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A Question of Degree: The Effects of Degree Class on Labor Market Outcomes

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Abstract
In this paper we estimate the sorting effects of university degree class on initial labor market outcomes using a regression discontinuity design that exploits institutional rules governing the award of degrees. Consistent with anecdotal evidence, we find sizeable and significant effects for Upper Second degrees and positive but smaller effects for First Class degrees on wages. In additional results we explore differences across groups and find evidence consistent with a simple model of statistical discrimination on the basis of gender and types of degree programmes. When we split the sample by ability, we find that the signaling effects are similar in the high ability group but stronger for Upper Second degrees in the lower ability group. The evidence points to the importance of sorting in the high skills labor market.

Keywords: degree classification, regression discontinuity design, sorting effects
JEL Classifications: I24, J24, J31

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1 Introduction

In this paper we estimate the sorting (signaling or screening) effects of university degree class on labor market outcomes. As we explain below, the degree classification is a system of categorizing performance on university degree programmes in the United Kingdom (UK). The importance of the system is highlighted by the sizeable fraction of employers who report using the classification in hiring decisions and by universities that use degree class to screen applicants to postgraduate programmes. However, it is not obvious that the classification system is useful because degree transcripts provide more information about applicant quality. Finding any effect would suggest the presence of sorting in the skill market.

Using survey and administrative data from the London School of Economics and Political Science (LSE), we find significant effects of degree class on initial labor market outcomes. An Upper Second earns 7 percent higher wages compared to a Lower Second while a First Class earns 3 percent higher wages compared to an Upper Second. However we find no significant effects on the extensive margin of employment. These results are robust to a battery of specification checks and suggestive of sorting in the high skills labor market.

In additional results we explore differences across groups and find evidence consistent with a simple model of statistical discrimination on the basis of gender and types of degree programmes. Males, quantitative degrees and degrees with less course choices appear to display larger signaling effects. When we split the sample by ability, we find that signaling effects are similar in the high ability group but stronger for Upper Second degrees in the lower ability group.

Identifying the sorting effects of degree class is complicated by the fact that a naive comparison of, say, students who received a First Class with students who received an Upper Second could be biased by the differing ability composition of the two groups. In this paper, we adopt a regression discontinuity design (RD) that exploits institutional rules governing the award of degree class on the basis of marks received on courses taken. This amounts to comparing students who barely made and barely missed a degree class within a narrow window of the marks received. We argue that this generates quasi-experimental variation needed for clean identification of degree class effects.

1.1 Related Literature

Our paper is related to several strands of literature. Broadly, the signaling theory of education suggests that education provides a signal of unobserved worker productivity (Spence 1973). In the simplest model there is no productive role of education in human capital acquisition although this consideration does not alter the basic predictions of the theory: high ability types choose more education to separate themselves from low ability types (Riley 1979). Notice that both the Becker (1964) theory of human capital and signaling theories predict a positive correlation between ability and education. Thus discriminating between the two theories has proven challenging empirically (Weiss 1995). Complementing the signaling theories are screening models where employers take actions to separate workers into ability groups (Stiglitz 1975, Wolpin 1977). We follow Weiss (1995) in collectively describing these classes of signaling and screening theories as sorting models.

Empirical testing of sorting models has proceeded in two ways. Indirect evidence comes in the form of changes in the human capital investment decisions of one ability group from changes in the decisions made in other groups. Compulsory schooling laws for primary education that affect higher education groups (Lang and Kropp 1986) or tertiary enrolment changes that affect the high school margin (Bedard 2001) are seen as consistent with the signaling value of education but not human capital theories. More direct evidence imagines a randomized experiment where randomly selected individuals from the same ability group get treated with an educational signal. Tyler, Murnane, and Willet (2002) mimic this experiment by exploiting differences in passing standards for the GED diploma across US states. Their finding of significant effects for white males stands in contrast to Clark and Martorell (2010) who find no effects for receiving the high school diploma.

For tertiary education the early literature looked at the credential effects associated the completion of college degrees (Layard and Psacharopoulos 1974). Hungerford and Solon (1987), Belman and Heywood (1991) and Jaeger and Page (1996) include dummy variables for college completion in Mincer (1974) regressions and interpret the significant effects of college completion as signals of underlying correlates of productivity. In papers most closely related to ours, Di Pietro (2010), Ireland, Naylor, Smith, and Telhaj (2009) and McKnight, Naylor, and Smith (2007) examine the signaling effects of degree classification for students in the UK. Notably Di Pietro (2010) adopts a regression discontinuity design using final year marks and finds no effect on employment. We get similar results and extend the analysis by looking at wage differences. Ireland, Naylor, Smith, and Telhaj (2009) use OLS regressions and find 4 and 5 percent returns to First Class and Upper Second degrees respectively. Their sample consists of a much larger dataset of UK students across many universities and years but does not have the course history information we have to construct finer comparison groups.

The rest of the paper is organized as follows. In Section 2 we discuss the institutional setting, in Section 3 we explore the data sources and empirical strategy, in Section 4 we present our results and specification checks. Section 5 explores heterogeneity across programmes and ability groups. Finally, in Section 6 we conclude.

2 Institutional Setting

2.1 University Description

Our data comes from the London School of Economics and Political Science (LSE). LSE is a top ranked public research university located in London, UK, specializing in the social sciences. LSE offers a range of degree programmes and admission is highly competitive. In 2012, LSE students came top for employability in the Sunday Times University Guide with over three quarters of students in employment or further studies six months after graduating. Our results thus speak to the high end of the skills market within a selective tertiary institution.[1]

2.2 UK Degree Classification

The degree classification system in the UK is a grading scheme for degrees. The highest distinction for an undergraduate is the First Class honors followed by the Upper Second, Lower Second, Third Class and Pass degrees. While all universities in the UK follow this classification scheme, each university has the power and discretion to apply its own standards and rules to determine the distribution of degrees. The system has been applied in other countries including Australia, Canada, India and many Commonwealth nations. In the US, a system of grade point averages (GPA) and Latin Honors performs the similar purpose of classifying degrees. In principle, this implies that our results apply to a broad range of countries.[2] Anecdotal evidence points to the increasing importance of degree class in hiring decisions. One report points to 75 percent of employers in 2012 requiring at least an Upper Second degree as minimum entry requirement especially for competitive jobs–this compares to 52 percent in 2004.[3]

2.3 LSE Degree Classification Rules

To construct our identification strategy, we exploit a unique feature of the rules governing the award of degree class. Undergraduates in the LSE take nine courses over three years. Every course is graded out of 100 marks and fixed thresholds are used to map the marks to degree class. As shown in Table B.1, a First Class Honors degree requires 5 marks of 70 or above or 4 marks of 70 or above with aggregate marks of at least 590. This mapping from course marks to final degree class applies to all departments and years.[4]

[1]See LSE website http://www2.lse.ac.uk/intranet/CareersAndVacancies/graduateDestinations/6monthson.aspx.

[2]See wikipedia http://en.wikipedia.org/wiki/British_undergraduate_degree_classification and http://en.wikipedia.org/wiki/Latin_honors. The GPA is usually a scale from 0 to 4 with one decimal accuracy and is a finer measure of performance than the UK system. There have been calls to scrap the UK system in favor of a US-style points system, the Guardian, July 9th 2012.

[3]See the Daily Telegraph, July 4th 2012 and the Guardian, July 4th 2012.

[4]Four courses are taken each year, however only the average of the best three courses in the first year counts towards final classification. Undergraduate law students are an exception and follow a different set of rules. We exclude them from all analyses. Full details of the classification system is available online at http:

We exploit the discontinuous relationship between degree class and marks received on the fourth highest mark in a regression discontinuity design (RD). Our strategy is intuitive and amounts to comparing otherwise similar students who differ only in a critical course mark which determines their final degree class. To be specific, let us consider the award of a First Class degree which depends on the receipt of at least four first class marks. This suggests that the fourth highest mark for any student plays a critical role in determining the degree class. A student whose fourth highest mark is larger than 70 is much more likely to obtain a First Class degree than a student whose mark just missed 70, everything else equal. This can be seen clearly in Figure 1 which plots the fraction of students who receive a First Class degree against their fourth highest mark received. There is a clear jump in the probability of receiving a First Class after the 70-mark threshold. A similar story can be seen in the award of an Upper Second degree at the 60-mark threshold. To summarize, the fourth highest mark plays the role of the assignment variable in our RD strategy.

In reality, we employ a fuzzy RD design because there are complications to the rules. As shown in Table B.1 there is an aggregate mark requirement. Additionally, a failed course results in a downgrade in degree class.[5] These caveats do not threaten our research design because they are not applied on a case-by-case basis but are applied impartially at the department level.[6] Nevertheless it moves us away from a sharp RD design. We explore in detail the first-stage relationship between degree class and fourth highest mark in Section 4.1 and show that the relevant complier population is sizeable so that our results generalize to the larger LSE population.

3 Data and Empirical Strategy

3.1 Students' Demographics and Course History

From student records we obtain age, gender, nationality and country of domicile information. Course history includes information on degree programme, courses taken and grades awarded, and eventual degree classification. Table 1 reports the descriptive statistics of the variables used in our analysis. We have 5,912 students in the population from 2005-2010 of which 2,649 are included in the DLHE survey (described in detail below). Columns (1) and (4) report the mean and standard deviations of variables for surveyed and non-surveyed students, respectively, while column (5) reports the difference. Surveyed students are less likely to be female, more likely to be UK nationals, more likely to receive an Upper Second and less likely to receive a Lower

//www.lse.ac.uk/resources/calendar/academicRegulations/BA-BScDegrees.htm.

[5]Failed courses can be retaken up to three times and the better grade is used in calculating final degree class. We control for any failed or retaken courses in our estimation. Students can appeal on specific courses, but this does not worry us. First, appeals are difficult and rarely successful. Second, a student does not usually know before the completion of their degree which course is critical in determining their class.

[6]There could still be a concern if departments can upgrade students who appeal in their final degree classification. But this would not retroactively change grades on courses taken and reinforces the need to use a fuzzy RD design.

Second.

