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# (Knock, Knock) Knocking on the Glass Door: Socio-economic Inequalities in Access to High-Pay Careers

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# (Knock, Knock) Knocking on the Glass Door: Socio-economic Inequalities in Access to High-Pay Careers*


## Abstract

Access to professional jobs, particularly in large, high-wage firms, is a key determinant of career success for university graduates. Graduates from less advantaged backgrounds are less likely to gain access to these jobs. We use unique recruitment data from 17 large employers' graduate intake programmes to explore why. While applicants from lower socio-economic and ethnic minority groups are well represented among the applicant pool, they disproportionately do not receive job offers, even when considering similar applicants. Large gaps appear at the blind pre-interview screening stage. We demonstrate that this is unlikely to reflect screening on expected productivity. This raises questions of bias in screening tests and the potential for shifts to the use of more automated hiring tools to exacerbate existing labour market inequalities.



## JEL classification

J62, J15, J16, I24

## Keywords

social mobility, inequalities, occupations, applications, job offers, ethnicity



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# 1 Introduction

Access to professional and managerial jobs, particularly those in large firms, is a key determinant of career success and earnings (Deming, 2026; Arellano-Bover, 2024). Those from less advantaged backgrounds, for example from ethnic minorities and lower socio-economic class backgrounds, remain substantially under-represented in these jobs (Macmillan et al., 2015). This is despite marked increases in their university attendance, including at elite institutions. Why do these employment gaps persist? Are under-represented groups not applying? Or do these patterns reflect hiring practices? If so, which practices? These are critical questions, as differential access to high-pay career paths have the potential to generate sizeable wage differences and inequality (Pendakur and Woodcock, 2010; Weinstein, 2022; Hermansen et al., 2025).

We know little about why these differences persist. This is important as appropriate policy responses hinge on this. For example, they could reflect hiring discrimination. A now large literature demonstrates how information on group membership leads to lower call-back probabilities for minority applicants (Bertrand and Mullainathan, 2004), including in large firms (Kline et al., 2022), and where blinding of applications is a potential response (Goldin and Rouse, 2000; Åslund and Skans, 2012). They could also reflect differential job search patterns of workers (Cortés et al., 2023), or differential *ex ante* group productivity that could reflect pre-market disadvantage (Johnson and Neal, 1996; Speer, 2017). As well as highlighting different policy responses, these explanations suggest roles for different parts of the application and hiring process in generating gaps. These gaps could emerge at any point from the choice to apply through to points in the hiring process where the group membership of workers becomes apparent to firms. We provide the first at scale examination of this process across several large graduate recruiters.

We do so using novel data covering 17 large high-pay firms in England across a range of industries. A common feature of these firms is that they undertake large annual graduate employment intakes. These firms have securely shared individual-level anonymised data on their entry-level hiring into these graduate training programmes. Critically, this data covers all individuals from the application stage, through initial screening to, when relevant, interview and offer. Gaining access to these programmes provides the first stage on a career trajectory into professional and managerial occupations. These roles offer, on average, better long-term earning prospects, and greater economic security and stability than other occupations (García-Peñalosa et al., 2023; Goldthorpe et al., 2016). Our data and setting has a range of advantages. Alongside providing information on the types of roles applied for, and the stage of the process that the applicant makes it through to, the employers additionally collect information on a range of diversity characteristics, including the socio-economic background (SEB) of the applicant, gender, and ethnicity.

This unique and rich dataset allows us to directly investigate who applies to these entry-level roles, the stages that applicants from different backgrounds reach, and *why* we see inequalities in offer rates (and withdrawals from the recruitment process) among those from underrepresented groups.

Our initial result is to demonstrate that applicants from ethnic minorities and from lower socioeconomic backgrounds receive markedly lower job-offer rates. This does not reflect differences in the likelihood of applying across these groups. Ethnic minorities and low socio-economic background graduates are as likely, or more likely,to apply than their white, professional background, counterparts. Moreover, we show that large differences in job offer rates remain even after controlling for a range of factors likely to be closely linked to expected productivity such as prior-attainment, degree attained, university performance and university quality. This raises the question of why applicants, who on-paper appear equally qualified, have such different success rates?

As a first step in understanding these gaps we explore where in the hiring process these gaps emerge. Entry-level hiring to firms, and especially to large firms, has been characterised by a shift to standardised screening tests (Hoffman et al., 2018). These have proved popular as low-cost screening approaches when faced with large application volumes. [1] We observe large group-based gaps in the likelihood of passing these initial screening stages. For example, as much as half of the socio-economic background difference and almost all of the Black-White differences in offer rates occur at this initial sift. This is especially striking as these screening stages are blinded with respect to demographic information. Differences in offer rates are also to varying degrees apparent at the interview stage, but for Black applicants in particular these are dwarfed by the screening effects.

This raises additional questions. The first is simply how and why group membership can influence the probability of passing the screening stage in the absence of employer access to the relevant information on applicants? We first examine the potential role of *ex ante* applicant productivity. Do these initial tests, on average, work effectively to screen for applicants with lower expected productivity? Does this characterise applicants from minority / lower socio-economic backgrounds? We investigate this in a number of ways. The first is to simply introduce headline predictors of productivity such as university quality and degree major. As would be expected, these predict the probability of passing the screen. They do also reduce group differences, but these effects are small. For instance, the Black-White difference in passing the screen reduces from 47% to 37% once these factors are controlled for. We go further with a subset of our firms where both the task and the applicant pool is more homogeneous, and where we have access

[1] In our setting where there are approximately 30 applications for every job offer. As discussed later these screening tests include a mix of numerical, verbal reasoning, situational awareness and psychometric components

to extensive information on applicants' academic ability. This includes, for example, exact university entry scores and university degree grades. These characteristics are again informative in determining success at the screening stage, but play a small additional role in reducing group differences. In summary, while we cannot rule out a role for other salient unobservables, these would need to be both uncorrelated with the wide range of observable predictors of productivity we observe, and have an effect several orders of magnitude larger than these observables. This seems unlikely, but we explore this in a number of additional ways.

Finally, we explore the potential role for other patterns in applicant behaviour to drive these differences. Specifically, are there differences in job-seekers application behaviour? While roles may not always have set deadlines, candidates are generally considered according to the recruiter's hiring timeline, so applying early is often beneficial. This means that , in practice, screening and hiring processes may begin early. Given fixed job positions and scarce HR resources, this may lead to interview positions also 'filling up' early. This leads us to examine the role of *when* individuals apply for these jobs. We demonstrate that those from lower-socioeconomic backgrounds and ethnic minorities apply, on average, later, and applying later is predictive of passing screening and receiving an offer. Late applications by these groups therefore lead to lower chances of passing the screen, being interviewed, and ultimately receiving an offer. This raises issues of differential information regarding the nature of the hiring process. As these choices may reflect differential access to information and advice, this is an important avenue for future study.

This paper is related to three main areas of research.

First, there is a long history of research on discrimination in hiring. A prominent approach are audit-based studies that manipulate applicant information to provide credibly causal evidence on the effects of group membership on call-back rates (Bertrand and Mullainathan, 2004; Kline et al., 2022). Other research uses real-world settings to estimate the effect of blinding of hiring processes on group-based differences. An influential example is Goldin and Rouse (2000) which demonstrates how blinding of orchestra auditions leads to increased hiring rates of women. While Åslund and Skans (2012) find that anonymous applications increase likelihood of minorities receiving an interview in a Swedish public sector setting. This lead to higher hiring rates for women, but there is no effect on eventual hiring for minority background applicants. An interpretation of this literature is that removal of group identifying information in hiring processes can potentially reduce discrimination, and consequentially, group-based hiring inequalities. Our paper extends this literature by providing evidence from a high-stakes real world setting that includes both blind and a face-to-face component. We demonstrate that large-scale, blind, screening tests can lead to the widening of group-based hiring differences, leaving relatively muted inequalities at the subsequent non-blind interview stage.

Second, there is a literature in group-based differences in career progression. Recently Fadlon et al. (2025) demonstrates racial differences in job-ladder movements, Black workers are more likely to move laterally or down the ladder than white workers. This leads to detrimental effects of job mobility on Black-White wage differences across careers. Stansbury and Rodriguez (2026) demonstrates how class-based differences in background lead to marked differences in career outcomes in US tenure-track academic jobs. More broadly, access to high pay firms is an important source of wage growth and inequality (Pendakur and Woodcock, 2010; Arellano-Bover, 2024). We focus on sources of inequalities at the start of these careers insofar as they arise during the hiring process. Our research provides an important link between literature focusing on call-back rates and the analysis of differential career progression in high-pay firms.

