again this is based on survey data and does not control for confounding factors or self-selection. Hence overall, there is a lack of clear causal evidence to demonstrate that placements enhance earnings.

In contrast, there is a large economics literature that estimates the returns to higher education and schooling (Becker 1962; Bhuller, Mogstad, and Salvanes 2011; Black, Devereux, and Salvanes 2005; Blanden, Gregg, and Macmillan 2007; Mincer 1958, 1974). These studies utilise regression analysis to assess the difference in wages between graduates and non-graduates. This then allows the researcher to calculate the net present value of lifetime earnings for different cohorts in order to make comparisons across groups and assess the affordability of different funding regimes i.e. the size of tuition fees and whether the use of grants is financially viable. There are a number of studies that look at gender effects (Bobbitt-Zeher 2007), socioeconomic class (Laurison and Friedman 2016), course heterogeneity (Preston 1997), retention (Tinto 2004), institutional quality (Birch, Li, and Miller 2009), and ethnic background (Lu and Li 2021). Overall, there is a strong body of evidence, based on UK data, that supports the view that undertaking a degree has a significant impact on lifelong earnings. In a notable recent study, Britton, Dearden, Shephard and Vignoles (2016) provide the most comprehensive and recent study on the effects of higher education on graduate earnings. The authors link tax and student loan administrative data to investigate the variation in the earnings of the population of English graduates 10 years after they have entered the labour market. They find significant variation in graduate earnings, even between graduates from the same institutions and taking the same subjects. Furthermore, they show that graduates from almost all universities earn more than individuals at the 20th percentile of the non-university earnings distribution. Moreover, this research also finds that graduate family background is a significant driver of earnings variation long after graduation in that graduates from higher income households have much higher earnings (60% for males, 45% for females) relative to their peers from lower income households. Yet this research does not tell us anything about the impact of work placements on graduate earnings which is certainly a limitation – especially for those institutions who are wide-spread adopters of work placements. Our work builds on these authors findings but applies it to the placement context. Furthermore, by accounting for self-selection we build on Jones, Green, and Higson (2017) who are the first authors to utilise matching techniques to control for self-selection in the placements literature.

3. Methodology

In order to estimate the impact of a work placement on graduate starting salaries, we introduce a treatment indicator for each student i, $D_i \in \{0, 1\}$, that takes the value 1 if a student had been on placement (received the treatment) or takes the value of 0 if the student had not been on placement (did not receive the treatment). Hence, each student that undertook a placement belonged to the *treatment group*, while all the students that did not do a placement were part of the *control group*. Our primary interest was to estimate the potential impact of doing a placement (treatment indicator D_i) on the observed outcome variable w_i, students' starting salary 6 months after graduation. A natural estimator to choose in order to operationalise this is a standard ordinary least squares multivariate regression shown by equation (1) where the parameter β measures the difference in starting salary between placement and non-placement students:

$$\mathrm{w_i} = \propto + \beta D_i + \boldsymbol{\delta X} + \varepsilon_i \tag{1}$$

Equation (1) can typically be thought of as wage equation. The dependent variable in equation (1) is w_i the real starting salary of graduates six months after graduation. The explanatory variables are the treatment indicator D_i and a number of control variables contained in the vector **X** that include the 1st year mark as a proxy for student engagement, the final year mark[2] as a proxy for academic performance, year of graduation, university faculty where the student studied, gender, ethnicity, age, socio-economic class as measured for by parental employment type and the type of school students were enrolled at prior to University. All of these variables were chosen based on prior literature with respect to work placements and the extensive literature on wage determination in economics.

Although a regression of the kind above is useful and informative, it encompasses a number of weaknesses that may lead to biased estimates of the treatment parameter β. The most important is the issue of self-selection bias. Self-selection occurs when individuals select themselves into a particular group, causing a biased sample. In this context, this could be observed by mistakenly interpreting a positive estimate of β as suggestive of a causal effect of placements on graduate earnings when in reality the students would have had higher earnings regardless as to whether they went on placement or not. More specifically, it could be the case that relatively 'high ability' students opt more often for placements or that 'low ability' students opt out of the placement. Hence, a simple estimation of equation (1) could erroneously attribute a causal effect of placements on graduate earnings, while the main explanation could be due to the fact that a greater number of more academically able students have chosen to take a work placement.