To implement our empirical strategy, we further split the surveyed students into two samples. The First Class sample consists of students who received either a First Class or an Upper Second and the Upper Second sample consists of students who received either an Upper Second or Lower Second. This provides two discontinuities that we examine separately and narrows our comparisons to students who are on either side of each threshold. In Table 1 *First Class*, *Upper Second* and *Lower Second* are dummy variables for the degree classes. Among all surveyed students, the majority of 60 percent received an Upper Second with the remaining 40 percent roughly evenly split between First Class and Lower Second. $1[\mathit{4th\ MARK} \geq 70]$ and $1[\mathit{4th\ MARK} \geq 60]$ are dummy variables equal to one if the fourth highest mark is no less than 70 or 60 respectively.[7]

One shortcoming of this database is that we do not have measures of a student's pre-university ability. For a typical UK student this might include his GCSE and A-level results. Although admissions to LSE programmes require A-level or equivalent results, this data is not collected centrally but is administered at the department level. While controlling for ability is unnecessary in our identification strategy it would be useful for improving precision and interesting to check our results against different ability groups.[8] We take some steps to redress this shortcoming. First in all our regressions we control for department $\times$ year interactions. More directly we use the admissions offers made at the programme level as a measure of student ability. In Table B.3 we classify degree programmes into groups based on A-level requirements. The most stringent programmes require *A*AA* grades followed by *AAA*, *AAB* and *ABB* respectively. We also code a dummy variable indicating A-level mathematics' requirements for admissions.[9] Section 5 presents results exploring heterogeneity over these programme attributes.

3.2 Destination of Leavers from Higher Education Survey

The DLHE survey is a national survey of students who have recently graduated from a university in the UK. This survey is conducted twice a year to find out employment circumstances of students six months after graduation.[10] Due to the frequency of the survey and its statutory nature, LSE oversees the survey and reports the results to HESA (Higher Education Statistics Authority). The survey is sent by email and responded to online and in theory includes all students including non-domiciled and non-UK nationals. In practice response rates are higher

[7]We split the sample because anecdotes suggest that the Upper Second threshold may be more important. It also allows a cleaner non-parametric identification strategy around the two discontinuities. We dropped Third Class and below because they constituted less than 5 percent of the population. Including them among the Lower Second population does not change results.

[8]As noted in Lee and Lemieux (2010) an RD design mimics a natural experiment close to the discontinuity. Hence there should be no need for additional controls except to improve precision of estimates.

[9]Results in (McKnight, Naylor, and Smith 2007) suggest that controlling for degree programme reduces the importance of pre-university academic results.

[10]The surveys are conducted from November to March for the "January" survey, and from April to June for the "April" survey.

for domiciled and UK nationals.[11] The survey provides us with data from 2005-2010. Our key variables of interest are industry and employment status. Industry is coded in four digit SIC codes, although we aggregate to two digits for merging with LFS data (see Section 3.3). Employment status is a dummy variable equal to one if a graduate is employed in full-time work. Self-employed, freelance and voluntary work is coded as zero along with the unemployed or unable to work.[12]

Table 1 shows that 85 percent of students who responded are employed within six months of graduation. More than one-third of students are employed in the finance industry although this varies slightly across the degree classes. Given the importance of the finance industry, we construct a dummy variable for employment in finance and look at results excluding the finance industry.

Because the survey is conducted six months after graduation, we interpret our analysis as applying to first jobs. Although we do not observe previous job experience and cannot control for this in our analysis, 98 percent of our students were younger than 21 years of age when they started their degrees. Thus, any work experience is unlikely to have been in permanent employment. Also, we cannot follow students over longer periods of employment to examine the dynamic effects of degrees. While these are limitations of our data, we do not see these as limitations of our analysis: according to the employer learning and statistical discrimination models (Altonji and Pierret 2001), any sorting effect from degree class should be most relevant in the first job.

Another concern is that employment six months after graduation may have been secured before the final degree class is known. Anecdotes suggest that students start Summer internships, work experience and job applications prior to graduation.[13] While this may explain the insignificant effects we find on employment, it cannot explain the results on wages. Furthermore, if degree class has no effect for those students who have secured employment, our results would underestimate the full effects for the students who have not.

3.3 Labor Force Survey

We merge wage data from the LFS into the DLHE survey at the industry $\times$ year $\times$ gender level. We calculate mean log hourly wages for each industry $\times$ year $\times$ gender cell unconditional on skills or experience. One concern with this approach is that mean wages are not representative of the earnings facing undergraduates. To address this concern we also calculate mean log wages conditional on university and three experience levels. To match the labor market prospects of undergraduates we chose 1, 3 and 5 years of potential experience. To ensure that the finance industry is not driving our results, we look at wages for the sub-sample of students not employed in finance.

[11] Formally, LSE is required to reach a response rate of 80 percent for UK nationals and 50 percent for others.
[12] An annual salary question is included but response is voluntary and had too many missing values.
[13] Although many employers may offer jobs conditional on the final degree class.

This gives us five different measures of industry wages–overall mean, university with 1, 3 and 5 years of experience and overall mean for non-finance industries. Our preferred measure is the overall mean because it provides a clean measure of the industry's "rank" compared to other industries. In any case the five measures are highly correlated with pairwise correlations never less than 0.8. Table 1 shows that the mean log wage is 2.45 which is roughly £11.60 per hour in 2005£. As expected, industry wages increase in years of experience.

Using industry wages implies that we do not have within-industry variation in outcomes. To the extent that within-industry comparisons matter, our results will not be representative of the true effects of degrees. We acknowledge that this is an imperfect measure and are cautious in interpreting our results as effects on industry not individual wages.[14] Table B.2 shows the top 15 industries ranked by total share of employment. Even accounting for the large share in finance, there is substantial distribution in employment across industries–of the 84 two-digit SIC codes, 66 are represented in our data.

3.4 Empirical Strategy

Our unit of observation is a student. For each student we observe his degree classification and his course grades. In particular, we observe his fourth highest mark out of nine courses taken over three years of the degree. As described in Section 2.3, institutional rules imply that the fourth highest mark is critical in determining his degree class. When the fourth highest mark crosses the 70-mark or 60-mark cutoff, there is a discontinuous jump in the probability of receiving a First Class and Upper Second respectively. In Section 4.4 we show that including the other marks as controls does not change our results.

Identification in an RD setup requires two assumptions (Lee and Lemieux 2010). First, agents cannot precisely manipulate the assignment variable. Second, apart from the treatment–in this case degree class–all other observables and unobservables vary continuously across the threshold. The first assumption cannot directly be tested although institutional knowledge and the McCrary test provide supporting evidence. These are discussed in Section 4.2. The second assumption can be tested using data on observables once the assignment variable has been controlled for flexibly. Flexible control of the assignment variable can be done in several ways. A parametric function such as a high order polynomial is parsimonious but is found to be quite sensitive to polynomial order (Angrist and Pischke 2009). A non-parametric approach observes that a regression discontinuity can be thought of as a kernel regression at a boundary point (Imbens and Lemieux 2008). This motivates the use of local regressions with various kernels and bandwidths (Fan and Gijbels 1996, Li and Racine 2007).[15]

In our benchmark specification we use the simplest non-parametric local linear regression

[14]The lack of a more direct wage measure is an issue for other studies in the literature as well (Di Pietro 2010, McKnight, Naylor, and Smith 2007).

[15]Regression discontinuity was introduced by Thistlethwaite and Campbell (1960) and formalized in the language of treatment effects by Hahn, Todd, and van der Klaauw (2001).

with a rectangular bandwidth of 5 marks above and below the cutoff (Imbens and Wooldridge 2009). This means we include the fourth mark linearly and interacted with the dummy variable as additional controls. In specification checks we vary the bandwidth and try polynomial functions to flexibly control for the fourth mark. As discussed in Section 4.4 these specification checks produce consistent results. The non-deterministic relationship between fourth highest mark and degree class means that in practice we employ a fuzzy RD design. This uses the fourth highest mark as an instrument for degree class.[16]

In theory, identification in an RD setup comes in the limit as we approach the discontinuity asymptotically (Hahn, Todd, and van der Klaauw 2001). In practice, this requires sufficient data around the boundary points–as we get closer to the discontinuity estimates tend to get less precise because we have fewer data. Furthermore, when the assignment variable is discrete by construction, there is the additional complication that we cannot approach the boundary infinitesimally.[17] In this paper, we choose the 5 mark bandwidth as a reasonable starting point and accept that some of the identification necessarily comes from marks away from the boundary. We follow Lee and Card (2008) in correcting standard errors for the discrete structure of our assignment variable by clustering on marks throughout.

We can write the first-stage equation as:

$$
\begin{aligned}
(1) \qquad & \text{CLASS}_i \\
&= \delta_0 + \delta_1 1[\text{4th MARK} \geq \text{cutoff}]_i + \delta_2(\text{4th MARK}_i - \text{cutoff}) + \\
&\quad \delta_3(\text{4th MARK}_i - \text{cutoff}) \times 1[\text{4th MARK} \geq \text{cutoff}]_i + X_i\delta_4 + u_i
\end{aligned}
$$

where CLASS is either First Class or Upper Second and the cutoff is 70 or 60 respectively. $1[\text{4th MARK} \geq \text{cutoff}]$ is a dummy variable for the fourth mark crossing the cutoff and our instrument for the potentially endogenous degree class. X is a vector of covariates including female dummies, age and age squared, dummies for being a UK national, dummies for having resat or failed any course, 15 dummies for department, 5 year dummies and 75 dummies for department $\times$ year interactions.

We can use the predicted degree class from our first-stage regression in our second-stage equation:

$$
\begin{aligned}
(2) \qquad Y_i =& \beta_0 + \beta_1 \text{CLASS}_i + \beta_2(\text{4th MARK}_i - \text{cutoff}) + \\
& \beta_3(\text{4th MARK}_i - \text{cutoff}) \times 1[\text{4th MARK} \geq \text{cutoff}]_i + X_i\beta_4 + \epsilon_i
\end{aligned}
$$

where Y are various labor market outcomes including employment status, employment in finance

[16] The close connection between fuzzy RD and instrumental variables is noted in Lee and Lemieux (2010), Imbens and Lemieux (2008) and Imbens and Wooldridge (2009). Instead of the usual exclusion restrictions, however, we require the continuity assumption and non-manipulation of the assignment variable.

[17] This is also a problem facing designs where age in years or months is the assignment variable, e.g. Carpenter and Dobkin (2009).

industry and five measures of industry wages.