Finally, our research is relevant to a growing literature on the use and efficacy of screening methods in hiring. Earlier research demonstrates how the introduction of test-based screening leads to improved quality hiring (Autor and Scarborough, 2008; Hoffman et al., 2018). These methods have potential implications for minority hiring, however Autor and Scarborough (2008) finds no effect on minority-majority hiring gaps in a large retail firm. This literature focuses primarily on low to medium skills where the firm's problem is to select productive workers with heterogeneous, and often low quality, resumes. Our setting is high-pay firms that operate graduate intake programmes are faced with a large volume of qualified applicants. A central problem is screening these applicants so as to ration scarce interviewing resources. This, along with technological changes, has lead to a shift to automated screening tools including, recently, algorithmic screening. This has the potential to reduce group-based differences due to discrimination by moving to more objective evaluation of candidates. However, as discussed in the context of criminal justice this depends on the extent to which training occurs on previously biased data (Kleinberg et al., 2018). Li et al. (2025) engage with this point focusing on one Fortune 500 company. They demonstrate how algorithmic design can lead to productivity gains, increase minority representation, without explicit diversity goals. Our setting is similar, but spans multiple firms that are also characterised by large applicant to job volumes. We examine the effect of screening tools on diversity of job offers in this setting.

In the next section we describe the data collection and analytical approach, before describing our main findings in section 3. Section 4 concludes with policy recommendations.

# 2 Data

## 2.1 Sampling

Initially we drew a sample of employers from those listed in the Times Top 100 Graduate Employers rankings, and featured in either the Social Mobility Index 2020, the Times Top 50 Employers for Women 2020, or the Race at Work Charter Signatories (from December 2020). This provided a sample of 63 employers across 13 sectors, including accounting and professional services, banking and finance, law, IT and telecoms, and the public sector. Our initial plan was to recruit 12 employers in total. We approached 59 employers, with support through introductions from the Social Mobility Commission and the Careers and Enterprise Company. This led to some form of initial contact (email discussion or initial call) with 27 employers. Employers were offered anonymity and employer-specific reports in return for sharing individual-level anonymised data on all applicants to all entry routes. This outreach led to signed Data Sharing Agreements (DSAs) covering 21 employers. 4 employers who signed DSAs are yet to share any data with us at this point.

## 2.2 Data

We received anonymised individual level data from 17 employers for applicants to entry-level graduate programmes (and internship and school leaver programmes) across a range of sectors, including accountancy and professional services, law, and the public sector. For these named sectors, we have more than two employers in each sector and so can present sector level analysis. Employers in the accountancy sector collected and shared more detailed information on applicants than other sectors. We utilise this detail to explore why inequalities arise for ethnic minority and lower SEB applicants. We focus on the most recent data available from each employer as this data is most consistent across firms, in practice this is typically from the 2023 hiring round.

All employers were asked for a common set of measures from their recruitment systems (see Dilnot et al., 2025 technical appendix for details). Our sample is defined based on applications to entry level roles for UK based jobs for applicants from a UK region of origin with a valid recruitment outcome for the latest round of recruitment. This provides a final sample of 117,043 applicants to graduate programmes.

We received a range of information on applicants to entry-level roles including key diversity characteristics such as parental occupation, which was used to create measures of the National Statistics Socio-Economic Classification (NS-SEC), school type, eligibility for Free School Meals (FSM) which is proxy for poverty in childhood, whether at least one parent has a degree education, gender, and ethnicity. These characteristics are asked by participating employers as part of the equal opportunities section of application forms for

Figure 1: Overview of data structure

| | Graduate | | | |
|---|---|---|---|---|
| | All | Accounting | Legal | Public |
| **Sample N (offer models)** | 86,960 | 46493 | 3280 | 36081 |
| **Sample N (withdraw models)** | 117,043 | 64016 | 3503 | 46647 |
| **Number of employers** | 17 | 3 | 3 | 10 |
| **Characteristic of interest** | | | | |
| Parental occupation | ✓ | ✓ | x | ✓ |
| School type | ✓ | ✓ | ✓ | ✓ |
| Parent degree | ✓ | ✓ | ✓ | x |
| FSM | ✓ | ✓ | ✓ | x |
| Gender | ✓ | ✓ | ✓ | ✓ |
| Ethnicity (major) | ✓ | ✓ | ✓ | ✓ |
| Intersection | ✓ | ✓ | x | ✓ |
| **Controls** | | | | |
| **1. Fixed effects** | | | | |
| Employer | ✓ | ✓ | ✓ | ✓ |
| **2. Demographics** | | | | |
| Gender | ✓ | ✓ | ✓ | ✓ |
| Ethnicity major | ✓ | ✓ | ✓ | ✓ |

| | Graduate | | | |
|---|---|---|---|---|
| | All | Accounting | Legal | Public |
| SEB (parental occupation) | ✓ | ✓ | x | ✓ |
| Region of origin (UK) | ✓ | ✓ | ✓ | ✓ |
| Visa status | ✓ | ✓ | x | x |
| Nationality | x | ✓ | x | x |
| **3. School** | | | | |
| GCSE maths grade | x | x | x | x |
| A-level grades | x | ✓ | x | x |
| **4. University** | | | | |
| University category (Boliver) | ✓ | ✓ | ✓ | ✓ |
| UG or PG | x | ✓ | x | x |
| UG degree class | x | ✓ | x | x |
| UG degree class - obtained or predicted | x | ✓ | x | x |
| UG subject group | ✓ | ✓ | x | ✓ |
| **5. Application** | | | | |
| Networks | ✓ | ✓ | x | ✓ |
| Month of application | x | ✓ | x | x |
| Region of office | ✓ | ✓ | x | ✓ |
| Job role | ✓ | ✓ | x | ✓ |

Notes: offer models refer to data after withdrawals are removed;

monitoring and research purposes but are not used in recruitment decisions.

Figure 1 illustrates the data received for the full sample and across sectors where we are able to provide this breakdown (3 or more firms from the same industry). We osberve 117,043 applicants in our full sample, and 64,016 in our accountancy sample. While individual level reporting on these equality characteristics is high (upward of 80% for all measures), and the majority of employers report parental occupation, school type, gender, and ethnicity, information on FSM eligibility and parental education are less frequently collected by employers. This is due to the recommendation of how to measure SEB emphasising parental occupation as the preferred focus, followed by school type, then FSM and parental education. For this reason, the focus here is on parental occupation for our analysis of inequalities by SEB for the graduate route.

The primary outcome of interest is whether an applicant was made an offer. We also observe which stage of the application process the applicant reached in the recruitment process. While application processes for graduate recruitment programmes vary across employers, all follow the generic format of beginning with an online phase, where the primary focus is online testing (98% of applicants). Our employers, in common with the majority of graduate employers in the UK, use screening tests that are originally sourced from 3rd party providers but may be customised for the particular employer. While they differ somewhat in content, they are broader than aptitude tests. They may include numerical and verbal reasoning, but also situational awareness and psychometric elements. If applicants pass this screen they go to face-to-face interviews which may include assessment centres (for 80% of applicants), and in-person interviews (all applicants).

These processes are very competitive with overall offer rates for our full sample of 3.95% and 4.6% for our accountancy sample. Note in our offer models we remove any candidates who choose to withdraw from the process, reducing our analytical sample to N=86,960 for all employers and N=46,493 for accountancy firms (withdrawal rates of 23% and 27% respectively). We check for differential bias in withdrawal rates by key characteristics in our analysis and find similar withdrawal rates across key demographic charcateristics.

As part of the information gathered through recruitment systems, we observe measures of prior attainment including university attended (university grouping taken from Boliver (2015)) and subject studied, and indicators of the region of origin (based on school attended) of the applicant. We also have measures that provide information about the application including how the applicant found out about the role, the region of the office they applied to, and the job role applied to. For the accountancy sector, in addition to these characteristics, we can also observe A level UCAS points scores, degree classification, the nationality of the applicant, and the month of application to the programme.

Table 1: Demographic characteristics of graduates by SEB, ethnicity, and gender

| | Parental occupation | | | Ethnicity | | | | Gender | |
|---|---|---|---|---|---|---|---|---|---|
| | Professional | Interm'te | Working class | White | Asian | Black | Mixed | Male | Female |
| Russell Group attendance % | 56.3 | 45.1 | 39.7 | 55.1 | 44.3 | 33.8 | 50.3 | 47.8 | 52.3 |
| Region of origin London % | 19.2 | 24.8 | 32.8 | 13.1 | 35.8 | 49.9 | 42.2 | 23.7 | 26.0 |
| Region of origin South % | 41.1 | 29.4 | 22.9 | 42.2 | 23.5 | 21.7 | 26.8 | 33.6 | 33.7 |
| Region of origin Midlands % | 17.2 | 20.9 | 20.3 | 17.0 | 22.5 | 16.5 | 14.1 | 19.7 | 18.1 |
| Region of origin North % | 22.5 | 24.9 | 24.0 | 27.7 | 18.3 | 11.9 | 16.9 | 23.1 | 22.2 |

Table 1 presents demographic characteristics of our applicants from different groups. Working class and ethnic minority applicants are less likely to attend a Russell Group university than their professional background and white counterparts. They are also more evenly spread across the country, with a high proportion attending school in London relative to applicants from other backgrounds. White and professional applicants more commonly attended school in the South. Women are slightly more likely to attend a Russell Group university than men, and the spread across regions is equal by gender.