Hence, in order to control for self-selection bias, we follow Jones, Green, and Higson (2017) and utilise propensity score matching to determine whether the OLS estimator captures the casual effect in question and whether it is upward biased. Ideally, in order to control for self-selection bias, one would set up an experiment that randomly assigns students to the treatment (going on placement) and non-treatment (not going on placement) groups. In our context this is clearly infeasible due to ethical considerations. Hence, in order to overcome this problem one solution is to mimic a randomised experiment by matching students of the two groups based on their predicted probability of doing a placement after controlling for certain personal characteristics.

The propensity score matching methodology has two stages. In stage 1 a logit probability model is estimated. This model estimates the probability that a specific student would have done a placement given certain student-specific characteristics. This can be seen in equation (2)

$$\Pr\,(Placement_i = 1|\boldsymbol{X}) = F(\boldsymbol{X}'\gamma) = \frac{\exp(\boldsymbol{X}'\gamma)}{1+\exp(\boldsymbol{X}'\gamma)} \tag{2}$$

Where $\Pr(\mathrm{Placement}_i = 1|X)$ indicates the probability that student *i* has done placement after controlling for all **X** and F(.) follows the logistic distribution. $Placement_i$ is the treatment $D_i \in \{0, 1\}$, that takes the value 1 if student *i* has been on placement or takes the value 0 if student *i* has not been on placement. The **X** variables are the same as in Equation (1) above.

In the second stage, the propensity scores (the estimated probability from Equation (2)) are used to match students in order to calculate the average treatment effect of the treated (ATET). Hence, the method tries to match every student that has gone on placement with a student that did not go on placement, but both have very similar or even identical propensity scores. Thus, two groups of students are constructed – a control group and a treatment group. The ATET measures the mean difference in real wages between students assigned to the treatment group compared to those students assigned to the control group. The results can then be compared to the β parameter estimates from the multivariate regression to determine whether there was indeed any bias in the OLS estimation.

Having estimated the causal impact of placements on graduate starting salaries for the overall sample we can then use the same matching technique to investigate the impact of placements on starting salaries for subsets of our sample. We do this to analyse whether the placement effect on salaries differed for males versus females (gender wage inequality); white versus non-white (ethnic wage inequality); and white-collar versus blue collar (class wage inequality).[3]

4. Data

The data utilised in this research was based on a subset of undergraduate students from Aston University over the period 2004–11 that were in full time employment 6 months after graduation.[4] During this time, students who were part of this subset had the option to choose whether or not to go on a work placement. This is a crucial element of our research design and also of the time period we use in our analysis. The fact that students were given a choice of whether to do a placement or not, created the self-selection issue in the estimation, but at the same time it enables us to use Propensity Score Matching to control for it. After 2011 at Aston University, the work placement became a compulsory part of the curriculum for almost all of the institution's undergraduate offering. This was, and still is, a core component of the University's strategy as a leading provider of sandwich degrees in the UK. This means it is not possible to estimate the causal impact of placements on graduate earnings after 2011, because by design, we are not able to construct a control group, since there were no academic programmes available to students with an optional work placement after 2011, Only after 2011 did the work placement become a compulsory aspect of the sandwich degrees offered.

In 1966X, Aston University gained its University status by Royal Charter and prior to this was the UKs first college of advanced technology. Aston has been one of the pioneers of the placement concept and has one of the highest percentages of students undertaking placements in the UK. During the time frame of our sample, students were given the option to do a year-long placement. This takes place after the second year of university and before the final year. It is credit-bearing and comprises 15% of the final degree classification. There is a significant infrastructure at the university to match students to placement providers, but often students will seek their placements themselves. During the placement year, students were given regular contact with their placement supervisor – an academic who helps to manage the placement and undertakes a visit to the place of work, meets the student onsite and has a discussion with the student's line manager. The placement was assessed by a piece of coursework that asked students to apply an academic concept that they have encountered prior to the placement to a work-based problem they encountered. In addition, students also had to submit a portfolio that reflected on their placement experience.