4 Results

4.1 First-Stage and Reduced Form Regressions

In this section we look at estimates of the first-stage Equation (1) and the reduced form regressions:

$$
\begin{aligned}
(3) \qquad Y_i = &\gamma_0 + \gamma_1 1[\text{4th MARK} \geq \text{cutoff}]_i + \gamma_2(\text{4th MARK}_i - \text{cutoff}) + \\
&\gamma_3(\text{4th MARK}_i - \text{cutoff}) \times 1[\text{4th MARK} \geq \text{cutoff}]_i + X_i\gamma_4 + \nu_i
\end{aligned}
$$

where Y are the various labor market outcomes. Table 2, column (1) reports the first-stage results for the First Class discontinuity (panel A) and Upper Second discontinuity (panel B). Both first-stage F-statistics are above the rule-of-thumb threshold of 10 and mitigates any concerns about weak instruments (Stock, Wright, and Yogo 2002).[18] In order to better interpret the first-stage, we can look at the relationship between fourth highest mark and degree class without controlling for any covariates. This also allows us to do a simple count of the complier population in LSE (Angrist, Imbens, and Rubin 1996, Imbens and Angrist 1994). In Figure 2 the schematic shows the breakdown of students into compliers, always takers and never takers around the discontinuity. For instance, always takers are students who receive a First Class regardless of their fourth highest mark, while compliers are students who receiver a First Class *because* their fourth highest mark crosses the threshold. The breakdown suggests that the complier population is sizeable at 87 percent. This is expected because the institutional rules are strictly followed and supports the validity of our results to the rest of the LSE population.

Columns (2) to (8) regress the outcome variables on the excluded instrument always controlling for covariates. In panel A, the small magnitudes and insignificant results suggest that the First Class may not be important in labor market outcomes. The larger and significant results for Upper Second in panel B are consistent with the idea that an Upper Second is important as a signal or screening device for employers.

4.2 Randomization Checks and McCrary Test

As discussed in Section 3.4, identification in an RD setup requires continuity in the observables (and unobservables) across the threshold as well as non-manipulation of the assignment variable. To test for continuity in the observables, we regress each covariate on the treatment dummy in Table 3, columns (1) to (5). Apart from age in the First Class sample and gender in the Upper Second sample, the results are consistent with the lack of discontinuity in the

[18]The sample size varies over outcome variables but we confirmed that the first-stage and other results are not sensitive to these sample differences.

observables. The apparent discontinuity in age and gender does not worry us because these are non-manipulable attributes (Holland 1986). In other words, there is less concern that agents could have taken actions to manipulate these attributes around the discontinuity to improve their degree class. This would be the case if we saw discontinuities in the students who resat or failed any courses.

To test for the manipulation of the assignment variable itself, McCrary (2008) suggests using the frequency count as the dependent variable in the RD setup. The idea is that manipulation of the assignment variable should result in bunching of individuals at the cutoff. In the education literature, this was shown to be an important invalidation of the RD approach (see for e.g. Urquiola and Verhoogen (2009)). In our case, we should see a jump in the number of students at the threshold of 70 or 60 marks. In column (6) of Table 3 we perform the McCrary test and find large and (in the case of the Upper Second threshold) significant jumps in the number of students. *Prima facie* this might suggest that students are manipulating their marks in order to receive better degrees.

We argue that this bunching is not the result of manipulation but is a consequence of institutional features. Figure 3 plots the histogram of the fourth, fifth and highest marks. In every case there is a clear bunching of marks at 60 and 70 even for the highest mark which is not critical for eventual degree class. This is because exam graders actively avoid giving borderline marks (i.e. 59 or 69) and either round up or down.[19] One may still worry that students who received 58 or 68 may appeal to have their script re-graded. From discussions with staff, the appeals process is arduous and rarely successful. Nonetheless we follow the literature in dealing with the potential manipulation of marks by excluding the threshold in specification checks reported in Section 4.4 (see for e.g. Almond and Doyle (2011)). This does not change our results.

4.3 Effects of Degree Class on Labor Market Outcomes

Table 4 reports the results for the effects of receiving a First Class degree compared with an Upper Second. In panel A, we compare average differences in outcomes without controlling for any covariates. There are no differences in employment in general or in the finance industry specifically. However, there are significant differences in industry wages. Using our preferred measure of mean industry log wages, a First Class receives 7 percent higher wages. Panel B includes covariates to allow for closer comparisons of students. This corresponds to Equation (2). The employment outcomes remain insignificant while the wage coefficients halve but remain significant. Finally in panel C, we instrument for First Class using a dummy variable for the fourth highest mark, as in Equation (1). Although the difference in industry mean wages remains significant at 5 percent, the conditional experience measures are insignificant suggesting that the

[19] In LSE, exams are taken anonymously and each script is graded by one internal and one external examiner. Having graded each script separately, graders convene to deliberate on the final mark.

wage differences for a First Class are not sizeable.

Table 5 reports the same specifications as Table 4 but for the Upper Second degree. Surprisingly, there are no differences in average outcomes across students without controlling for covariates in panel A. This is because of inter-departmental comparisons we are making in the absence of department fixed effects. Once we control for covariates including department by year fixed effects in panel B we observe that an Upper Second receives 4 percent higher wages than a Lower Second. An Upper Second also has a 7 percentage point (20 percent) higher probability of working in finance. Using the threshold dummy variable $1[\text{4th MARK} \geq 60]$ as an instrument for Upper Second, panel C reveals that the returns are significant and sizeable at 7 percent for mean wages and 12 percentage points (37 percent) for finance industry employment.

To interpret these results we translate the percentage differences to pounds. Using our preferred measure of wages in the specification in column (3) we find that a First Class and Upper Second are worth around £1,000 and £2,040 per annum respectively in current money.[20]

4.4 Specification Checks

Here we conduct a battery of specification tests for our benchmark models given in panels C of Table 4 and Table 5. In Table 6 we report checks for the First Class degree while Table 7 reports the same for Upper Second. Row (1) reports the benchmark results for convenience. Rows (2) to (10) report results using different bandwidth sizes (our benchmark is a 5-mark bandwidth) and rows (11) to (14) report specifications using parametric polynomial controls. In rows (14) and (15) we include controls for the sum of marks and other marks separately to show that our results are not driven by omission of other course grades. In row (16) we address the concern that our results misrepresent students who are not domiciled in UK by looking only at domiciled students. In row (17) we deal with the worry that bunching of marks around the threshold reflects manipulation.

Employment outcomes appear to be sensitive to bandwidth choice. For the First Class some specifications even suggest a negative effect on employment, e.g. rows (3) and (4). Likewise for the Upper Second degree, employment overall and in finance does not display a consistent pattern across specifications. To be conservative we interpret this as suggesting that the extensive margin is not affected by degree class. This may be due to the limited variation we have in employment and requires further investigation in future work. It also accords with the earlier findings in Di Pietro (2010) who did not find significant effects on employment. In the following sections we focus on the industry wage outcomes.

We find more consistent results for our preferred outcome of industry mean wages. Looking at industry means for First Class degrees, we find effects significant at 5 percent ranging from 2.5 to 6.8 percent with the benchmark result of 3.3 percent. For Upper Second, the range is 5.7

[20]Assuming a 40 hour week for 52 weeks for a full time worker using 23 percent CPI inflation from 2005-2012. First Class: $\exp(2.473) \times 40 \times 52 \times 1.23 \times 0.033$. Upper Second: $\exp(2.418) \times 40 \times 52 \times 1.23 \times 0.071$.

to 13 percent with the benchmark of 7.1 percent.

5 Additional Results

5.1 Statistical Discrimination by Gender and Degree Programmes

The theories of statistical discrimination are closely related to signaling and screening theories. In this section we explore differences in degree class across groups and explain this in the context of a simple model of statistical discrimination. Table 8 splits the sample by gender and estimates separate effects for males and females. We find that First Class effects are significant and positive for males at 6 percent (£1,780 a year) but insignificant and basically zero for females.[21] Upper Second effects are larger in magnitude for males but imprecisely estimated for both.Table 9 splits the sample by degree programmes. Using information on the math entry requirements, we distinguish between programmes which required at least A-level in maths and those which do not (see Table B.3). We interpret this as a measure of how quantitative the programmes are. For both First Class and Upper Second, quantitative programmes display larger and significant effects. Finally, in Table 10 we split the programmes by the number of course options available to students. This measure is weighted by department size because larger departments may mechanically offer more options. We interpret this measure as capturing how heterogenous the transcripts are across programmes and thus how noisy the degree class signal is. Programmes with less heterogenous transcripts may provide less noisy signals of ability. We find that there are no significant differences for First Class, but for Upper Second, programmes which have less course choices have larger and significant effects.

In Appendix Section A we present a simple model of statistical discrimination to rationalize these findings. Employers observe group characteristics and discriminate on the basis of ability distributions across groups. In our context, a First Class or Upper Second degree has a stronger effect if a student belongs to a group that has higher expected ability, higher variance in abilities or lower variance in the noise associated with the degree class signal.[22] Table B.4 provides summary statistics for the three group definitions we have used. We can explain the stronger effects for males and quantitative programmes as resulting from the higher mean and variances of these groups. Our interpretation of the number of course options available on programmes as a measure of the noise in the signal is supported by the smaller variance in the Upper Second sample for programmes with less options but does not explain the First Class sample.

These findings are suggestive of statistical discrimination but there could be alternative explanations. First, we are cutting the sample quite finely and these results may simply be statistical artifacts. Second, there may still be unobservable characteristics correlated with these

[21] Assuming a 40 hour week for 52 weeks for a full time worker using 23 percent CPI inflation from 2005-2012, $\exp(2.454) \times 40 \times 52 \times 1.23 \times 0.06$.

[22] Both First Class and Upper Second are positive signals because we are always comparing to the next lower class.

group characteristics that employers observe but not the econometrician. Our results would then reflect selection rather than statistical discrimination.[23] Third, there may be non-statistical forms of discrimination that generate these patterns.

Furthermore, these differences may not persist. The literature on employer learning argues that any signal used in initial labor market outcomes attenuates over time as employers discover more about ability (Altonji and Pierret 2001). An interesting research topic would be to follow students over the course of their careers to see if these group differences do, in fact, become less important.