While we only observe applicants, we seek to compare these to the relevant populations of available hires. We do so using linked administrative data of all graduates with a UK degree in 2021, having attended a school in England at age 16 (N=251,380) from the National Pupil Database (NPD) linked to the Higher Education Statistics Authority (HESA) data. This is the latest available data that is not affected by Covid-related examination issues such as Centre Assessed Grades in 2020, and Teacher Assessed Grades in 2021.

# 3 Empirical Approach

## 3.1 Applications

We first examine application patterns. As an initial step, we illustrate the proportion of applicants: overall; passing the online stage of recruitment; and getting an offer; by key diversity characteristics, and relative to the graduate population from linked administrative data. These illustrate the extent to which applicants from different groups (professional vs working class applicants for example) 1) are prevalent in the overall population as a baseline benchmark of graduates, 2) are represented in the overall pool of applicants, 3) make it past the online stages (including sifting and any online testing), and 4) make it through any face-to-face recruitment stages to receive an offer. By tracking the proportion of each group across these stages, we can illustrate whether young people from underrepresented groups are simply not applying to these routes, or if they are applying at a representative rate but are dropping out of the recruitment process at different stages. Note that this simple analysis does not distinguish between people withdrawing from the process (individual action) or being rejected by the employer (employer action), but simply presents a descriptive picture of the relevant populations at each stage.

## 3.2 Offers and Screening

Our main empirical approach is to estimate the likelihood of a given applicant receiving an offer:

$$Offer_{ij} = \beta SEB_{ij} + \delta eth_{ij} + \gamma female_{ij} + \phi \mathbf{X}_{ij} + \theta_j + \epsilon_{ij} \quad (1)$$

Where offer is our main outcome and is a binary indicator that individual $i$ received an offer from employer $j$. $\beta$ and $\delta$ provide estimates of conditional differences in offer rates by socioeconomic background and ethnicity, respectively. We additionally include a control for gender (and explore gender differences more generally), while $\boldsymbol{X}$ is a set of increasing complete controls including demographic and educational characteristics of the applicant and characteristics of the job. Finally, we include a fixed effect for each *jth* employer. We estimate (1) using OLS but stress that the patterns of results are unchanged in non-linear estimation (e.g. Probit, Logit). We additionally, explore withdrawal patterns using the same estimation approach.

Our data allows us to consider differences in success rates at multiple stages of the recruitment process. We are able to separately analyse inequalities in passing the online stage and inequalities in passing the face-to-face stage. Crucially, at the online stages, recruitment is blind.

The probability of passing the initial screen is given by:

$$Pass\ Screen_{ij} = \beta SEB_{ij} + \delta eth_{ij} + \gamma female_{ij} + \phi \mathbf{X}_{ij} + \theta_j + \epsilon_{ij} \tag{2}$$

where $Pass\ Screen_{ij}$ is a binary measure of passing the screen, and as above $\theta$ is the estimated SEB gap, $\gamma$ is the estimated gender gap, $\delta$ is the estimated ethnicity gap, $\beta$ represents employer fixed effects, conditional on a range of background characteristics.

We subsequently estimate the probability of passing the face-to-face interview.

$$Pass\ f2f_{ij} = \beta SEB_{ij} + \delta eth_{ij} + \gamma female_{ij} + \phi \mathbf{X}_{ij} + \theta_j + \epsilon_{ij} \tag{3}$$

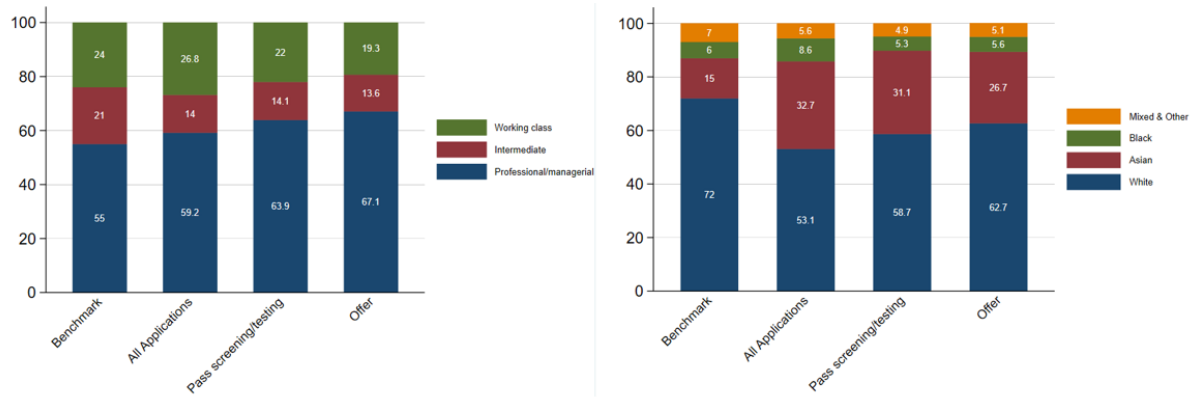
This provides estimates in differences in receiving an offer at the face-to-face stage conditional on passing the screen. This can be thought of as a partial observability problem. We explore the potential for this to influence the interpretation of our estimates of interest from (3).

# 4 Results

**Differences in Application Behaviour**. A first question is whether differences in employment outcomes simply reflect differential application behaviour by graduate group? We explore this by comparing the proportion of applicants from each group to the national benchmarks of graduates, using linked administrative data records, to illustrate the available talent pool.

The left-hand panel of Figure 2 reports application rates by socioeconomic background

Figure 2: Proportion of graduates benchmarked to the national pool, and across stages of the recruitment process, by parental NS-SEC and ethnicity




compared to our benchmark calculations for the relevant graduate population. While, the right-hand panel of Figure 2 provides the corresponding comparisons for ethnic background. In both cases, we also provide proportions who pass screening and those receiving an offer. This illustrates the manner in which we observe graduates through the hiring process from application through to eventual offer (or not).

Focusing first on the left-hand panel of Figure 2, working class applicants are broadly well-represented in our sample of all applicants, while those from intermediate backgrounds are underrepresented and those from professional backgrounds are overrepresented. The proportion of working class applicants declines at each stage of the recruitment process, in favour of applicants from professional backgrounds, from almost 27% of all applicants, to just 19% being made an offer, while the proportion of intermediate applicants remains broadly stable.

In contrast, the right-hand panel of Figure 2 shows that Black and Asian minority ethnic groups are overrepresented in the applicant pool, relative to the national graduate benchmark population, with 33% of applicants coming from an Asian background relative to 15% of all graduates, and 9% of applicants coming from a Black background relative to 6% of all graduates. While Asian applicants remain overrepresented in terms of final offers, their proportion decreases across the recruitment process. Similarly, the proportion of Black candidates decreases across the process.

Together, these patterns suggest that lower application rates are not a probable source of lower working class and ethnic minority offer rates. Working class graduates are applying to these graduate entry roles at a representative rate, while ethnic minority graduates are over-represented in the applicant pool.

**Job Offers**. These previous figures provide a first indication of how low socioeconomic background and ethnic minority applicants shares decrease across the application stages

through to offers. We now explore this by estimating variants of (1).

Figure 3 presents linear probability model estimates of the likelihood of receiving an offer by socio-economic and ethnic minority background, relative to those from professional and white backgrounds, respectively.[2] We present estimated offer-gaps from increasing complete specifications. Focusing first on socio-economic background, working class applicants are 32% less likely to receive an offer to a graduate programme than their counterparts from professional backgrounds who are applying to the same employer.[3] When we adjust for region of origin, gender, ethnicity, and visa status, this gap reduces slightly to just below 30%, and adjusting for university attended and course studied leaves a gap of just under 20%. Applicants from an intermediate background have a slightly smaller disadvantage than working class applicants relative to professional applicants. They are 20% less likely to get an offer to a graduate programme than those from professional backgrounds. Comparing applicants with similar demographics, university experiences and applying to similar roles, this gap is reduced to just below 10%.

Estimates for ethnic minority applicants relative to white applicants show large raw gaps in offer rates. The raw gaps between offer rates for Black (Asian) applicants relative to white applicants applying to the same employer are 45% (30%). Again, while controls play a role, these gaps remain marked after including demographic and university controls. Black (Asian) applicants with the same demographics, prior attainment, and applying to similar roles are still 33% (25%) less likely to receive a job offer.