The data for this study is obtained via Aston University's student records system and matched to data on starting salaries from the Destination of Leavers Survey obtained via the Higher Education Funding Council for England (HEFCE).[5] We utilise data that is commonly used in other econometric papers that analyse the impact of work placements (see Jones, Green, and Higson 2017; Wilton 2012). Summary statistics are presented in Table 3 where we report means standard deviations and the number of observations for our all variables. It is important to note that all data on salaries are calculated at 2004 prices in order to control for inflation over the period. This is achieved by deflating the salary data using the Consumer Price Index (CPI). Hence, throughout this paper we refer to real wages/salaries which are nominal wages adjusted for inflation. They are therefore a true measure of purchasing power.

The data includes students from four of Aston Schools: (1) Languages & Social Sciences; (2) Life & Health Sciences; (3) Engineering & Applied Sciences; and (4) Combined Honours. Data on Aston Business School students is excluded because on the whole those students had to undertake compulsory placements as part of their programmes prior to 2011. In contrast, all of the students in our sample, which comprises of 822 students, had a choice as to whether or not to undertake a work placement.

As can be seen in Table 3, 59% of students in the sample chose to go on a work placement as part of their programme. The average starting salary of students was £17,786 ($22,218) per year with a standard deviation of £4926 ($6153). Figure 1 shows the dispersion of starting salaries for non-placement versus placement students. As can be clearly seen the starting salaries of the latter appear to be higher than the former. On average, students who did placements have an average starting salary of £18,682 (green line) ($23,337) compared to an average salary of £ 16,482 (red line) ($20,589) for non-placement students. The difference between the average salary for placement and non-placement graduates is a simple estimate that measures the effect of placements on earnings (in other words is a somewhat 'naïve' estimator). Indeed, this shows initial evidence that demonstrates a placement effect on earnings, but below we follow an empirical strategy that tries to control for self-selection issues. That is, students that have done a placement have certain characteristics that would have led them to earn higher salaries even without any placement experience.

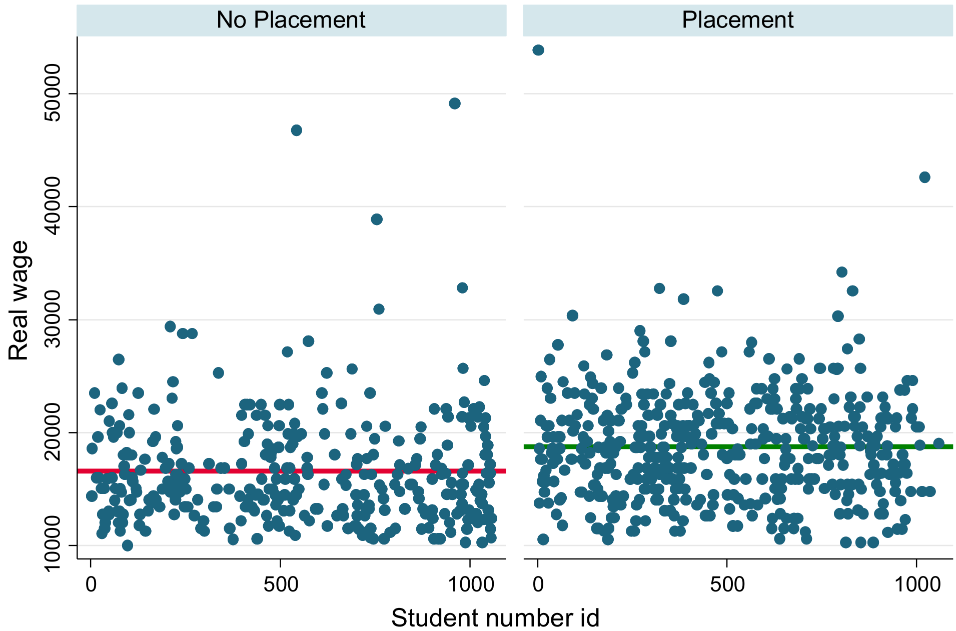

Figure 1. Real wage for placement & non placement graduates.

In terms of the other control variables, as shown in Table 1, the average 1st year mark (which in our view is a good measure of student engagement as the 1st year does not count towards a student's final degree classification at Aston University) was approximately 55%. In terms of final average mark the students in our sample averaged approximately 61%, providing evidence of improvement from the 1st year. On average, the students in the sample were approximately 19-year-old as the standard deviation for age is very small at 1.58. There were only a handful of mature students included in the data. The gender split was 50/50; whilst students who were ethnically classified as White comprised 59% of the sample. Furthermore, in terms of class and socio-economic status, 10% of the students came from White Collar[6] backgrounds and just 5% of students went to an Independent School.