5.2 Heterogeneity Across Ability Groups

As noted in Section 3 one shortcoming of our data is that we do not observe measures of pre-university ability. To redress this, we split programmes by their A-level entry requirements, as shown in Table B.3. There are four types of requirements measuring the grades that are needed on A-level courses with *A*AA* being the highest followed by *AAA*, *AAB* and *ABB*. A few points are worth noting. First, LSE is a selective school so these A-level grades reflect the upper-end of the national distribution and there may be little difference between the abilities of the *ABB* and *A*AA* students. Second, these grades reflect the typical offer made and there may be heterogeneity even within a programme on the actual entry grades.[24] Third, the choice of programme is an endogenous decision and this programme-level measure of ability does not distinguish between innate or acquired differences (Arcidiacono 2004).

In Table 11 we report the results of splitting our sample by ability, with high ability defined as programmes with *A*AA* or *AAA* entry requirements.[25] For the high ability group in panel A we see that the First Class and Upper Second effects are similar–4.5 percent vs 5.3 percent returns to a First Class. In panel B, the returns to an Upper Second are large and significant at 7.9 percent but the First Class coefficient is negative albeit imprecisely estimated.

If we are measuring ability correctly, these results are interesting and add to the literature on employer learning and statistical discrimination. The fact that the returns to a First Class or Upper Second are similar in the high ability group is consistent with Arcidiacono, Bayer, and Hizmo (2010) who find that ability is revealed directly for high ability compared to lower ability groups. There are two differences, however. First, they define all college graduates as high ability while we split college students further and find differences even within a relatively

[23]The difference between statistical discrimination and selection is that in the former, employers and econometricians both do not observe underlying ability and make inferences on the basis of observable factors (Weiss 1995). With selection bias, employers observe characteristics that are not observed by the econometrician and thus statistical estimates are biased by these omitted factors. In principle, the RD strategy should mitigate selection effects because we are comparing students who are close to the discontinuity.

[24]This is a particular issue in LSE with a large fraction of overseas students who may not have taken A-levels.There are entry requirements based on the international baccalaureate and these map directly into A-level grades.

[25]Table B.5 shows the correlation across the programme-level measures we have used. It shows that the variables are not perfectly correlated and are thus unlikely to be capturing the same underlying measure.

skill-homogenous group. Second, whereas they find that ability is revealed perfectly for high ability types, here we find significant albeit modest returns to degree class. If productivity were revealed perfectly for the high ability group we should find no First Class or Upper Second effects at all.

Our finding that the Upper Second matters but not the First Class for the lower ability group presents a puzzle. Going back to the simple model of statistical discrimination, an explanation could be that the First Class is a noisier signal than the Upper Second for the lower ability group. While we do not have a full explanation here, we think that this is an interesting area for future research.

6 Conclusion

In this paper we estimate the sorting effects of university degree class on initial labor market outcomes using a regression discontinuity design that exploits institutional rules governing the award of degrees. Consistent with anecdotal evidence, we find sizeable and significant effects for Upper Second degrees and positive but smaller effects for First Class degrees on wages–we find that a First Class and Upper Second are worth around £1,000 and £2,040 per annum respectively. However, we do not find significant effects on the extensive margin of employment. These results generally survive a battery of specification checks.

In additional results we explore differences across groups and find some evidence of statistical discrimination on the basis of gender and types of degree programmes. We find that signaling effects are stronger for males, quantitative degree programmes and programmes with less course choices. We interpret these findings using a simple model of statistical discrimination. When we split the sample by ability, we find that the signaling effects are similar in the high ability group but stronger for Upper Second degrees in the lower ability group. We do not have a full explanation of the differences across ability groups and propose that this is an area of interest for future research.

Overall, the evidence points to the importance of sorting in the high skills labor market. It would be interesting to study how these effects on initial labor market outcomes change over time as employers learn more about workers.

References

AIGNER, D. J., AND G. G. CAIN (1977): "Statistical Theories of Discrimination in Labor Markets," *Industrial and Labor relations review*, 30(2), 175–187.

ALMOND, D., AND J. DOYLE (2011): "After Midnight: A Regression Discontinuity Design in Length of Postpartum Hospital Stays," *American Economic Journal: Applied Economics*, 3(3), 1–34.

ALTONJI, J., AND C. PIERRET (2001): "Employer Learning and Statistical Discrimination," *Quarterly Journal of Economics*, 116(1), 313–350.

ANGRIST, J., G. IMBENS, AND D. RUBIN (1996): "Identification of Causal Effects Using Instrumental Variables," *Journal of the American Statistical Association*, 91(434), 444–472.

ANGRIST, J., AND J.-S. PISCHKE (2009): *Mostly Harmless Econometrics*. Princeton University Press.

ARCIDIACONO, P. (2004): "Ability Sorting and the Returns to College Major," *Journal of Econometrics*, 121(1), 343–375.

ARCIDIACONO, P., P. BAYER, AND A. HIZMO (2010): "Beyond Signaling and Human Capital: Education and the Revelation of Ability," *American Economic Journal: Applied Economics*, 2(4), 76–104.

ARROW, K. (1973): "The Theory of Discrimination," *Discrimination in labor markets*, 3(10).

BECKER, G. (1964): *Human Capital*. The University of Chicago Press.

BEDARD, K. (2001): "Human Capital versus Signaling Models: University Access and High School Dropouts," *Journal of Political Economy*, 109(4), 749–775.

BELMAN, D., AND J. HEYWOOD (1991): "Sheepskin Effects in the Returns to Education: An Examination of Women and Minorities," *Review of Economics and Statistics*, 73(4), 720–24.

CARPENTER, C., AND C. DOBKIN (2009): "The Effect of Alcohol Consumption on Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age," *American Economic Journal: Applied Economics*, 1(1), 164–82.

CLARK, D., AND P. MARTORELL (2010): "The Signalling Value of a High School Diploma," *Princeton University Industrial Relations Section Working Paper 557*.

DI PIETRO, G. (2010): "The Impact of Degree Class on the First Class Destinations of Graduates: A Regression Discontinuity Approach," *IZA Discussion Papers 4836*.

FAN, J., AND I. GIJBELS (1996): *Local Polynomial Modelling and its Applications*. Chapman and Hall.

FARBER, H., AND R. GIBBONS (1996): "Learning and Wage Dynamics," *Quarterly Journal of Economics*, 111(4), 1007–1047.

HAHN, J., P. TODD, AND W. VAN DER KLAAUW (2001): "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 69(1), 20109.

HOLLAND, P. (1986): "Statistics and Causal Inference," *Journal of the American Statistical Association*, 81(396), 945–960.

HUNGERFORD, T., AND G. SOLON (1987): "Sheepskin Effects in the Returns to Education," *Review of Economics and Statistics*, 69(1), 175–177.

IMBENS, G., AND J. ANGRIST (1994): "Identification and Estimation of Local Average Treatment Effects," *Econometrica*, 61(2), 467–476.

IMBENS, G., AND T. LEMIEUX (2008): "Regression discontinuity designs: A guide to practice," *Journal of Econometrics*, 142(2), 615–635.

IMBENS, G., AND J. M. WOOLDRIDGE (2009): "Recent Developments in the Econometrics of Program Evaluation," *Journal of Economic Literature*, 47(1), 5–86.

IRELAND, N., R. A. NAYLOR, J. SMITH, AND S. TELHAJ (2009): "Educational Returns, Ability Composition and Cohort Effects: Theory and Evidence for Cohorts of Early-Career UK Graduates," *Centre for Economic Performance Discussion Papers*.

JAEGER, D., AND M. PAGE (1996): "Degrees Matter: New Evidence on Sheepskin Effects in the Returns to Education," *Review of Economics and Statistics*, 78(4), 733–740.

LANG, K., AND D. KROPP (1986): "Human Capital versus Sorting: The Effects of Compulsory Attendance Laws," *Quarterly Journal of Economics*, 101(3), 609–624.

LANGE, F. (2007): "The Speed of Employer Learning," *Journal of Labor Economics*, 25, 1–35.

LAYARD, R., AND G. PSACHAROPOULOS (1974): "The Screening Hypothesis and the Returns to Education," *Journal of Political Economy*, 82(5), 985–98.

LEE, D., AND D. CARD (2008): "Regression Discontinuity Inference with Specification Error," *Journal of Econometrics*, 142(2), 655–674.

LEE, D., AND T. LEMIEUX (2010): "Regression Discontinuity Designs in Economics," *Journal of Economic Literature*, 48(2), 281–355.

LI, Q., AND J. RACINE (2007): *Nonparametric Econometrics*. Princeton University Press.

McCrary, J. (2008): "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test," *Journal of Econometrics*, 142(2), 698–714.

McKnight, A., R. Naylor, and J. Smith (2007): "Sheer Class? Returns to educational performance : evidence from UK graduates first destination labour market outcomes," *The Warwick Economics Research Paper Series*.

Mincer, J. (1974): *Schooling, Experience, and Earnings*. Columbia University Press.

Phelps, E. (1972): "The Statistical Theory of Racism and Sexism," *American Economic Review*, 62(4), 659–661.

Riley, J. (1979): "Testing the Educational Screening Hypothesis," *Journal of Political Economy*, 87(5), 227–252.

Spence, M. (1973): "Job Market Signalling," *Quarterly Journal of Economics*, 87(3), 355–374.

Stiglitz, J. (1975): "The Theory of Screening, Education, and the Distribution of Income," *American Economic Review*, 65(3), 283–300.

Stock, J., J. Wright, and M. Yogo (2002): "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business and Economic Statistics*, 20(4), 518–529.

Thistlethwaite, D., and D. T. Campbell (1960): "Regression-Discontinuity Analysis: An Alternative to the Ex Post Facto Experiment," *Journal of Educational Psychology*, 51(6), 30917.

Tyler, J., R. Murnane, and J. Willet (2002): "Estimating the Labor Market Signaling value of the GED," *Quarterly Journal of Economics*, 115(2), 431–468.

Urquiola, M., and E. A. Verhoogen (2009): "Class-Size Caps, Sorting, and the Regression-Discontinuity Design," *American Economic Review*, 99(1), 179215.

Weiss, A. (1995): "Human Capital and Sorting Models," *Journal of Economic Perspectives*, 9(4), 133–154.

Wolpin, K. (1977): "Education and Screening," *American Economic Review*, 67(5), 949–958.