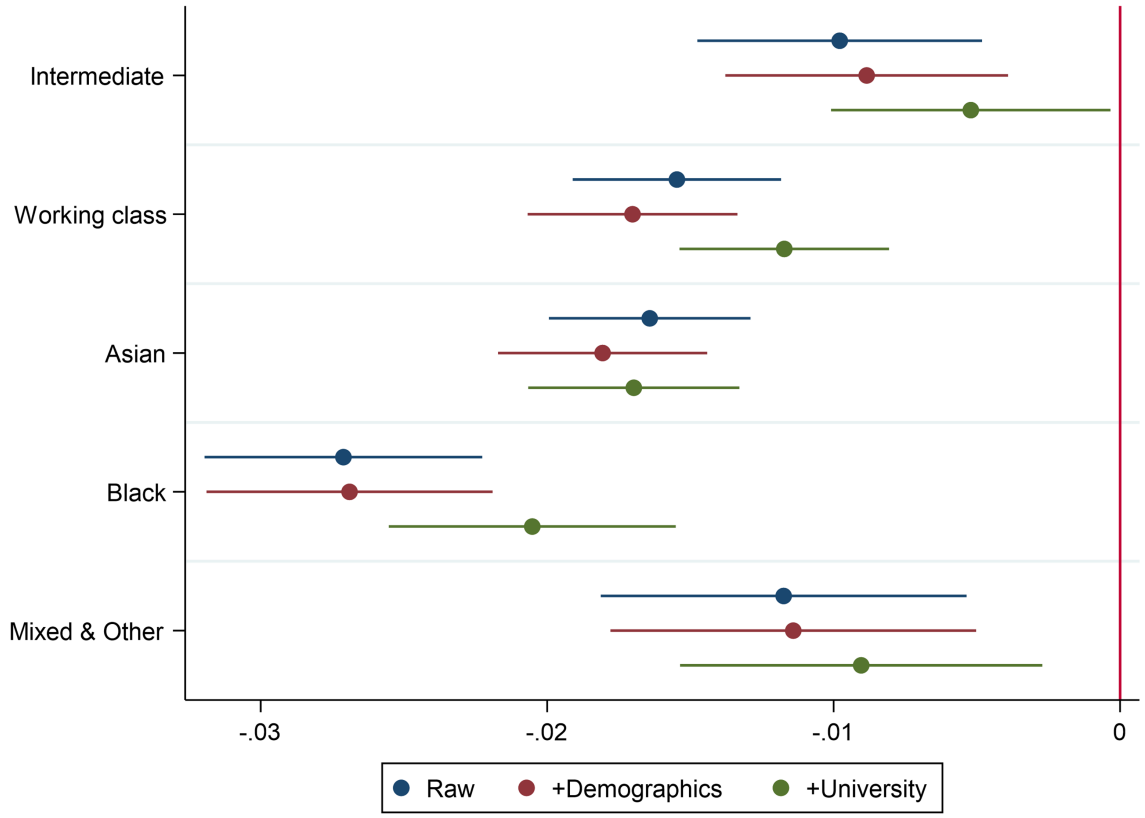
Note that in all offer regressions we exclude cases where individuals withdraw their application before receiving a final decision. This could affect the interpretation of our results if there are marked differences in withdrawal rates by applicant group. Table A2 shows the likelihood of withdrawing from the recruitment process by socio-economic background and ethnicity. Working class applicants are only 3% more likely to withdraw from the recruitment process than their professional counterparts, in both the raw and conditional models. To put this in context, the inequalities in offers are six to ten times larger than the inequalities in withdrawals. There are also very small inequalities in withdrawal rates across ethnic groups with Asian applicants 4% less likely to withdraw and Black applicants 2% more likely to withdraw than their White counterparts. In unreported estimates, we re-estimated our main models including withdrawals. Doing so, did not change the tenor of our main results.

Our demographic controls for our SEB models also take into account the ethnicity and gender of applicants. While women are overrepresented among the pool of graduates from our national benchmarks, they are underrepresented in the pool of applicants to these

[2]Full estimates are provided as Table A1.

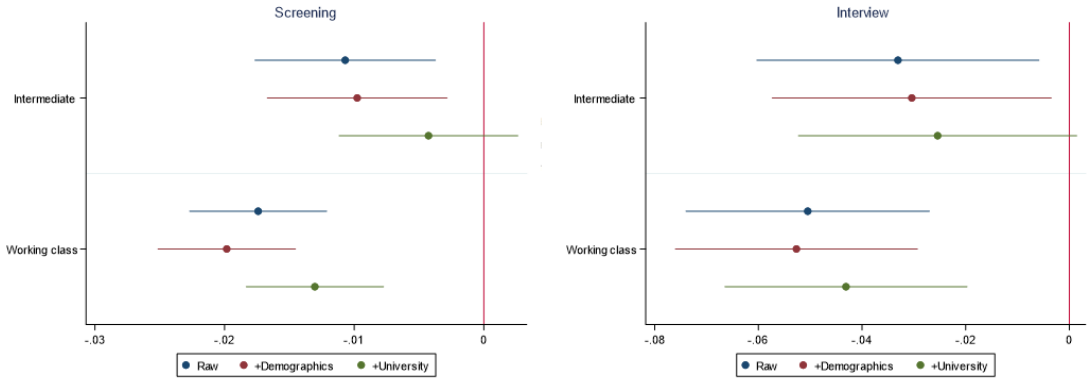
[3]Estimate of 1.9 percentage points difference between working class and professional applicants relative to a baseline offer rate of 6% for professional applicants.

Figure 3: Estimated Probability of Receiving a Job Offer by Parental Background and Ethnicity




Omitted Category; White Applicants from Professional Backgrounds; Raw: Provides unconditional differences. Demographic Controls: *Region of origin, Eligible to work in the UK status, Nationality.* University Controls: *Higher education institution, subject studied.*

Figure 4: Hiring Stages, conditional on observable differences across applicants, by Socioeconomic Background

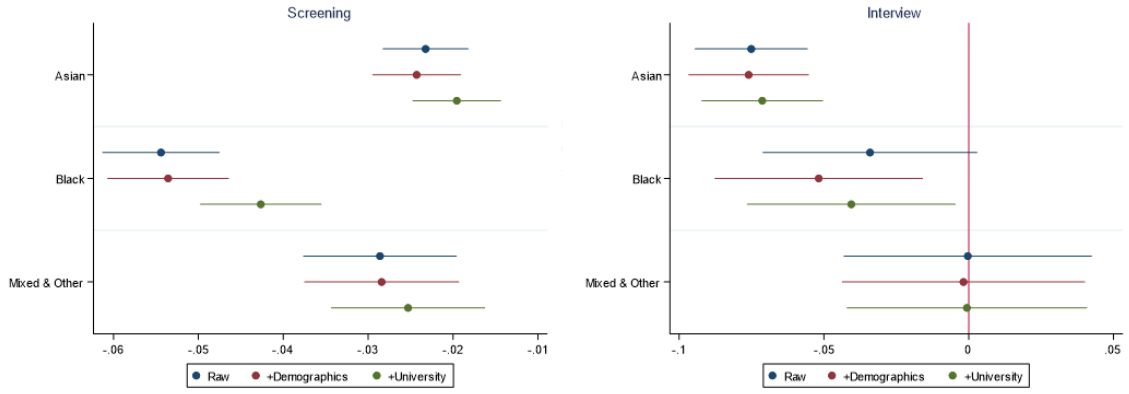



graduate programmes, comprising 56% of the overall pool of graduates and only 46% of the pool of applicants. There is some drop off in the proportion of women passing the online screening and testing phase, but then women are more represented among the proportion who receive a final offer. This suggests some positive selection of women at the face-to-face stage of recruitment. But conditional on applying, there is no significant gender gap in the chances of being made an offer, when we consider the range of characteristics that we can observe about applicants, we can see that women are just over 5% more likely to receive an offer than men with otherwise similar demographics, prior attainment, applying to similar roles. As with SEB, the withdrawal rates are also very similar across genders with women 3% less likely to withdraw from the recruitment process relative to men.

**Screening and Interviews**. In practice, differences in offer rates reflect two distinct parts of the hiring process, pre-interview screening tests and face-to-face interviews. A feature of our data is the ability to observe both of these outcomes. We explore this by estimating variants of (2) and (3) where the dependent variable is the probability of passing the screen, and receiving an offer at interview conditional on passing the screen, respectively.

Figures 4 and 5 summarise the relationship between socioeconomic background and ethnicity and passing the screening tests. These demonstrate large estimated gaps that are particularly pronounced for ethnic minority students. For example, black applicants are approximately 47% less likely to pass the screening test than white applicants. Naturally, this may reflect differential average applicant quality. Including our standard battery of controls does diminish this gap markedly. Black applicants are 37% less likely to pass the screening/test stage than their *comparable* peers of white ethnicity. Smaller, but marked gaps exist for Mixed and Asian applicants. Notably for these groups, including controls for demographics, university background has little effect on these gaps. Likewise, smaller

Figure 5: Hiring Stages, conditional on observable differences across applicants, by Ethnicity




but substantial gaps exist for working class applicants who are 9% less likely to pass the screening/test stage than their comparable peers from a professional background,

These figures additionally provide the estimated probability of gaining an offer *conditional* on receiving an interview. These present, in general, much more muted differences than at screening. For example, we cannot reject that there is no black-white gap in receiving an offer conditional on interview in our most complete model. There is no mixed ethnicity-white gap, while Asian applicants are 11% less likely to receive an offer. Notably, controlling for demographic and university characteristics plays little role in explaining differences in offer rates. There also remains a 9% lower chance of receiving a job offer for working class applicants. Together this highlights a key role for screening processes which we explore further.[4]

**Remaining Sources of Differences?**. The large role of screening tests in generating gaps in offer rates raises a range of questions. One possible argument is that these work effectively to screen individuals and that the differences we observe reflect average group differences in *ex ante* measured productivity of applicants. As a first point, we highlight the relatively small effect of controls for university quality, student performance, and other productive characteristics, on reducing these gaps. Yet, we acknowledge that we do not observe an exhaustive list of controls for applicant quality. These unmeasured skills could be precisely what screening captures and selects on.