It is important to note that the demographics of the cohort of students utilised in this sample are very much representative of Aston University's student body and the culture of the University which is committed to widening participation in higher education. Aston University has a strong reputation for attracting students from the local area. These areas comprise of an ethnically diverse population

Table 1. Summary statistics.

Variables	Mean	Std. Dev	Observations
Placement dummy	0.59	0.49	822
Real wage	17,786	4926	822
Final year mark	61.14	7.38	822
Year 1 mark	55.66	12.54	822
Age at Year 1	18.75	1.58	822
Combined Honours	0.30	0.46	822
Engineering & Applied Sciences	0.40	0.49	822
Life & Health Sciences	0.25	0.43	822
Languages & Social Sciences	0.04	0.19	822
Female	0.49	0.50	822
White ethnic background	0.59	0.49	822
White collar	0.10	0.30	822
Independent School	0.05	0.22	822

with lower living standards on average (as measured by regional gross value added) relative to other regions of the UK. Therefore, when interpreting the results of this study it is important to bear in mind the impact of the institutional context in that it may differ to other higher education institutions.

5. Empirical results

5.1. Multivariate regression model

Table 2 reports the results for the ordinary least squares regression where the dependent variable is equal to the real salary 6 months after graduation. As can be seen, the placement dummy coefficient β is equal to 2128 and is highly statistically significant. This means that the average salary is £2128 ($2658) higher for students who undertook a placement compared to those who choose not to do so. In terms of the other coefficients, the results are also quite interesting. Student engagement, as measured by the 1st year mark and the final year mark appear to contribute positively to starting salaries, but the former is not statistically significant. In terms of magnitude, a 1 percentage point increase in a student's final year mark boosts the starting salary by £83.56 ($104.38). Furthermore, age has a positive and statistically significant impact with older students earning more – an additional year adds £233 ($291.06) – this is the typical effect of an additional year of experience one would expect. We find that female graduates had much lower initial starting salaries on average compared to males with the discrepancy equal to £1072 ($1339) – this is a statistically significant finding and is suggestive of gender inequality in earnings as soon as student's graduate. The coefficient for white students was statistically insignificant whilst holding all other variables constant. This unexpected result suggests that white graduates from Aston did not have significantly different starting salaries after graduation compared to their non-white peers. It would be interesting for future studies to test the robustness of this finding by looking at other higher education institutions. Finally, socio-economic class and the level of schooling appeared to have a statistically insignificant impact on graduate starting salaries. Which is again an interesting finding and perhaps specific to the institution.

5.2. Propensity score matching

As discussed above, the OLS results need to be interpreted with caution due to potential self-selection issues. For this reason, we implemented a matching algorithm to determine if there was upward

Table 2. Simple estimator from ordinary least squares regression.

Dependent variable: Real wage	Coefficient	Std. Error	*p*-value
Placement	2128.8	351.66	.000
Final year mark	83.56	24.83	.001
Year 1 mark	17.64	14.10	.211
Combined Honours Dummy	1412.99	932.29	.130
Engineering Dummy	2019.99	929.39	.030
Health Sciences Dummy	−710.60	929.11	.445
Age	233.52	101.81	.022
Female	−1072.50	391.75	.006
Graduation year	−48.76	86.63	.574
White ethnic background	−427.63	341.31	.211
White collar	489.96	529.19	.355
Independent School	728.29	716.14	.309
Constant	103,578.2	174,167.4	.552
Adj R2	0.142		
F(12, 809)	12.30		
Root MSE	4563.9		
Number of observations	822		

Table 3. Average treatment on the treated effect of placement on real wages.

Estimator	Propensity Score Matching		
	Coefficient	Std. Error	p-value
ATET	1686.72	540.16	.002
Number of observations	822		

bias from the placement effect. We report the results for the 1st stage Logit Model in the Appendix. The results appeared to have good overall predictive power and we obtained statistically significant estimates for a solid majority of the controls. From the logit model[7] we first estimated the propensity scores, then we matched control and treatment observations in order to calculate the ATET.