Tables and Figures

Table 1: Descriptive Statistics

		Surveyed				
	No. of obs	Total	First Class sample	Upper Second sample	Not surveyed	Difference (1) - (4)
		(1)	(2)	(3)	(4)	(5)
Number of observations	5912	2649	1136	1406	3263	
Female	5912	0.453	0.448	0.476	0.510	-0.0576***
Age	5912	22.06	22.03	22.06	22.10	-0.0358
UK national	5912	0.604	0.586	0.656	0.416	0.187***
Resat any course	5912	0.104	0.0317	0.132	0.105	-0.00131
Failed any course	5912	0.0615	0.0238	0.0782	0.0631	-0.00160
First Class	5912	0.234	0.387	0	0.249	-0.0154
Upper Second	5912	0.573	0.613	0.720	0.530	0.0431***
Lower Second	5912	0.193	0	0.280	0.221	-0.0277**
4th highest mark	5912	65.10	68.63	61.31	65.08	0.0148
1(4th mark ≥ 70)	5912	0.242	0.406	0	0.253	-0.0106
1(4th mark ≥ 60)	5912	0.834	1	0.770	0.806	0.0272**
Employed	2649	0.849	0.864	0.832		
Finance industry	2244	0.381	0.420	0.318		
Industry mean log wages (2005£)						
Industry mean	2244	2.454	2.473	2.418		
		(0.239)	(0.228)	(0.246)		
College with 1 year experience	2244	2.142	2.155	2.113		
		(0.184)	(0.179)	(0.190)		
College with 3 years experience	2244	2.338	2.350	2.311		
		(0.179)	(0.175)	(0.186)		
College with 5 years experience	2244	2.481	2.495	2.452		
		(0.186)	(0.181)	(0.192)		
Industry mean excluding finance industry	1389	2.378	2.398	2.351		
		(0.233)	(0.221)	(0.238)		

Notes: This table shows means and standard deviations in brackets where applicable. Surveyed students are respondents to the Destination of Leavers from Higher Education (DLHE) survey conducted six months after a student graduates. Students who were not in the survey are included for comparison. The First Class sample includes surveyed students who received either a First Class or Upper Second degree and whose fourth highest mark is within 5 marks of 70. The Upper Second sample includes surveyed students who received either an Upper Second or Lower Second degree and whose fourth highest mark is within 5 marks of 60. *First Class, Upper Second* and *Lower Second* are dummy variables for degree class. *4th highest mark* is the fourth highest mark received by the student among all full-unit equivalent courses taken. *1(4th mark ≥ 70)* and *1(4th mark ≥ 60)* are dummy variables for the fourth highest mark being at least 70 or 60, respectively. *Employed* is an indicator for whether a student is in employment 6 months after graduation. Self-employment, voluntary work and further studies are not considered employment. *Finance industry* is an indicator for working in the finance industry. *Industry mean log wages* are measures of hourly wages in two-digit SIC industry × year × gender cells. Two-digit SIC industry wage data is taken from the Labor Force Survey and rebased to 2005£.

Table 2: First Stage and Reduced Form Regressions of Labor Market Outcomes on Instruments for First Class and Upper Second Degrees

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: First Class discontinuity								
				Industry mean log wages				
	First Class	Employed	Finance industry	Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
1(4th mark ≥ 70)	0.67***	0.0074	0.0066	0.022	0.014	0.0091	0.012	0.035
	(0.12)	(0.034)	(0.054)	(0.014)	(0.013)	(0.012)	(0.011)	(0.023)
Observations	1,136	1,136	978	978	978	978	978	567
R-squared	0.803	0.205	0.255	0.606	0.437	0.405	0.466	0.496
First-stage F-stat	29.2							
Panel B: Upper Second discontinuity								
				Industry mean log wages				
	Upper Second	Employed	Finance industry	Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
1(4th mark ≥ 60)	0.67***	-0.024	0.080	0.048**	0.036**	0.046**	0.032*	0.042*
	(0.078)	(0.030)	(0.050)	(0.020)	(0.015)	(0.016)	(0.016)	(0.019)
Observations	1,406	1,406	1,168	1,168	1,168	1,168	1,168	796
R-squared	0.722	0.103	0.203	0.484	0.353	0.321	0.368	0.405
First-stage F-stat	74.8							

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks. Each cell reports a different regression. All regressions are estimated by OLS. All regressions include female dummies, age and age squared, dummies for being a UK national, dummies for having resat or failed any course, 15 dummies for department, 5 year dummies and 75 dummies for department × year interactions. Column (1) reports the first-stage regression of degree class on an indicator for marks crossing the relevant cutoff. The first stage F-stat for excluded instruments is reported in the last row of each panel.

Table 3: Testing the Randomization of Instruments Around the First Class and Upper Second Discontinuities

	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Age	UK national	Resat any course	Failed any course	No. of students in each mark
Panel A: First Class discontinuity						
1(4th mark $\geq$ 70)	-0.00069	-0.16*	0.012	-0.00072	-0.0088	62.8
	(0.055)	(0.071)	(0.060)	(0.022)	(0.011)	(40.0)
Observations	1136	1136	1136	1136	1136	1136
Panel B: Upper Second discontinuity						
1(4th mark $\geq$ 60)	0.10**	0.12	-0.031	0.041	0.0022	80.8**
	(0.036)	(0.38)	(0.066)	(0.054)	(0.064)	(31.9)
Observations	1406	1406	1406	1406	1406	1406

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks. Each cell reports a different regression. All regressions are estimated by OLS. All regressions include covariates, 15 dummies for department, 5 year dummies and 75 dummies for department × year interactions.

Table 4: The Effects of Obtaining a First Class Degree Compared to an Upper Second Degree on Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Industry mean log wages				
	Employed	Finance industry	Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
Panel A: OLS without any covariates							
First Class	0.019	0.069	0.070***	0.062***	0.061***	0.062***	0.077***
	(0.023)	(0.042)	(0.015)	(0.013)	(0.012)	(0.013)	(0.020)
Observations	1136	978	978	978	978	978	567
Panel B: OLS							
First Class	-0.022	0.013	0.037***	0.033***	0.035***	0.030***	0.052***
	(0.019)	(0.035)	(0.0068)	(0.0074)	(0.0081)	(0.0072)	(0.013)
Observations	1136	978	978	978	978	978	567
Panel C: RD							
First Class	0.011	0.0099	0.033**	0.021	0.014	0.018	0.054**
	(0.045)	(0.074)	(0.016)	(0.015)	(0.015)	(0.014)	(0.024)
Observations	1136	978	978	978	978	978	567

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks. Each cell reports a different regression. All regressions include female dummies, age and age squared, dummies for being a UK national, dummies for having resat or failed any course, 15 dummies for department, 5 year dummies and 75 dummies for department × year interactions. See notes to Table 1 for descriptions of variables.

Table 5: The Effects of Obtaining an Upper Second Degree Compared to a Lower Second Degree on Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Industry mean log wages				
	Employed	Finance industry	Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
Panel A: OLS without any covariates							
Upper Second	-0.0040	0.029	0.020	0.0011	0.0014	0.0050	-0.0066
	(0.015)	(0.022)	(0.011)	(0.013)	(0.015)	(0.012)	(0.015)
Observations	1406	1168	1168	1168	1168	1168	796
Panel B: OLS							
Upper Second	0.027	0.069**	0.040***	0.025**	0.027**	0.028**	0.028**
	(0.015)	(0.030)	(0.0085)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	1406	1168	1168	1168	1168	1168	796
Panel C: RD							
Upper Second	-0.035	0.12**	0.071***	0.052***	0.067***	0.048**	0.063**
	(0.043)	(0.058)	(0.024)	(0.019)	(0.019)	(0.019)	(0.026)
Observations	1406	1168	1168	1168	1168	1168	796

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks. Each cell reports a different regression. All regressions include female dummies, age and age squared, dummies for being a UK national, dummies for having resat or failed any course, 15 dummies for department, 5 year dummies and 75 dummies for department × year interactions. See notes to Table 1 for descriptions of variables.

Table 6: Specification Checks for First Class Degree

				Industry mean log wages				
		Employed	Finance industry	Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
(1)	Benchmark	0.011	0.0099	0.033**	0.021	0.014	0.018	0.054**
		(0.045)	(0.074)	(0.016)	(0.015)	(0.015)	(0.014)	(0.024)
		1136	978	978	978	978	978	567
(2)	1 mark above and below disc.	0.033	0.19	0.018	0.016	0.023	0.0058	-0.12
		(0.12)	(0.21)	(0.058)	(0.050)	(0.052)	(0.052)	(0.12)
		310	270	270	270	270	270	150
(3)	2 marks above and below disc.	0.15	0.73*	0.20*	0.014	0.037	0.049	-0.21
		(0.28)	(0.40)	(0.11)	(0.080)	(0.091)	(0.085)	(1.00)
		537	469	469	469	469	469	252
(4)	3 marks above and below disc.	-0.16**	0.25*	0.042**	0.010	0.014	0.0063	0.0089
		(0.065)	(0.14)	(0.019)	(0.017)	(0.017)	(0.021)	(0.071)
		730	629	629	629	629	629	345
(5)	4 marks above and below disc.	-0.12***	0.21***	0.068***	0.050***	0.038**	0.047***	0.046*
		(0.026)	(0.057)	(0.017)	(0.015)	(0.015)	(0.014)	(0.027)
		906	774	774	774	774	774	426
(6)	6 marks above and below disc.	-0.017	0.0091	0.044***	0.031***	0.031**	0.027***	0.074***
		(0.030)	(0.053)	(0.011)	(0.011)	(0.013)	(0.0099)	(0.021)
		1346	1147	1147	1147	1147	1147	671
(7)	7 marks above and below disc.	-0.012	-0.0096	0.025*	0.015	0.015	0.012	0.054***
		(0.028)	(0.037)	(0.013)	(0.012)	(0.012)	(0.010)	(0.018)
		1552	1322	1322	1322	1322	1322	790
(8)	8 marks above and below disc.	-0.022	0.0048	0.038***	0.032**	0.032**	0.029**	0.061***
		(0.024)	(0.037)	(0.013)	(0.013)	(0.013)	(0.013)	(0.017)
		1742	1478	1478	1478	1478	1478	884
(9)	9 marks above and below disc.	-0.025	0.038	0.051***	0.045***	0.046***	0.044***	0.071***
		(0.024)	(0.043)	(0.0089)	(0.010)	(0.010)	(0.011)	(0.013)
		1894	1602	1602	1602	1602	1602	953
(10)	10 marks above and below disc.	-0.018	0.011	0.056***	0.049***	0.050***	0.047***	0.080***
		(0.025)	(0.043)	(0.0073)	(0.0082)	(0.0087)	(0.0088)	(0.015)
		2048	1735	1735	1735	1735	1735	1045
(11)	2nd order polynomial	0.0093	0.054	0.043***	0.033***	0.026**	0.030**	0.058**
		(0.037)	(0.055)	(0.013)	(0.013)	(0.013)	(0.012)	(0.024)
		1136	978	978	978	978	978	567
(12)	3rd order polynomial	-0.0057	0.11	0.049*	0.032	0.016	0.032	0.010
		(0.063)	(0.13)	(0.026)	(0.030)	(0.029)	(0.027)	(0.033)
		1136	978	978	978	978	978	567
(13)	4th order polynomial	-0.13***	0.20**	0.051*	0.029	0.015	0.026	0.011
		(0.029)	(0.093)	(0.029)	(0.034)	(0.033)	(0.032)	(0.037)
		1136	978	978	978	978	978	567
(14)	5th order polynomial	-0.086*	0.025	-0.0019	-0.026	-0.036	-0.024	-0.0072
		(0.045)	(0.14)	(0.033)	(0.047)	(0.044)	(0.040)	(0.060)
		1136	978	978	978	978	978	567

