Board of Governors of the Federal Reserve System

International Finance Discussion Papers

Number 1331

September 2021

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Please cite this paper as:
Shukla, Soumitra (2021). "Between College and That First Job: Designing and Evaluating Policies for Hiring Diversity," International Finance Discussion Papers 1331. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2021.1331.

Between College and That First Job: Designing and Evaluating Policies for Hiring Diversity

Soumitra Shukla*

Despite widespread caste disparities, compensatory hiring policies remain absent from the Indian private sector. This paper employs novel administrative data on the job search from an elite college and evaluates policies to promote hiring diversity. Application reading, written aptitude tests, large group debates, and job choices do not explain caste disparities. Disparities arise primarily between the final round, comprising non-technical personal interviews, and job offers; the emergence closely parallels caste revelation. For promoting diversity, hiring subsidies — similar in spirit to the government-proposed Diversity Index — are twice as cost-effective as improving pre-college achievement. Conversely, quotas mirror a hiring tax and reduce university recruitment by 7%.

JEL codes: J71, J78, J15, J44

Keywords: Labor Markets, Inequality, Affirmative Action, Disadvantaged Communities

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> We also ask a lot of questions related to family background. Questions like how many family members are there, how many are educated, etc. The basic assumption behind these questions is that a good person comes from a good and educated family. If parents have good education, the children also have good education. Some questions about their schooling ... and the locality where they [grew up]. — H.R. head of an elite Indian private sector firm on the role of personal interviews (Jodhka and Newman, 2007).

1 Introduction

Labor market disparities are commonplace world over (Berg, 2015). The design of remedial policies hinge upon peeling the often obscure layers of firm-worker matching. However, collecting information on every step of job search has remained difficult, preventing a panoramic picture of the mechanisms driving labor market outcomes.

In this paper, I employ novel administrative data on every step of job search from an elite technical college and evaluate policies to improve diversity in the Indian private sector. To this day, private sector jobs in India do not have compensatory hiring policies for disadvantaged castes. Meanwhile, caste disparities remain stark: 93 percent of board members in India's top 1,000 businesses belonged to advantaged castes, who make up less than 15 percent of the overall population (Dayanana et al., 2012).

External interventions might be imperative toward promoting caste diversity, especially given the Indian private sector's overt reluctance toward corrective measures. In a detailed survey of H.R. managers at elite private sector firms in the New Delhi area, employing a total of nearly 2 million workers, Jodhka and Newman (2007) documented unanimously unfavorable sentiments toward corrective policies. These opinions have not only been expressed in anonymous surveys but also publicly, with some insisting that hiring processes in the private sector are "caste-blind" (Jodhka, 2008; The Wall Street Journal, 2011). Such attitudes have unsurprisingly resulted in lackluster efforts. Government-led informal discussions have found support from the private sector wanting, even for voluntary adoptions of basic codes of conduct for affirmative action in hiring (The Wall Street Journal, 2011; The Wire, 2019). However, in the absence of a formal EEO-like ombudsman, government pressure has been weak. Internal institutional pressure to rectify recruitment processes has also been sluggish. As recently as 2018, only 3 of the top 100 firms listed on India's premier stock exchange claimed to maintain caste data for internal H.R. purposes (BusinessLine, 2018). Diversity practices in multinational firms employing Indians are overwhelmingly influenced by considerations of the West, where caste is not a protected category (The Times of India, 2020; The New York Times, 2021).

I make three main contributions. My first contribution is to quantify the earnings gap across castes and uncover the mechanisms driving it. The unconditional earnings gap is 17%. In the presence of detailed controls on pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills, the gap reduces to 11%. There are no caste differences in pay for a given job. So, the earnings gap arises due to differences in job compositions across castes. There is substantial heterogeneity in the earnings gaps across sectors and job types. Earnings gaps are largest in the consulting (10%) and technology sectors (8%), which make up nearly three-quarters of advertised jobs. Similarly, disadvantaged castes earn 7% less in non-client facing jobs, which comprise almost 85% of all available jobs. The earnings gap is 12% in client-facing jobs. Almost all firms hire only for domestic locations.

To better understand the mechanisms driving the earnings differentials, I offer the first quantitative decomposition of the residual earnings drop off at successive stages of job search. For this purpose, I make use of two key features in my setting. First, administrative data is collected on every step of the job placement process, including job applications, pre-interview screening, job interviews, job offers and job choices. Second, firms pre-commit to advertised wages and non-pecuniary amenities per job. Bargaining over wages and amenities is disallowed and compensation bundles are verified ex-post by the college's placement office. I show that the compositions of job applications and job choices do not explain the earnings gap. Pre-interview screening including application reading (first round), online written aptitude tests (second round) and large group debates typically comprising 25-30 students (third round) explain only a small fraction (14%) of the drop off in earnings. Therefore, almost all of the earnings drop off (86%) occurs between one-on-one interviews (fourth round) and job offers. The drop off is more concentrated for technology and non-client facing jobs. The entire earnings drop off among these jobs occurs after one-on-one interviews. One-on-one (personal) interviews are not technical or case-based interviews: they are typically a combination of small talk, employers advertising their job, assessing "culture fit" and asking potential employees about competing firms. These findings suggest that policies which provide information about jobs, modify student preferences, or improve performance at university are unlikely to close the earnings gap.