Table 3 reports the results for the matching exercise for the whole sample. As can be seen the ATET was equal to 1686. This suggested that students who undertook a placement had on average starting salaries £1686 ($2106) higher compared to students who did not undertake a work placement. The estimate is highly statistically significant, large in magnitude and does indicate that there was some upward bias in the OLS estimates reported in Table 4 above due to self-selection. This is an important finding and unique to the literature as it suggests that work placements really did have a causal, and statistically significant, impact upon graduate earnings six months after graduation, whilst accounting for self-selection.[8]

5.3. Gender, ethnicity and socioeconomic class

In addition to the headline result, the matching estimation also allowed us to investigate how graduate salaries between placement and non-placement students varied by gender, ethnicity and socio-economic class.

Table 4 reports the results for the propensity score matching when applied to gender. As can be seen the ATET was equal to 2781 and was highly significant. This suggests that for males who did a placement, starting salaries were £2781 ($3474) higher compared to students who choose not to do a placement. The associated ATET for females was £706 ($881) and was significant only at the 10% level. So, although placements appeared to increase female starting salaries, the increase was much smaller in magnitude compared to males. This suggests that placements may have increase gender pay inequality.

Table 5 reports the results for the causal effect of placement on starting salaries of graduates when applied to ethnic background. For both Whites and Non-Whites, the ATET was positive, quite large in magnitude and highly significant. For white students who undertook a placement, starting salaries were £1478 ($1846) higher compared to students who choose not to do a placement. For non-white students who undertook a placement, starting salaries were £2078 ($2595) compared to students who choose not to do a placement. Hence, placements appeared to boost earnings for both white and non-white students but the increase for the latter group is much higher. This suggests that placements reduced pay inequality based on ethnicity.[9]

Table 6 reports the results for the ATET when applied to socio-economic class which is measured by parental occupational background. We distinguish between white-collar and blue-collar occupations with the former including 'Higher Managerial and Professional Occupations' and the latter including all other employment categories. Clearly this is somewhat simplistic, but the results do

Table 4. ATET of placement on real wages by gender.

Estimator		Propensity Score Matching			
		Coefficient	Std. Error	p-value	Observations
ATET	Male	2781.51	451.99	.000	230
	Female	706.94	421.22	.094	257

Table 5. ATET of placement on real wages by ethnic background.

Estimator		Propensity Score Matching			
		Coefficient	Std. Error	*p*-value	Observations
ATET	White	1478.58	378.73	.000	318
	Non-white	2078.36	545.76	.000	169

indicate that students from a white-collar background who go on to do placements had higher starting salaries compared to students from a blue-collar background, £2153 ($2689) and £1623 ($2027), respectively even if placements for both groups do in fact boost earnings. This suggested that placements may help to solidify class norms and result in higher income inequality.

6. Conclusion

This paper assessed the role of placements on graduate starting salaries for Aston University students between 2004 and 2011. The findings show clear evidence of a causal placement effect. In that starting salaries appear to be higher for placement students by £1686 ($2105) after controlling for self-selection. Additional insights show that class and gender pay inequality were enhanced by work placements, but this is not the case for pay inequality based on ethnicity. Hence overall, the results indicate that work placements may indeed be a useful means to enhance the quality of employment after graduation based on remuneration. Furthermore, given the positive relationship between wages and productivity, our analysis suggests that work placement may be a key driver of higher productivity for those students who choose to do a work placement. This suggests that work-integrated learning may be of significant benefit not only to students, but wider society in general. In the UK, degree apprenticeships, where employers and universities build close relationships and design academic programmes collaboratively may therefore be a promising avenue for future productivity gains. It may also alter the funding landscape as employers cover the cost of student fees.

Hence, these results have important implications for higher education institutions across the world. They indicate that work-integrated placements did generate stronger graduate outcomes in terms of labour market earnings after graduation. And, that this effect held even when we controlled for self-selection. Hence, higher education institutions that offer work-integrated learning may generate powerful effects in terms of workplace accessibility and equity in terms of employment opportunities. Nevertheless, institutions should monitor the employment outcomes of their placement years very closely. Although the overall effect appeared positive, gender and class pay inequality may be reinforced once a placement is chosen. Higher education institutions therefore need to carefully consider the types of placements that students have access to as placement type could be a key driver of future student earnings success. One would expect that placement provision by so-called 'graduate employers', for example the Big 4 Accountancy firms that are strongly desired by business school undergraduates, may significantly drive graduate earnings. Indeed, this fact merits significant future research but would require more comprehensive data collection from the Higher Education Statistical Agency (HESA).