(Continued)

		Employed	Finance industry	Industry mean log wages: Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
(14)	Including controls	0.0095	0.0096	0.032**	0.020	0.013	0.017	0.052**
	for sum of marks	(0.044)	(0.073)	(0.015)	(0.015)	(0.015)	(0.013)	(0.022)
		1136	978	978	978	978	978	567
(15)	Including controls	0.011	0.021	0.034**	0.024	0.017	0.020	0.051**
	for other marks	(0.045)	(0.073)	(0.015)	(0.015)	(0.015)	(0.014)	(0.023)
		1136	978	978	978	978	978	567
(16)	UK domicile sample	-0.015	0.14	0.031	0.047**	0.035*	0.039**	-0.0072
		(0.063)	(0.094)	(0.025)	(0.021)	(0.020)	(0.019)	(0.040)
		701	585	585	585	585	585	367
(17)	Excluding marks	-0.0016	0.0078	0.048***	0.035**	0.036***	0.028**	0.078***
	around disc.	(0.062)	(0.094)	(0.011)	(0.014)	(0.012)	(0.012)	(0.017)
		922	791	791	791	791	791	462

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks. This table reports specification checks of the benchmark model in Table 4, panel C. Each cell reports a different regression where the coefficients on *First Class* are reported in the first lines, standard errors in brackets and number of observations in the third lines.

Table 7: Specification Checks for Upper Second Degree

				Industry mean log wages				
		Employed	Finance industry	Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
(1)	Benchmark	-0.035	0.12**	0.071***	0.052***	0.067***	0.048**	0.063**
		(0.043)	(0.058)	(0.024)	(0.019)	(0.019)	(0.019)	(0.026)
		1406	1168	1168	1168	1168	1168	796
(2)	1 mark above and below disc.	-0.0041	0.0056	0.095**	0.046	0.063	0.042	0.19***
		(0.10)	(0.12)	(0.047)	(0.042)	(0.042)	(0.041)	(0.053)
		374	310	310	310	310	310	211
(3)	2 marks above and below disc.	-0.14**	0.022	0.054	-0.017	0.0076	-0.016	0.14
		(0.070)	(0.088)	(0.053)	(0.037)	(0.044)	(0.034)	(0.096)
		665	546	546	546	546	546	367
(4)	3 marks above and below disc.	-0.11*	-0.014	0.082***	0.043	0.064**	0.044	0.11**
		(0.063)	(0.079)	(0.031)	(0.028)	(0.028)	(0.029)	(0.048)
		922	759	759	759	759	759	517
(5)	4 marks above and below disc.	-0.029	0.068	0.093***	0.061**	0.075**	0.065**	0.100***
		(0.060)	(0.074)	(0.035)	(0.031)	(0.030)	(0.031)	(0.030)
		1160	954	954	954	954	954	648
(6)	6 marks above and below disc.	-0.018	0.13**	0.080***	0.059**	0.072***	0.054**	0.067**
		(0.038)	(0.064)	(0.030)	(0.025)	(0.025)	(0.024)	(0.028)
		1582	1310	1310	1310	1310	1310	877
(7)	7 marks above and below disc.	-0.0016	0.086	0.084***	0.056***	0.066***	0.052***	0.072***
		(0.032)	(0.060)	(0.026)	(0.021)	(0.021)	(0.020)	(0.023)
		1750	1448	1448	1448	1448	1448	962
(8)	8 marks above and below disc.	-0.030	0.11**	0.064**	0.042*	0.051**	0.038*	0.035
		(0.035)	(0.056)	(0.028)	(0.022)	(0.023)	(0.021)	(0.039)
		1925	1602	1602	1602	1602	1602	1047
(9)	9 marks above and below disc.	-0.011	0.095*	0.057**	0.033	0.045**	0.033*	0.033
		(0.037)	(0.054)	(0.026)	(0.021)	(0.021)	(0.020)	(0.032)
		1964	1637	1637	1637	1637	1637	1069
(10)	10 marks above and below disc.	-0.014	0.055	0.047*	0.021	0.030	0.021	0.024
		(0.032)	(0.058)	(0.024)	(0.021)	(0.022)	(0.020)	(0.027)
		2003	1672	1672	1672	1672	1672	1092
(11)	2nd order polynomial	-0.024	0.081	0.084***	0.061***	0.076***	0.055***	0.078***
		(0.041)	(0.075)	(0.026)	(0.018)	(0.019)	(0.017)	(0.025)
		1406	1168	1168	1168	1168	1168	796
(12)	3rd order polynomial	0.0060	-0.040	0.12***	0.090***	0.11***	0.080***	0.14***
		(0.053)	(0.076)	(0.033)	(0.023)	(0.026)	(0.024)	(0.028)
		1406	1168	1168	1168	1168	1168	796
(13)	4th order polynomial	-0.036	-0.11	0.12***	0.071**	0.095***	0.063*	0.16***
		(0.066)	(0.10)	(0.046)	(0.033)	(0.033)	(0.035)	(0.042)
		1406	1168	1168	1168	1168	1168	796
(14)	5th order polynomial	-0.035	-0.17	0.13***	0.069**	0.10***	0.053	0.18***
		(0.067)	(0.10)	(0.045)	(0.033)	(0.035)	(0.033)	(0.047)
		1406	1168	1168	1168	1168	1168	796

(Continued)

				Industry mean log wages				
		Employed	Finance industry	Industry mean	College with 1 year experience	College with 3 years experience	College with 5 years experience	Industry mean excl. finance
(14)	Including controls	-0.037	0.11*	0.065**	0.047**	0.063***	0.043**	0.060**
	for sum of marks	(0.042)	(0.059)	(0.026)	(0.020)	(0.020)	(0.020)	(0.027)
		1406	1168	1168	1168	1168	1168	796
(15)	Including controls	-0.043	0.12*	0.071***	0.052***	0.067***	0.046**	0.062**
	for other marks	(0.051)	(0.060)	(0.026)	(0.020)	(0.020)	(0.020)	(0.027)
		1406	1168	1168	1168	1168	1168	796
(16)	UK domicile sample	-0.083*	0.033	0.091***	0.076***	0.087***	0.064***	0.10***
		(0.042)	(0.059)	(0.023)	(0.021)	(0.023)	(0.022)	(0.032)
		974	792	792	792	792	792	574
(17)	Excluding marks	-0.036	0.21***	0.077***	0.055***	0.068***	0.056***	0.055*
	around disc.	(0.040)	(0.033)	(0.022)	(0.015)	(0.014)	(0.017)	(0.029)
		1182	978	978	978	978	978	654

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks. This table reports specification checks of the benchmark model in Table 5, panel C. Each cell reports a different regression where the coefficients on *Upper Second* are reported in the first lines, standard errors in brackets and number of observations in the third lines.

Table 8: RD Estimates by Gender

	(1) Industry mean	(2) College with 1 year experience	(3) College with 3 years experience	(4) College with 5 years experience	(5) Industry mean excl. finance
Panel A: First Class Degree					
Male					
First Class	0.059***	0.048***	0.048***	0.048***	0.054
	(0.013)	(0.013)	(0.013)	(0.013)	(0.050)
Observations	549	549	549	549	290
Female					
First Class	-0.022	-0.032	-0.032	-0.028	-0.034
	(0.029)	(0.024)	(0.023)	(0.022)	(0.057)
Observations	429	429	429	429	277
Panel B: Upper Second Degree					
Male					
Upper Second	0.084	0.081	0.089*	0.077	0.082
	(0.059)	(0.050)	(0.049)	(0.050)	(0.060)
Observations	618	618	618	618	397
Female					
Upper Second	0.052	0.034	0.036	0.029	0.062
	(0.042)	(0.041)	(0.037)	(0.038)	(0.075)
Observations	550	550	550	550	399

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks

Table 9: RD Estimates by Programme Admissions Math Requirements

	(1) Industry mean	(2) College with 1 year experience	(3) College with 3 years experience	(4) College with 5 years experience	(5) Industry mean excl. finance
Panel A: First Class Degree					
At least A level maths					
First Class	0.063***	0.045**	0.039**	0.039	0.12***
	(0.015)	(0.021)	(0.019)	(0.024)	(0.047)
Observations	576	576	576	576	259
No math requirement					
First Class	0.038	0.0022	-0.0023	0.0029	0.034
	(0.036)	(0.038)	(0.041)	(0.037)	(0.031)
Observations	402	402	402	402	308
Panel B: Upper Second Degree					
At least A level maths					
Upper Second	0.15***	0.11***	0.12***	0.091***	0.17*
	(0.051)	(0.030)	(0.031)	(0.028)	(0.10)
Observations	550	550	550	550	304
No math requirement					
Upper Second	-0.0042	-0.011	0.0049	-0.0036	-0.0066
	(0.042)	(0.032)	(0.031)	(0.036)	(0.031)
Observations	618	618	618	618	492

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks.