Personal interactions, including interviews for elite Indian jobs and interpersonal communication in the workplace, have a well-documented history of being used to screen on family characteristics, personal hobbies and cosmopolitan attitudes (henceforth, "background"). Such "background" traits include educational qualifications of family members, father's job, neighborhood of residence, preference for living in a cosmopolitan city, desire for traveling etc. Examples of such screening exist both in the private and public sector, and even in Indian-dominated firms abroad. In the aforementioned survey of H.R. managers, Jodhka and Newman (2007) also documented opinions regarding the role of personal interviews in the hiring process. The authors found unanimous agreement on the importance of asking questions pertaining to "family background" in one-on-one interviews. Interestingly, H.R. managers saw little contradiction in judging a candidate's individual merit through the "data" on family background characteristics, arguing instead that trustworthiness, attrition and work ethic could be reasonably gleaned through such inquiries. One H.R. manager at a large New Delhi-based firm expressed the signalling value of "family background" as follows:

> As personal traits are developed with the kind of interaction you have with society. Where you have been brought up, the kind of environment you had in your family, home, colony and village, these things shape the personal attributes of people. This determines his behaviour, and working in a group with different kinds of people. We have some projects abroad, and if a person doesn't behave properly with them, there is a loss for the company. Here the family comes in, whether the person behaves well and expresses himself in a professional way, for a longer term and not for a short term. This is beneficial.

Relatedly, in a separate survey of students from elite educational backgrounds in New Delhi, Deshpande and Newman (2007) found that almost all of them were asked about family background in personal interviews. Personal interview questions also included queries into their hobbies and cosmopolitan attitudes, like preference for living in a big city. As one student put it:

> Most of my interviews were very relaxed. No one was assessing my knowledge or anything, but . . . seeing how well and efficiently I contribute to the company . . . For example, when I had my interview with [information firm], he asked me why I want to work in Bombay? . . . So the interview was more in terms of what I like, what I dislike and general chit chat about what I was looking to do in the future rather than quizzing me about, let's say what particular topics I had done in a particular [academic] subject or something like that.

These prevailing personal interview conventions have also influenced advice provided to job seekers by online employment platforms. For example, Naukri.com, India's leading job search portal with over 60% market share, suggests that the "best way to answer this common interview question [when asked by recruiters to introduce oneself] is to tell the hiring manager about your education and family background" (Naukri.com, 2019). Additionally, the portal also advises candidates to answer commonly asked interview questions about personal hobbies by sharing "something that adds value to [their] skills such as travelling and meeting people if [they] are appearing for a client-meeting role" (Naukri.com, 2019). Personal interviews for selection into the elite Indian Administrative Services (IAS) have also historically been plagued by "background" bias (Gould, 2010). Such tendencies prompted the Kothari Committee to formally recommend reducing weights on interviews in the recruitment process of civil servants, which were often "influenced by accidental, and sometimes even trivial factors" (Kothari Committee Report, 1976, p. 62). Away from Indian shores, interpersonal interactions, instead of performance, have allegedly led to caste differences in promotion and career growth in Silicon Valley (The Washington Post, 2020; The New York Times, 2020).

"Background" traits, such as family characteristics, personal hobbies and cosmopolitan attitudes, are arguably related to desirable attributes. However, they are also a window into an Indian's caste (Jodhka and Newman, 2007; Deshpande and Newman, 2007). This is especially the case in urban India, which is characterized by rising education levels, social mobility, and migration. As a consequence, last names, facial features, and dialect have become unreliable signals of caste, especially among educated urbanites. For example, surnames like "Singh", "Sinha", "Verma", "Chaudhary", "Mishra", "Das" etc. are shared across castes (Anthropological Survey of India, 2009).[1] Scholars have also argued that there is no association between skin color and caste, especially since Indian skin color is influenced mostly by geographic location rather than caste status (Mishra, 2015; Parameswaran and Cardoza, 2015). Among English-educated elites, like those in my sample, English has emerged as a caste-neutral language with no memory of caste dialects, which plague most Indian languages (Ambedkar, 2002; Kothari, 2013; The New Polis, 2018; Ransubhe, 2018). Instead, perception of accent variation among young, English-speaking, university graduates in India is linked to broad regional factors (Wiltshire, 2020). Yet, "background" characteristics still provide an enduring stamp of caste in an otherwise rapidly changing urban landscape. Therefore, the standard H.R. practice in India of screening on "background" information in personal interviews is a potential barrier for disadvantaged castes in their access to elite jobs for myriad reasons, including raw discrimination, a perception (right or wrong) about lower productivity or unintentional biases due to homophily. My descriptive results quantify the salience of this channel.