Given our significant and novel findings it is important to point out some of the limitations of this research that future research may be able to address. The first area of caution concerns whether the positive placement effect on starting salaries remains persistent over time throughout a student's career. We simply do not know whether the placement effect is short-lived and dies out over the

Table 6. ATET of placement on real wages by socio-economic background.

Estimator		Propensity Score Matching			
		Coefficient	Std. Error	*p*-value	Observations
ATET	Blue collar	1623.63	336.89	.000	429
	White collar	2153.33	797.58	.009	58

course of a student's career or whether it remains intact. If there is no persistence, then it might be the case that the placement premium is not enough to cover the opportunity cost of doing a placement. The opportunity cost being an additional year in the labour market. Further research that tracks lifetime earnings, which might be possible if researchers can obtain access to student tax records, may enable us to gain a greater understanding of the persistence in graduate earnings caused by placements.

The second area of caution is in the way we have carried out the matching algorithm. Instead of matching placement students with non-placement students 6 months after graduation it may be interesting to match placement students 6 months after graduation with non-placement students 18 months after graduation. In that case both the control group and treatment group would have had at least 12 months of experience in the labour market. Although in principle this is possible, it would mean setting up separate survey data as the *Destination of Leavers Survey* does not track earnings 18 months after graduation. In any case, our current estimates are most likely a lower bound indication.

Thirdly, it is important to note that we don't control for the location of the graduate's employment. Aston University is located in the West Midlands and it is possible that a number of students migrate to London and the South East after graduation. Typically, London and the South East pay a wage premium over other locations. If placement students disproportionately migrate to the South East and London after graduation compared to non-placement students, then it is possible that the increase in salary is partially due to this location decision. Future research would have to have a clear understanding of the location of graduate employment in order to control for this possibility. Furthermore, it might also be the case that female students and students from a lower social economic class have a lower propensity to migrate so that fact could also impact upon the results.

Fourthly, as with any empirical study, the findings may be specific to the data set we have utilised. It is important that future studies explore this issue in greater detail by obtaining data from other higher education institutions to determine whether our findings are Aston University-specific or if they can be generalisable to other, HE institutions across the world. In addition, the data we use is taken from 2004 to 2011, hence it would be interesting for scholars to investigate the placement effect on wages for a newer vintage of data. It is important to note here that scholars must ensure that students have a choice if they are to control for self-selection. Indeed, this is the principal reason why we were forced to use the earlier time period in our analysis. It is of course possible that changes in the labour market may mean the placement effect on wages differs across time, perhaps depending on the economic cycle. But the time period in our analysis contains the years during and the aftermath of the Global Financial Crisis, when career prospects and wages were not very promising for all employees and in particular recent graduates. Hence, our estimates of the magnitude of the placement effect on graduate wages are probably conservative and at the lower bound. Future research that examines the placement effect on wages when the economy is growing above its trend would generate interesting insights.

Finally, it is also important to point out that student earnings should certainly not be the only metric by which work placements should be judged. Indeed, we do worry that the benefits of university are increasingly being quantified in monetary terms. But given the UKs move to a more market driven HE landscape with higher student fees and the fact that students are faced with a highly uncertain labour market, students will expect their university experience to generate a higher rate of return. The evidence in this paper suggests that a placement year may go some way to meeting this expectation.

Notes

1. We use an exchange rate of \$1.25/£1 throughout this paper. We acknowledge that at the time of writing the exchange rate is quite volatile due to economic instability in the UK.
2. The final year mark could be responsible for some methodological complications, because of the timing of events. For this reason, we estimated a logit specification substituting 2nd year mark for the final year mark and then conducting exactly the same PSM estimation. We found that the effect of placement on wages is