Table 10: RD Estimates by Number of Course Options

	(1) Industry mean	(2) College with 1 year experience	(3) College with 3 years experience	(4) College with 5 years experience	(5) Industry mean excl. finance
Panel A: First Class Degree					
Degree programme has less course choices than median					
First Class	0.024	0.0092	-0.0046	-0.000027	0.055
	(0.066)	(0.047)	(0.047)	(0.046)	(0.082)
Observations	458	458	458	458	288
Degree programme has more course choices than median					
First Class	0.043	0.027	0.026	0.026	0.071*
	(0.030)	(0.022)	(0.021)	(0.022)	(0.041)
Observations	520	520	520	520	279
Panel B: Upper Second Degree					
Degree programme has less course choices than median					
Upper Second	0.12***	0.086***	0.10***	0.084**	0.093**
	(0.038)	(0.032)	(0.032)	(0.035)	(0.037)
Observations	633	633	633	633	463
Degree programme has more course choices than median					
Upper Second	0.0034	0.021	0.036	0.014	-0.027
	(0.023)	(0.023)	(0.024)	(0.023)	(0.032)
Observations	535	535	535	535	333

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks.

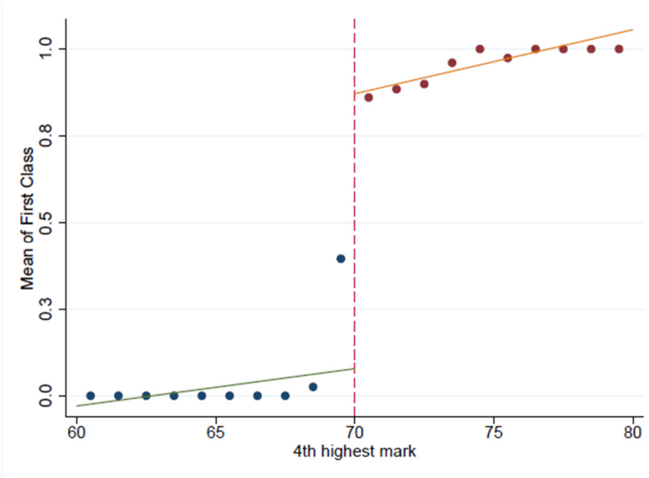
Table 11: RD Estimates by Ability Groups

	(1) Industry mean	(2) College with 1 year experience	(3) College with 3 years experience	(4) College with 5 years experience	(5) Industry mean excl. finance
Panel A: Higher ability, A*AA or AAA requirements for A levels or equivalent					
First Class	0.045***	0.032**	0.031**	0.030**	0.063**
	(0.015)	(0.015)	(0.014)	(0.015)	(0.024)
Observations	748	748	748	748	414
Upper Second	0.053*	0.035	0.052**	0.028	0.048
	(0.028)	(0.023)	(0.024)	(0.020)	(0.035)
Observations	770	770	770	770	487
Panel B: Lower ability, AAB or ABB requirements for A levels or equivalent					
First Class	-0.033	-0.036	-0.068	-0.051	0.018
	(0.091)	(0.063)	(0.062)	(0.062)	(0.098)
Observations	230	230	230	230	153
Upper Second	0.079**	0.074***	0.088***	0.073***	0.057
	(0.031)	(0.024)	(0.021)	(0.027)	(0.045)
Observations	398	398	398	398	309

Notes: ***, **, * significant at the 1, 5 and 10 percent level. Standard errors are clustered by marks.

Figure 1: Expected Degree Classification and Fourth Highest Marks

(a) Expected First Class degree, 10 marks above and below 70



(b) Expected Upper Second degree, 10 marks above and below 60

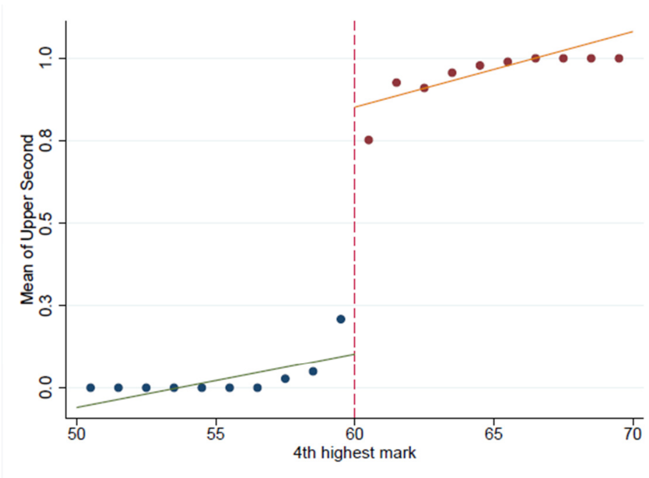


Figure 2: Counting Compliers

(a) Schematic

		Assignment variable is above threshold: **0**	Assignment variable is above threshold: **1**
Degree Class	**0**	Never takers + Compliers	Never takers
	1	Always takers	Always takers + Compliers

(b) First Class sample (N = 1,136)

		4th highest mark is above 70: **0**	4th highest mark is above 70: **1**
First Class	**0**	652	44
	1	23	417

Always Takers = 3% = 23/(23+652)
Never Takers = 10% = 44/(44+417)
Compliers = 87%

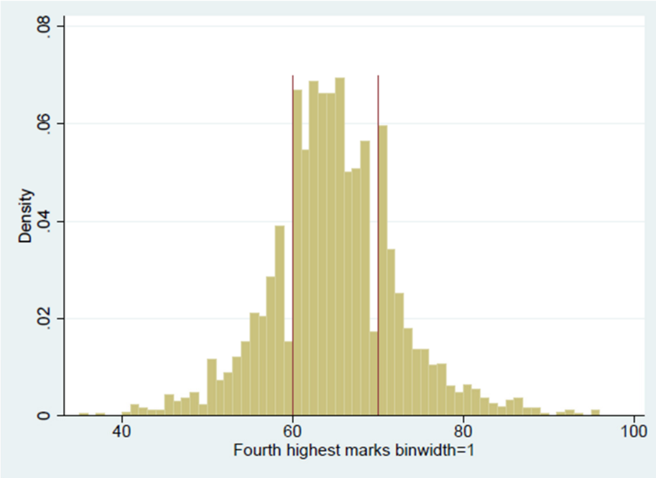
(c) Upper Second sample (N = 1,406)

		4th highest mark is above 60: **0**	4th highest mark is above 60: **1**
Upper Second	**0**	307	87
	1	16	996

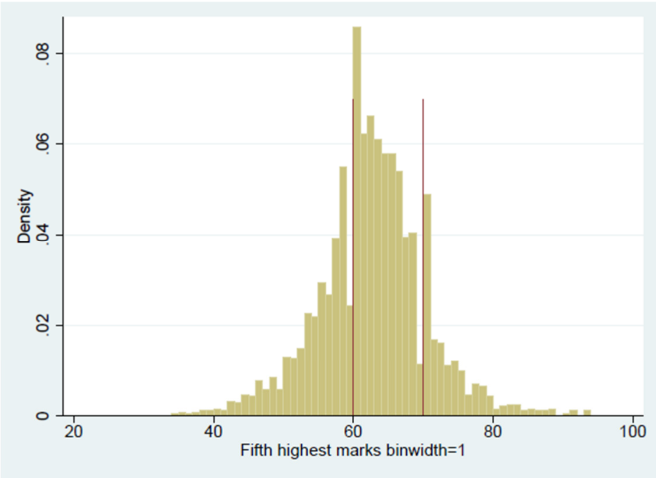
Always Takers = 5% = 16/(16+307)
Never Takers = 8% = 87/(87+996)
Compliers = 87%

Figure 3: Histogram of Marks

(a) Fourth highest marks



(b) Fifth highest marks



(c) Highest marks

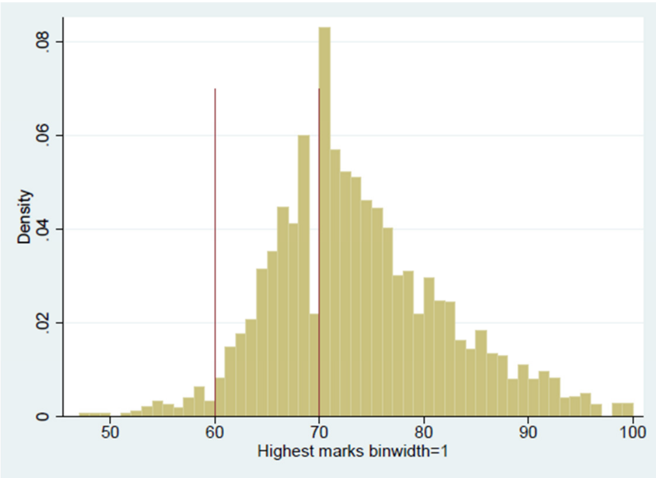
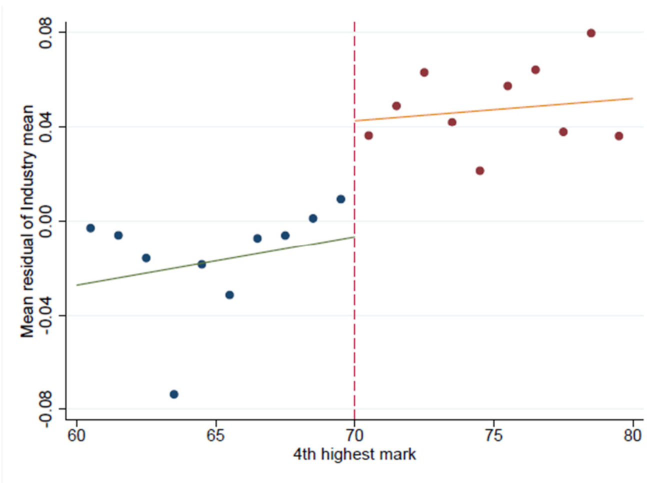
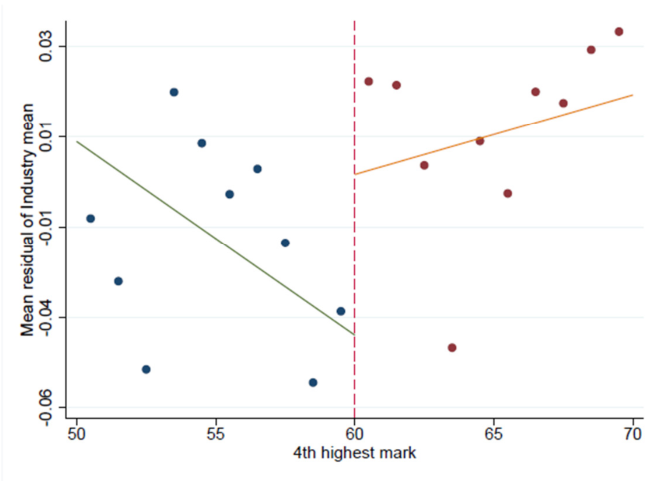


Figure 4: Expected Industry Mean Log Wages on Fourth Highest Marks

(a) 10 marks above and below 70



(b) 10 marks above and below 60



Appendices

A Simple Model of Statistical Discrimination

Statistical discrimination is closely related to signaling and screening theories of education (Phelps 1972, Arrow 1973, Aigner and Cain 1977). In statistical discrimination, employers differentiate across otherwise identical workers on the basis of observable group membership, for e.g. race or gender. More recent versions of these models introduce the dynamics of learning (Farber and Gibbons 1996, Lange 2007, Altonji and Pierret 2001, Arcidiacono, Bayer, and Hizmo 2010).