To explore this point further we focus on a specific subset of firms, those in the accounting sector. This has a range of advantages. These jobs are more homogeneous in terms of

[4]We additionally sought to explore sensitivity of group-based offer rates to the likelihood of passing the screen. Figure A5 reports estimates corrected via Heckman selection estimation. This has some small effects on observed differences but does not markedly change the pattern of estimated inequalities.

tasks and the academic background of those graduate who take these jobs. More critically, reflecting greater disclosure, we observe substantially more information on applicants to these firms. This includes applicants' university entrance score and the exact degree class they received. These can be viewed as likely to proxy productivity and allows for a finer comparison of applicants. It also provides us with an ability to more carefully assess the likelihood for remaining group-based differences in applicant productivity to be driving screening outcomes.

Table 2: Conditional offer rates - graduate programmes at accountancy and preofessional services firms

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intermediate | -0.011 | -0.010 | -0.007 | -0.005 |
| | (0.003)*** | (0.003)*** | (0.003)** | (0.003) |
| Working class | -0.020 | -0.022 | -0.017 | -0.013 |
| | (0.003)*** | (0.003)*** | (0.003)*** | (0.003)*** |
| Asian | -0.022 | -0.026 | -0.023 | -0.021 |
| | (0.003)*** | (0.003)*** | (0.003)*** | (0.003)*** |
| Black | -0.031 | -0.031 | -0.025 | -0.018 |
| | (0.004)*** | (0.004)*** | (0.004)*** | (0.004)*** |
| Mixed / other | -0.021 | -0.019 | -0.017 | -0.016 |
| | (0.005)*** | (0.005)*** | (0.005)*** | (0.005)*** |
| Constant | 0.115 | -0.011 | 0.018 | -0.108 |
| | (0.003)*** | (0.007) | (0.009)* | (0.014)*** |
| Gender controls | Yes | Yes | Yes | Yes |
| Demographics controls | No | Yes | Yes | Yes |
| Education controls | No | No | Yes | Yes |
| Detailed HK controls | No | No | No | Yes |
| Observations | 46,493 | 46,493 | 46,493 | 46,493 |
| R-squared | 0.012 | 0.050 | 0.058 | 0.063 |

*Notes*: Demographic Controls: *Region of origin, Eligible to work in the UK status, Nationality.* Education Controls: *Higher education institution, subject studied.* HK Controls: *University entry scores, university degree classification.* Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

As a first exploration, we re-estimate our models of offer probability for this subset of firms. We do so using the same approach as earlier but where our final set of estimates additionally include controls for university degree class and university entrance score. These results are summarised in Figure 6 and reported in Table 2. The first column provides raw differences which demonstrate that group based differences are comparable between this sub-sample of firms and the for the full sample. Including demographic controls does little to change these estimated differences. This is also true after including controls for university characteristics, even as doing so improves the fit of the model. The final column with the additional controls leads to some attenuation in the white-black and working-class to professional background applicants, but these remain large.

Figure 6: Offer rates to graduate programmes, conditional on observable differences across accountancy and professional services applicants, by parental NS-SEC and ethnicity

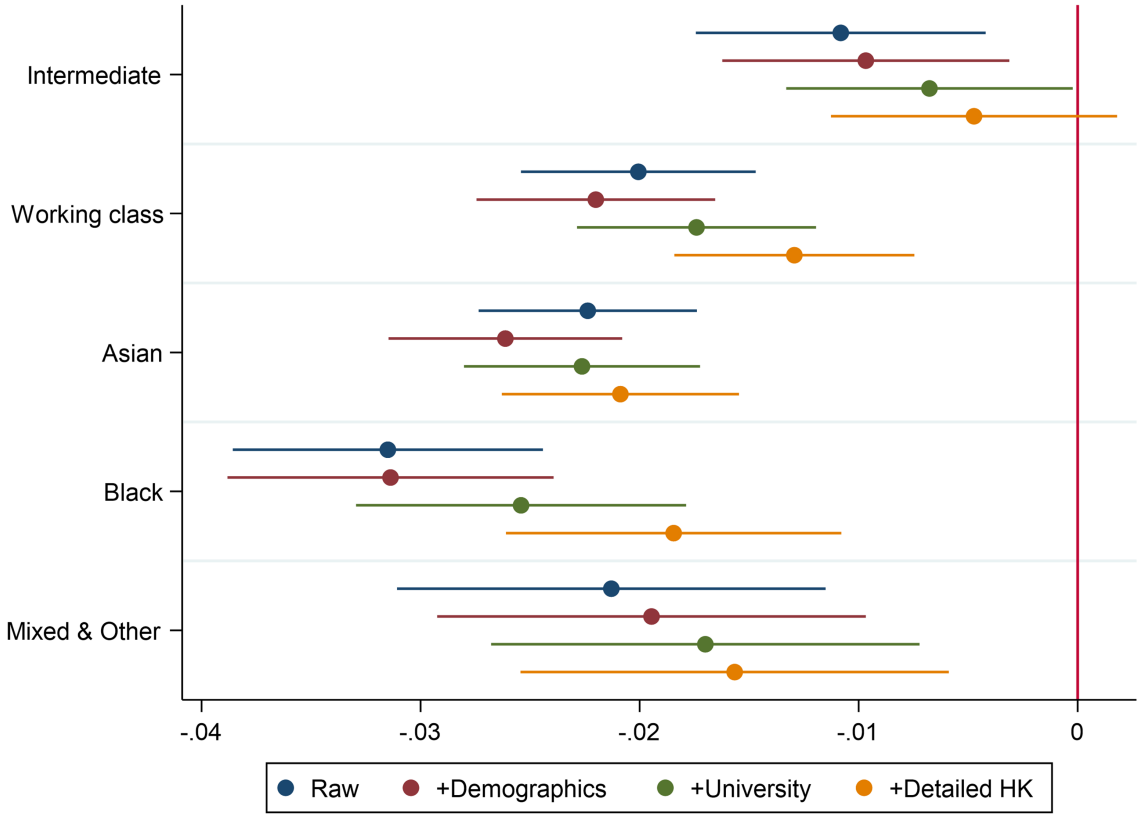


Figure 7 focuses on the role of screening with estimates of inequalities, with full results in Table 3. These reveal similar patterns to those for the full-sample. As an example, Black graduate applicants are 6.6 percentage points less likely to pass the screen, and this diminishes slightly to 5.4 percentage points with the controls available in the full data set (Column 3). The key question is whether observed inequalities in passing the screen change once university entrance scores and degree class (column 4) are included. Including these has an additional explanatory role in explaining who passes the screen. They have little effect on group inequalities which remain large. For example, estimates for black applicants reduce to 4.1 percentage points. Effects on other groups differences, for instance Asian or working class applicants, are much more muted.[5]

What is left? It could be that there is a role for other salient unobservables that the screen is capturing, however these would need to *both* uncorrelated with the wide range of observable predictors of productivity we observe. This seems unlikely but we explore this by conducting Oster (2019) bounds tests on our most complete models from Table 3 focusing on Working Class and Black Applicants. Using a maximum attainable $R^2$ of 1.3 times the *controlled* $R^2$ led to $\Delta$ estimates of 1.3 (Working Class) and 1.1 (Black). This leaves room for the possibility of remaining unobservable differences, but we note that this choice of maximum attainable $R^2$ is likely conservative given the binary nature of our outcome.

It is also possible that the screen is capturing differential (screening) task performance by applicant group that does not reflect academic ability. This is possible given the multi-dimensional nature of the screening tools being used. This leaves a question of what remaining factors could drive these differences. We consider two possible explanations.

The first is that groups of applicants differ in either their test skills (ability to perform on screening tests given productivity) and / or productive soft skills. General test skill differences seem *a priori* unlikely to vary conditional on equal performance on exams and assessment at *both* upper secondary school and university level. However, soft skills may not be perfectly correlated with academic ability. This is difficult to examine. One idea is that those ethnic minority applicants who are from *high socio-economic backgrounds* are less likely to differ in soft skills conditional on attending the same universities, and receiving the same grades.

We explore this by re-estimating our screening models for the accounting firms but allowing for intersectionalities (in practice, interactions) between ethnicity and social class.[6].