still highly statistically significant and positive with a value of £1888. Furthermore, the quality of the matching remains very high.
3. More specifically, we do not perform new estimations of placement probability on these sub-samples. We use the already estimated probabilities of the whole sample and the subsequent matching of placements and non-placement students. The difference is that the new ATETs are calculated on these new restricted sub-samples. For example, when we calculate the ATET for male students we use the original estimates of placement probabilities, but we perform the calculation of the average wage difference between the control and the treatment groups only for the sub-sample of male students.
4. Graduates in part time employment or self-employed are excluded, since we do not have enough information about the hours that they work and hence cannot construct comparable full time equivalent real wages. Furthermore, graduates employed outside the UK were not included in the sample in order to avoid issues with different national labour market characteristics. The final sample is further reduced because of missing values for some explanatory variables.
5. All of the data used is anonymous.
6. White collar is defined as students whose parents are classified as coming from 'Higher managerial and professional occupations'.
7. See Appendix for the estimates of the Logit model.
8. In the Appendix, we undertake many formal and informal tests in order to evaluate the robustness of our ATET estimate. The findings from these tests strongly indicate that the quality of our matching is of a high standard and that that the causal evidence is highly significant and robust.
9. In an ideal world it would be very informative if we were able to split up ethnicity into different ethnic groups; for example, by looking at the ATET for Black and Asian students separately. Unfortunately, due to sample size and the quality of the matching this is not possible but does suggest a promising area for future research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1 reports the results of the Logit model used to calculate the propensity scores.

Matching quality

In order to check the validity of the propensity score estimates we conduct a series of formal and informal tests. First, we depict in Figure A1 the estimated density of the predicted probability of not doing a placement for both the control and treatment groups. Neither of the estimated densities is concentrated either in the area around zero or around one. This

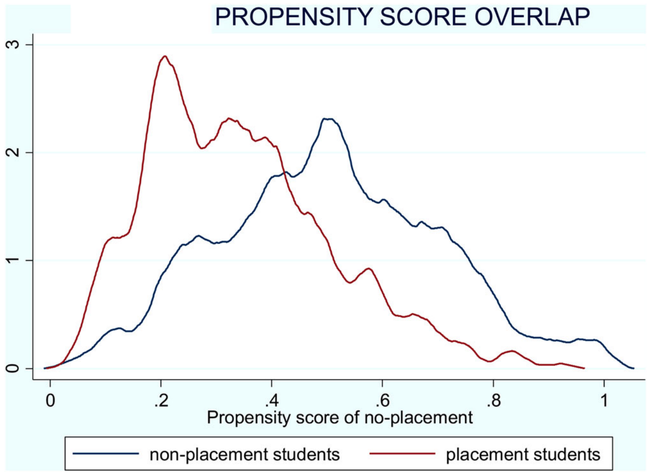

Figure A1. Propensity core overlap.

indicates that the probability of not going on placement for both the control and treatment group is relatively similar and hence we can construct a valid comparison group.

Then we check whether the estimated probability of doing a placement is balanced for each group after matching. This is shown in Figure A2, where on the left we plot the estimated density of the predicted probability of doing a placement for each of the two groups using the raw (unmatched) sample. It is clear that the treatment group has a higher probability of doing a placement, as expected, compared to the control. While on the right the estimated density of the propensity score for the two groups, when using the matched sample, is almost identical. This indicates that our propensity score approach satisfies the balancing property of the propensity score. This property assumes that students with a very similar probability of doing a placement have explanatory variables with very similar distributions independent of whether they actually did a placement. Furthermore, for a particular propensity score, the decision of students to do a placement appears to be random in the sense that students in the treatment and control groups have very similar confounding variables on average.

Furthermore, we also perform a formal test proposed by Smith and Todd (2005) in order to check whether the balancing hypothesis is satisfied. More specifically, we perform the following regression:

$$X_i = a + \Sigma_{j=1}^{4} \beta_j PS(X)^j + \Sigma_{j=1}^{4} \gamma_j [D \times PS(X)^j] + \varepsilon_i$$

Where X_i indicates each one of the RHS variables in the logistic regression, PS(X) indicates the propensity score that a student did placement, D is a dummy variable that takes the value of 1 if a student has done placement and zero otherwise and ε_i indicates an error term that is assumed to satisfy the standard OLS assumptions. The Balancing Property is satisfied when all the γ's from each regression are jointly insignificant. Hence, under the null hypothesis that the balancing hypothesis holds, selection on either treatment, for given propensity scores, should have no effect on each individual explanatory variable X. From Table A2 we can see for all regressions the γ's are jointly insignificant, hence the balancing hypothesis is satisfied. This provides clear statistical evidence that our matching estimation is robust.