In this section we interpret a simple model of statistical discrimination in the context of the signaling value of degree class. Our exposition follows Aigner and Cain (1977) and Belman and Heywood (1991) (see also Hungerford and Solon (1987) and Jaeger and Page (1996)).

Suppose employers observe a noisy signal of student ability–in our case the signal is the fourth highest mark and resulting degree class. That is, the employer observes

$$y = q + u$$

where y is the fourth highest mark, q is unobserved ability and u is a normally distributed mean zero random variable uncorrelated with q. Students know their own ability but employers only see y and know that q is distributed with mean $\bar{q}$ and some variance σ_q. Therefore, employers solve a signal extraction problem:

$$E[q|y] = (1-\gamma)\bar{q} + \gamma y$$

which is a regression of q on y where linearity follows from the normality assumption. The regression coefficient can be written as:

$$\gamma = \frac{\sigma_q}{\sigma_q + \sigma_u}$$

where σ_u is the variance of the noise term.

Additionally, employers observe a student's group–in our case gender and type of degree programme. Now suppose there are two groups, A and B, with means and variances $\bar{q}^A$, $\bar{q}^B$, σ^A and σ^B. For any observed signal y, the difference in predicted ability between groups is:

$$\begin{aligned} E[q|y,A] - E[q|y,B] =& (1-\gamma^A)\bar{q}^A + \gamma^A y - (1-\gamma^B)\bar{q}^B - \gamma^B y \\ =& (\bar{q}^A - \bar{q}^B)(1-\gamma^B) + (y - \bar{q}^A)(\gamma^A - \gamma^B) \end{aligned}$$

This formula gives us three predictions that we corroborate with the data. Given y,

$E[q|y, A] - E[q|y, B] > 0$, if

1. $\bar{q}^A - \bar{q}^B > 0$
2. $\sigma_q^A - \sigma_q^B > 0$ and $y > \bar{q}$
3. $\sigma_u^A - \sigma_u^B < 0$ and $y > \bar{q}$.

In the data we interpret y as the fourth highest mark so $\bar{q} = E[y]$. The total variance can be calculated as $\sigma_y = \sigma_q + \sigma_u$ but we do not observe σ_q or σ_u separately. Because we do not observe σ_u we cannot recover the exact importance of each factor in determining group differences. Our application of the model to the data should necessarily be interpreted loosely. When we translate the predictions to the data, at any given mark and degree class, a student from group A has a higher predicted ability than an otherwise identical student from group B if group A has:

1. higher expected abilities;
2. higher variance in abilities and y is a positive signal;
3. lower variance in the noise term and y is a positive signal.

In our context, a positive signal is receipt of the higher degree class. Both First Class and Upper Second are positive signals because we are always comparing to the next lower class. As discussed in Section 5.1 we define groups by gender and degree programmes and find results supportive of this simple model statistical discrimination.

B Appendix Tables

Table B.1: Mapping From Course Marks to Final Degree Class

Final degree class	Course grade requirements
First Class Honors	5 marks of 70 or above or
	4 marks of 70 or above and aggregate marks of at least 590
Upper Second Class	5 marks of 60 or above or
	4 marks of 60 or above and aggregate marks of at least 515
Lower Second Class	5 marks of 50 or above or
	4 marks of 50 or above and aggregate marks of at least 440

Notes: Institutional rules governing award of degree class taken from
http://www.lse.ac.uk/resources/calendar/academicRegulations/BA-BScDegrees.htm

Table B.2: Top 15 Industries Ranked by Total Share of Employment

Industry (LFS, SIC two-digit)	Industry mean log wages (2005£)	Share of employment: Total	First Class	Upper Second	Lower Second and below
financial ex insurance and pension	2.58	38.10	47.90	36.28	31.00
legal and accounting activities	2.52	16.22	21.21	14.43	15.15
public admin, defence, social sec	2.35	7.44	5.85	8.52	6.29
head offices; management consultanc	2.51	6.51	8.04	6.23	5.36
insurance, reinsurance and pension	2.45	4.55	4.75	3.79	6.53
education	2.36	3.88	2.01	4.97	3.03
advertising and market research	2.48	2.01	1.10	2.37	2.10
security & investigation activities	1.99	1.74	0.37	2.05	2.56
office admin, support and other	2.15	1.52	0.18	1.58	3.03
retail trade, except vehicles	1.88	1.47	0.73	1.58	2.10
auxiliary to financial and insuranc	2.55	1.34	1.46	1.50	0.70
other prof, scientific and technica	2.22	1.07	0.73	1.26	0.93
publishing activities	2.40	0.85	0.37	0.87	1.40
employment activities	2.24	0.80	0.18	1.18	0.47
human health activities	2.24	0.80	0.18	0.87	1.40

Notes: This table shows the industry mean log wages for all skills and experience groups. Industries are ranked by total share of employment.

Table B.3: A-Level Admissions Requirements for Degree Programmes

department	programme	No. of students	More than median no. of options	Math required	A-level requirements
Accounting	BSc in Accounting and Finance	367	1	0	AAA
Anthropology	BA in Anthropology and Law	20	0	0	AAB
Anthropology	BA in Social Anthropology	26	0	0	AAB
Anthropology	BSc in Social Anthropology	63	0	0	AAB
Economic History	BSc in Economic History	72	0	0	AAB
Economic History	BSc in Economic History with Economics	8	0	1	AAB
Economic History	BSc in Economics and Economic History	30	0	1	AAB
Economics	BSc in Econometrics and Mathematical Economics	23	0	1	A*AA
Economics	BSc in Economics	510	1	1	A*AA
Economics	BSc in Economics with Economic History	11	0	1	A*AA
Employment Relations and Organisational Behaviour	BSc in Human Resource Management and Employment Relations	32	0	0	AAB
Employment Relations and Organisational Behaviour	BSc in Industrial Relations and Human Resource Management	7	0	0	AAB
Geography & Environment	BA in Geography	65	0	0	AAB
Geography & Environment	BSc in Environmental Policy	12	0	0	AAB
Geography & Environment	BSc in Environmental Policy with Economics	12	0	1	AAB
Geography & Environment	BSc in Geography and Population Studies	2	0	0	AAB
Geography & Environment	BSc in Geography with Economics	53	0	1	AAB
Government	BSc in Government	68	1	0	AAA
Government	BSc in Government and Economics	96	1	1	AAA
Government	BSc in Government and History	48	0	0	AAA
International History	BA in History	89	1	0	AAA
International History	BSc in International Relations and History	60	0	0	AAA
International Relations	BSc in International Relations	132	1	0	AAA
Management Science Group	BSc in Management Sciences	78	0	1	AAB
Managerial Economics and Strategy Group	BSc in Management	132	0	1	AAB
Mathematics	BSc in Mathematics and Economics	126	0	1	A*AA
Philosophy	BA in Philosophy	2	0	0	AAA
Philosophy	BSc in Philosophy	5	0	0	AAA
Philosophy	BSc in Philosophy and Economics	70	0	1	AAA
Philosophy	BSc in Philosophy, Logic and Scientific Method	30	0	0	AAA
Social Policy	BSc in Population Studies	1	0	0	ABB
Social Policy	BSc in Social Policy	21	0	0	ABB
Social Policy	BSc in Social Policy and Administration	5	0	0	ABB

Social Policy	BSc in Social Policy and Criminology	11	0	0	ABB
Social Policy	BSc in Social Policy and Economics	11	0	1	ABB
Social Policy	BSc in Social Policy and Government	2	0	0	ABB
Social Policy	BSc in Social Policy and Sociology	11	0	0	ABB
Social Policy	BSc in Social Policy with Government	20	0	0	ABB
Social Policy	BSc in Social Policy with Social Psychology	1	0	0	ABB
Social Policy	BSc in Social Policy, Criminal Justice and Psychology	10	0	0	ABB
Sociology	BSc in Sociology	77	0	0	ABB
Statistics	BSc in Actuarial Science	137	0	1	AAA
Statistics	BSc in Business Mathematics and Statistics	93	0	1	AAA

Notes: Admissions requirements for degree programmes. Taken from http://www2.lse.ac.uk/study/undergraduate/degreeProgrammes2013/degreeProgrammes2013.aspx. *More than median number of options* indicates whether a degree programme has more than the student-weighted median number of course choices offered to students. This offers a raw measure of how diverse the transcripts are across programmes. *Math required* is a dummy variable for whether the programme requires A-level maths for admissions. This is a measure of how quantitative the programme is. *A-level requirements* display the typical grades required for entry into the programme and is an indicator of the minimum student ability.

Table B.4: Summary Statistics by Groups

	First Class Sample		Upper Second Sample	
	4th Mark mean	4th Mark S.D.	4th Mark mean	4th Mark S.D.
By gender				
Male	67.56	6.00	62.33	4.47
Female	66.60	5.40	62.32	4.32
By math requirements				
At least A level maths	68.74	6.57	62.33	4.75
No math requirement	65.39	4.07	62.32	4.06
By number of course choices				
Less choices than median	67.08	6.21	62.26	4.27
More choices than median	67.18	5.23	62.40	4.54

Notes: This table shows summary statistics by gender and programme characteristics.

Table B.5: Correlations Between Programme Level Measures

	Mean	More than median no. of options	Math required	A-level score A*AA or AAA
More than median no. of options	0.47	1.00		
Math required	0.52	-0.09	1.00	
A-level score A*AA or AAA	0.70	0.62	0.14	1.00

Notes: Each variable is a programme-level dummy variable described in detail in the main text. This table shows mean and correlations weighted by number of students.

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