[5]Table A4 provides a summary of Blinder-Oaxaca decompositions for both offer and screening success outcomes, where for ease of presentation we collapse the categories into professional background vs others, and white background vs others. These again highlight that while endowments have a role to play in reducing the relevant gaps, there remain substantial unexplained gaps

[6]To this point all models have included both ethnicity and class separately

Table 3: Conditional probability of passing online screening for accountancy and professional services programmes

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intermediate | -0.018 | -0.017 | -0.011 | -0.009 |
| | (0.005)*** | (0.005)*** | (0.005)** | (0.005)** |
| Working class | -0.027 | -0.030 | -0.023 | -0.017 |
| | (0.004)*** | (0.004)*** | (0.004)*** | (0.004)*** |
| Asian | -0.034 | -0.037 | -0.030 | -0.026 |
| | (0.003)*** | (0.004)*** | (0.004)*** | (0.004)*** |
| Black | -0.066 | -0.066 | -0.054 | -0.041 |
| | (0.005)*** | (0.005)*** | (0.005)*** | (0.005)*** |
| Mixed / other | -0.052 | -0.051 | -0.046 | -0.043 |
| | (0.007)*** | (0.007)*** | (0.007)*** | (0.007)*** |
| Constant | 0.147 | 0.023 | 0.107 | -0.008 |
| | (0.004)*** | (0.009)*** | (0.012)*** | (0.019) |
| Gender controls | Yes | Yes | Yes | Yes |
| Demographics controls | No | Yes | Yes | Yes |
| Education controls | No | No | Yes | Yes |
| Detailed HK controls | No | No | No | Yes |
| Observations | 46,493 | 46,493 | 46,493 | 46,493 |
| R-squared | 0.109 | 0.129 | 0.142 | 0.148 |

*Notes*: Demographic Controls: *Region of origin, Eligible to work in the UK status, Nationality.* Education Controls: *Higher education institution, subject studied.* HK Controls: *University entry scores, university degree classification.* Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Offer and screening probabilities, conditional on application behaviours

| | Offer | Screening |
|---|---|---|
| Intermediate | -0.006 | -0.009 |
| | (0.003)* | (0.004)** |
| Working class | -0.010 | -0.014 |
| | (0.003)*** | (0.004)*** |
| Asian | -0.018 | -0.022 |
| | (0.003)*** | (0.004)*** |
| Black | -0.012 | -0.032 |
| | (0.004)*** | (0.005)*** |
| Mixed / other | -0.011 | -0.037 |
| | (0.005)** | (0.007)*** |
| Constant | 0.776 | 0.828 |
| | (0.016)*** | (0.021)*** |
| Gender controls | Yes | Yes |
| Demographics controls | Yes | Yes |
| Education controls | Yes | Yes |
| Detailed HK controls | Yes | Yes |
| Application controls | Yes | Yes |
| Observations | 46,493 | 46,493 |
| R-squared | 0.185 | 0.208 |

*Notes*: Demographic Controls: *Region of origin, Eligible to work in the UK status, Nationality.* Education Controls: *Higher education institution, subject studied.* HK Controls: *University entry scores, university degree classification.* Application controls: *Month of application, regional office applied to, job role applied to, how did you find out about the job?.* Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Figure 7: Relative likelihood of passing online stage, conditional on observable differences across accountancy and professional service applicants, by parental NS-SEC and ethnicity

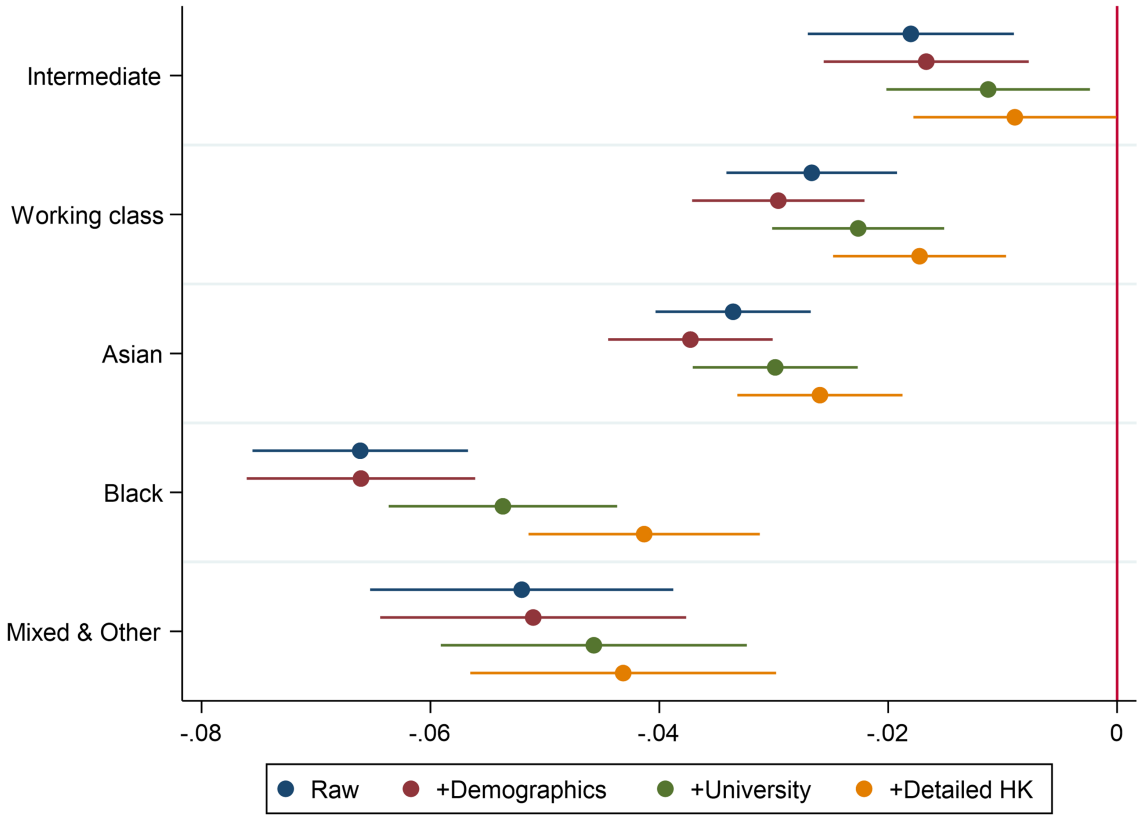
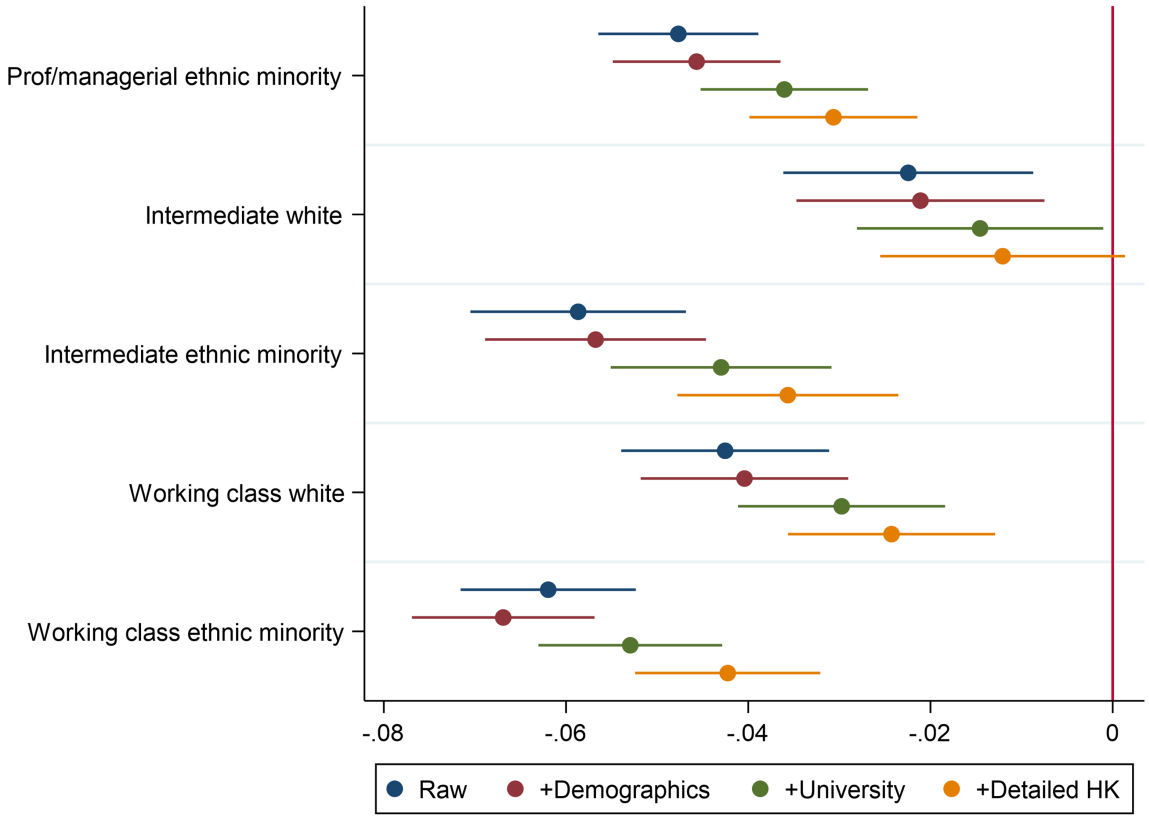


Figure 8: Relative likelihood of passing online stage, conditional on observable differences across accountancy and professional services applicants, by the intersection of parental NS-SEC and ethnicity (Omitted Case - White & Professional Background)



To aid with precision and ease of presentation we pool Asian, Black, Mixed and other applicants into one ethnic minority group. The estimates are in reported in Figure 8. This closes some gaps for example, working class minorities are substantially less likely to pass the screen than their professional background minority applicants. Yet, this group remains substantially less likely than white professional background applicants. Moreover, it is notable that detailed applicant characteristics plays no role in explaining this gap.