Finally, we also check whether the balancing hypothesis is satisfied for each confounding variable X. Similarly, this implies that the distribution of a confounding variable is the same (or very similar) for both the control and treatment group. In Table A3, we compare the first two moments of the distribution between control and treatment groups for both the raw (unmatched) and matched samples. For the balancing property to hold for the confounding variables, we should observe that the standardised difference of means tends to approach zero while the ratio of the variance approaches one in the matched sample. From Table A3, we show that there is strong evidence for this.

Table A1. Logit estimates.

Dependent variable: Placement Dummy	Coefficient	Std. Error	*p*-value
Final Year mark	0.1182	0.0141	.000
Year 1 mark	−0.0198	0.0076	.007

(*Continued*)

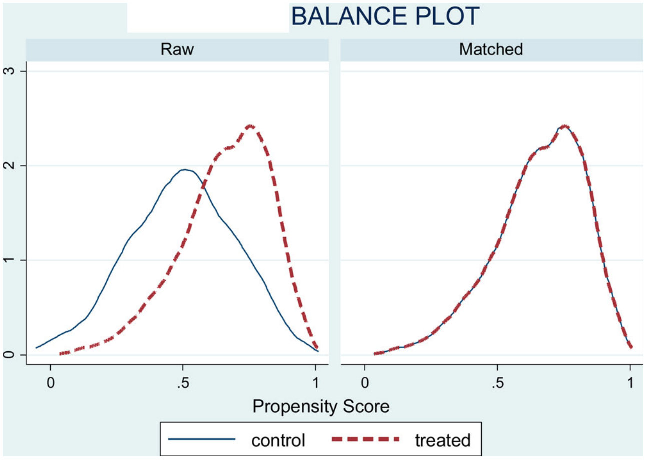

Figure A1. Balance plot.

Table A1. Continued.

Dependent variable: Placement Dummy	Coefficient	Std. Error	*p*-value
Age at Year 1	−0.2112	0.0616	.001
Combined Honours Dummy	1.3351	0.4389	.002
Engineering Dummy	1.3092	0.4409	.012
Health Sciences Dummy	1.0943	0.4369	.006
Female	0.3911	0.1914	.041
Graduation year	0.1228	0.0422	.004
White ethnic background	0.3512	0.1641	.032
White collar	0.2939	0.2628	.263
Independent School	0.2962	0.3545	.403
Constant	−249.943	84.92037	.003
LR chi2(11)	140.03		
Prob > chi2	0.0000		
Log likelihood	−485.6161		
Number of observations	822		

Table A2. Balancing hypothesis test.

	H_o: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$	
Dependent variable	F-statistic	*p*-value
Final Year mark	0.28	.887
Year 1 mark	1.25	.288
Combined Honours Dummy	0.79	.534
Engineering Dummy	2.16	.072
Health Sciences Dummy	0.45	.770
Age at Year 1	0.75	.557
Female	0.97	.421
Graduation year	1.09	.361
White ethnic background	1.15	.333
White collar	0.22	.925
Independent School	1.09	.359

Table A3. Comparing distributions between control and treatment groups.

	Standardised differences		Variance ratio	
Variable	Raw sample	Matched sample	Raw sample	Matched sample
Final Year mark	0.6727786	−0.0490026	0.5806069	0.8928567
Year 1 mark	0.1039869	−0.0931187	1.971388	1.11318
Combined Honours Dummy	0.0624006	−0.0436841	1.053773	0.9685677
Engineering Dummy	−0.1090142	−0.08768	0.962057	1.139353

(*Continued*)

Table A3. Continued.

	Standardised differences		Variance ratio	
Variable	Raw sample	Matched sample	Raw sample	Matched sample
Health Sciences Dummy	0.1190926	0.1098054	1.152718	2.309209
Age at Year 1	−0.2786028	−0.0232642	0.5154525	0.9971323
Female	0.1844721	0.0698007	1.01268	0.669219
Graduation year	0.1550461	0.041152	0.7007645	0.9818401
White ethnic background	0.2673145	0.0300259	0.9073646	1.138764
White collar	0.1285277	0.0522819	1.41448	1.256305
Independent School	0.0435484	0.0557934	1.190381	1.139353