Another possibility is that there are salient differences in job-seekers application behaviour across applicant groups? While roles may not always have set deadlines, candidates are generally considered according to the recruiter's hiring timeline, so applying early likely to be beneficial. In practice, firms' screening processes run throughout the entire recruitment cycle. Given fixed job positions and scarce HR resources, this may lead to interview positions 'filling up' early. This would manifest itself by time-variation in the probability of passing the screening process. We observe when individuals apply for jobs. One feature, is that minorities apply, on average, later in the hiring cycle.[7] The date of application is predictive of both receiving an offer and passing screening. In addition we observe information on how applicants heard about the job, the region of the office and the line of service (e.g. job role) they applied to. Figure 9 and 10 report estimates of the impact of controlling for these behaviours on inequalities in offers and screening success. Controlling for these generally reduces inequalities, most notably for black applicants. This raises issues of the role of differential information regarding the nature of the hiring process even amongst otherwise similar graduate applicants.

[7]For example, applicants from professional backgrounds apply 14 days earlier (on average) than applicants from working class backgrounds

Figure 9: Offer rates to graduate programmes for accountancy programmes, conditional on observable differences across applicants and application behaviour, by parental NS-SEC and ethnicity

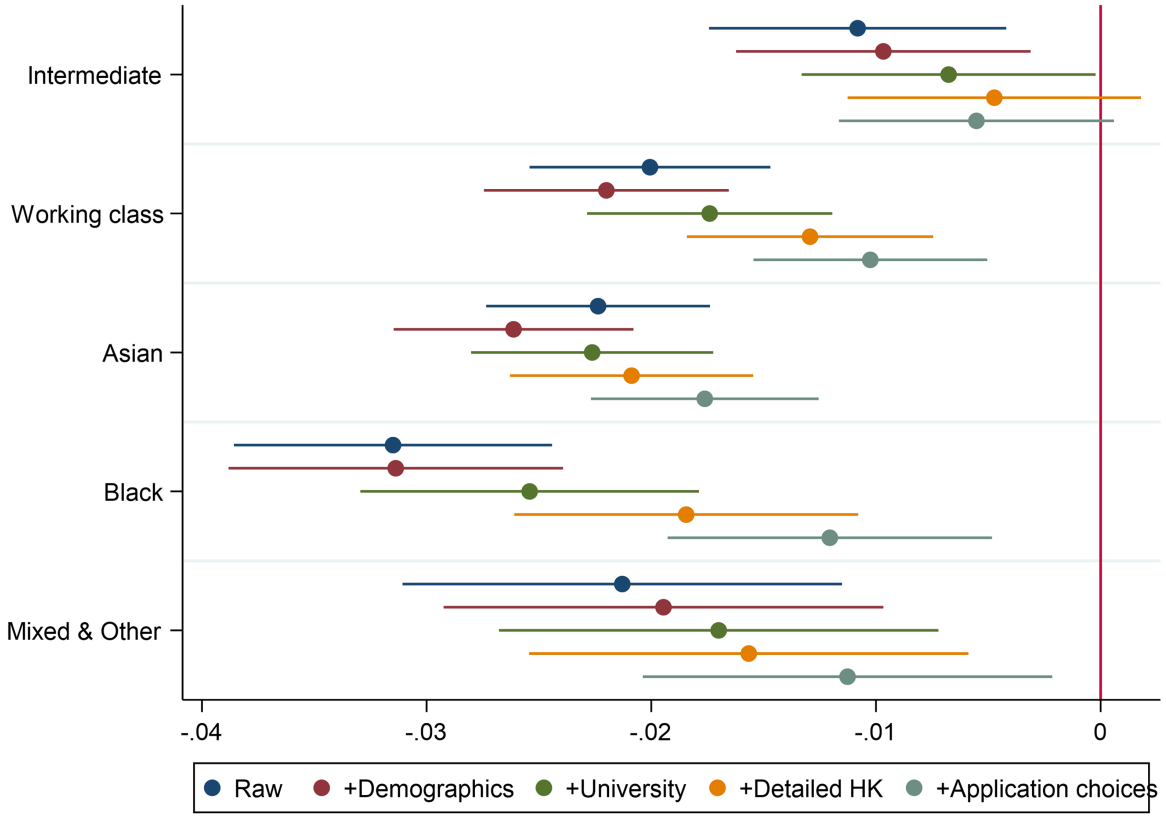
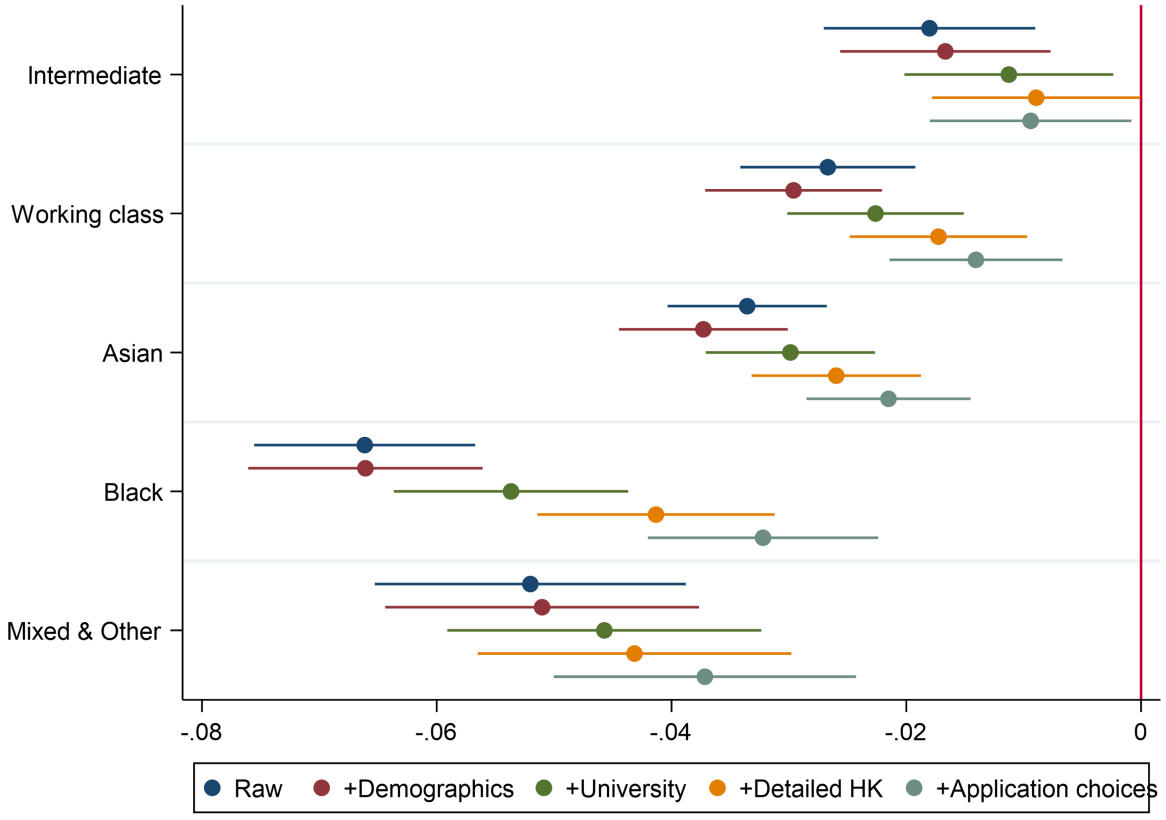


Figure 10: Relative likelihood of passing the online stage of the process for accountancy programmes, conditional on observable differences across applicants and application behaviour, by parental NS-SEC and ethnicity



# 5 Conclusion

Gaining access to professional jobs in large firms is a clear pathway to career success and high earnings. Individuals from low socio-economic and ethnic minority backgrounds have historically faced significant barriers to entry into these career paths. This has persisted even as these groups have dramatically increased their acquisition of higher education. This paper sought to examine where these barriers exist using unique administrative recruitment data for graduate entry programs at 17 large UK firms.

Our main finding is that the inequalities observed by socio-economic background and by ethnicity in entry to professional occupations are, to a large extent, driven by employer-side decisions made during the recruitment process. They do not, for example, reflect differential application patterns. Instead, there are large group based differences in offer rates across narrowly compared applicants. A particularly critical role is played by screening tests, where group-membership is not observable. Low socio-economic background and, in particular, ethnic minority applicants are substantially less likely to pass the screen. We demonstrate that this is unlikely to reflect differences in applicant quality.

We explore potential roles for applicant behaviour. Low socioeconomic background and ethnic minority students apply later than their white, professional background peers. Timing of application is predictive of receiving an offer, and explains as much as 11% of differences in offer rates by applicant group.

In summary, our results demonstrate that large socio-economic and ethnic minority gaps in hiring rates emerge before the face-to-face interview stage. This raises questions about the effect of greater reliance on blinded screening mechanisms on hiring inequalities, and through this, career opportunities. This is a timely observation given current pushes to more automation of hiring processes.

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# A Appendices

Table A1: Conditional offer rates to graduate entry programmes by applicant background

| | (1) | (2) | (3) |
|---|---|---|---|
| Intermediate | -0.010 | -0.009 | -0.005 |
| | (0.003)*** | (0.003)*** | (0.003)** |
| Working class | -0.015 | -0.017 | -0.012 |
| | (0.002)*** | (0.002)*** | (0.002)*** |
| Asian | -0.016 | -0.018 | -0.015 |
| | (0.002)*** | (0.002)*** | (0.002)*** |
| Black | -0.027 | -0.027 | -0.021 |
| | (0.002)*** | (0.003)*** | (0.003)*** |
| Mixed / other | -0.012 | -0.011 | -0.010 |
| | (0.003)*** | (0.003)*** | (0.003)*** |
| Constant | 0.113 | -0.016 | 0.020 |
| | (0.003)*** | (0.006)*** | (0.008)** |
| Gender controls | Yes | Yes | Yes |
| Demographics controls | No | Yes | Yes |
| Education controls | No | No | Yes |
| Observations | 86,960 | 86,960 | 86,960 |
| R-squared | 0.016 | 0.037 | 0.047 |

*Notes*: Demographic Controls: *Region of origin, Eligible to work in the UK status, Nationality.* Education Controls: *Higher education institution, subject studied.* Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A2: Conditional withdrawal rates to graduate entry programmes

| | (1) | (2) | (3) |
|---|---|---|---|
| Intermediate | 0.004 | 0.003 | 0.004 |
| | (0.004) | (0.004) | (0.004) |
| Working class | 0.009 | 0.008 | 0.009 |
| | (0.003)*** | (0.003)*** | (0.003)*** |
| Asian | -0.009 | -0.011 | -0.008 |
| | (0.003)*** | (0.003)*** | (0.003)*** |
| Black | 0.007 | 0.004 | 0.006 |
| | (0.004) | (0.004) | (0.004) |
| Mixed / other | 0.003 | 0.002 | 0.003 |
| | (0.005) | (0.005) | (0.005) |
| Constant | 0.522 | 0.510 | 0.572 |
| | (0.004)*** | (0.007)*** | (0.009)*** |
| Gender controls | No | No | No |
| Demographics controls | No | Yes | Yes |
| University controls | No | No | Yes |
| Observations | 117,043 | 117,043 | 117,043 |
| R-squared | 0.188 | 0.188 | 0.191 |

*Notes*: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Conditional probability of passing online screening

| | (1) | (2) | (3) |
|---|---|---|---|
| Intermediate | -0.011 | -0.010 | -0.004 |
| | (0.004)*** | (0.004)*** | (0.004) |
| Working class | -0.017 | -0.020 | -0.013 |
| | (0.003)*** | (0.003)*** | (0.003)*** |
| Asian | -0.023 | -0.024 | -0.020 |
| | (0.003)*** | (0.003)*** | (0.003)*** |
| Black | -0.054 | -0.054 | -0.043 |
| | (0.004)*** | (0.004)*** | (0.004)*** |
| Mixed / other | -0.029 | -0.028 | -0.025 |
| | (0.005)*** | (0.005)*** | (0.005)*** |
| Constant | 0.141 | 0.013 | 0.109 |
| | (0.003)*** | (0.008)* | (0.011)*** |
| Gender controls | Yes | Yes | Yes |
| Demographics controls | No | Yes | Yes |
| Education controls | No | No | Yes |
| Observations | 85,808 | 85,808 | 85,808 |
| R-squared | 0.078 | 0.090 | 0.103 |

*Notes*: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4: Decomposition of offer and screening differences

| Comparison / Outcome | Group 1 | Group 2 | Gap | Endow. | Coeff. | Interaction |
|---|---|---|---|---|---|---|
| Socio-economic offer made | 7.0% | 4.8% | 2.2pp | 1.24pp (55.7%) | 1.10pp. (49.7%) | -0.12pp. (-5.5%) |
| Socio-economic pass screen | 15.3% | 11.5% | 3.7pp | 1.88pp (50.1%) | 1.32pp. (35.2%) | 0.56pp. (14.7%) |
| Ethnicity offer made | 7.8% | 4.3% | 3.46pp | 2.06pp (59.5%) | 0.78pp. (22.5%) | 0.62pp. (18.1%) |
| Ethnicity pass screen | 15.3% | 8.7% | 6.65pp | 2.60pp (39.1%) | 3.00pp. (45.0%) | 1.05pp. (15.8%) |

Group 1 refers to Professional Background (socio-economic) and White (ethnicity), respectively. Group 2 refers to Working Class (socio-economic) and Black (ethnicity), respectively.

Figure A4: Relative likelihood of receiving an offer, conditional on having an interview across applicants, by parental NS-SEC and ethnicity

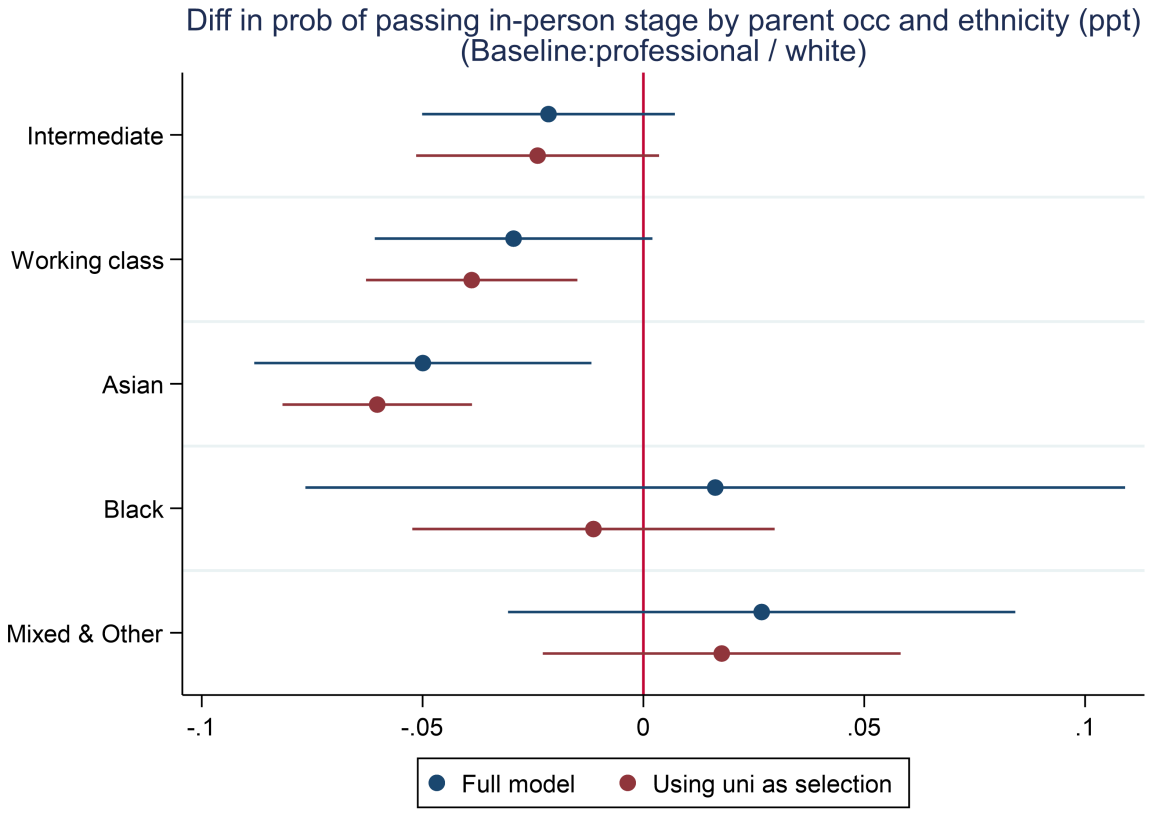


Figure A5: Relative likelihood of receiving an offer, conditional on having an interview across accountancy applicants, by parental background and ethnicity - Heckman Correction Estimates