In Section 4.2.1, I argue that the earnings drop off due to one-on-one interviews closely parallels caste revelation. The arguments make use of the aforementioned evidence which suggest that last names, facial features and perception of accent variation confound caste identification, especially in urban India. However, "background" characteristics screened upon in personal interviews can often provide a clearer picture of caste status. It must be noted that I do not put a label on the "caste penalty" quantified through the earnings gap decomposition. Statistical discrimination seems most plausible given that 85% of the jobs are non-client facing and, especially, given the survey evidence documented by Jodhka and Newman (2007) and Deshpande and Newman (2007). Moreover, even if one were to grant the unlikely scenario that caste is strongly signaled at the rounds prior to one-on-one interviews, as I argue against in Section 4.2.1, it only shifts the interpretation of the "caste penalty" as one most plausibly stemming from statistical discrimination. In Section 4.2.2, I discuss other alternative explanations.

My second contribution is to build a model of the job placement process, which is closely guided by the sequential decomposition of the earnings gap. This is the first empirically estimated model of the entire job recruitment process of an elite college. In particular, the model incorporates economically relevant stages of job search in my setting: firm hiring and final job choices. I also show how the model can be extended to include application behavior, which may be important in other settings. Firms evaluate student characteristics, like pre-college performance measures, college major, college grades, prior work experience etc. Additionally, firms value a student specific unobserved heterogeneity component which also affects student choices. Crucially, firms care about caste. I do not distinguish between taste-based, statistical or client-based discrimination. I assume that firms have hiring constraints (in expected value) and show that they follow cutoff rules, or reservation utilities, in deciding whom to make offers to. In

[1] Relatedly, in a recent audit study based on firms in the New Delhi area, Banerjee et al. (2009) state that the "enormous regional variations [in last names] mean that the precise coding of a particular last name is unlikely to be familiar to people from a different linguistic region of India."

doing so, they account for competition from other firms as well as the distribution of student preferences and qualifications. Once job offers have been made, students make final job choices by evaluating job characteristics, which include salaries and other non-pecuniary amenities.

The model serves four main purposes: it allows us to assess displacement effects of counterfactual hiring policies, quantify the role of unobservables in jointly determining observed choices, evaluate cost-effectiveness of policies, and calculate willingness-to-pay for non-pecuniary amenities. Since private sector firms in India have not experimented with affirmative action policies, there is no readily available variation in the data which can be used to directly evaluate displacement effects of compensatory hiring practices. However, under some assumptions about student and firm behavior, I show how one can bound displacement effects under certain counterfactual policies. In particular, consider policies which explicitly improve employers' valuation of disadvantaged castes, like improvements in pre-college test scores or hiring subsidies favoring one group. Bounding the effects of such policies would depend upon the elasticity of labor demand. When labor demand is perfectly elastic, firms do not raise their reservation utility levels and thus hire everyone who qualifies, without displacing any advantaged castes. However, when labor demand is perfectly inelastic, firms do not relax their employment targets and thus raise their reservation utility levels, displacing advantaged castes in favor of disadvantaged castes. The reality is likely somewhere in between. Furthermore, by imposing additional structure, I also show that modelled unobservables play an economically small role in determining both job hiring and job choices.

The model also helps us quantify the cost-effectiveness of policies and students' valuation of non-pecuniary amenities, both of which hinge on willingness-to-pay (WTP) measures of key characteristics. To credibly calculate WTP measures, I also take advantage of rich data on job characteristics, a highly regulated placement process and representative wage setting. The data allows us to account for over 50 unique non-pecuniary amenities per job designation. Ex-ante commitment by firms and ex-post verification by the college's placement office regarding advertised wages and amenities rules out potential confounders. Finally, comparing salaries for the same job designation in my setting to those on Glassdoor suggest modest differences, averaging to only about 2%. These features combine to offer a unique advantage, effectively allowing us to take wage setting as given, thereby helping evaluate cost-effectiveness of counterfactual policies.

My third contribution is to evaluate three counterfactual policies for promoting hiring diversity. I begin by comparing the effects of two counterfactual policies, both of which explicitly improve employers' valuation of disadvantaged castes. In the first such policy, I consider a hiring subsidy which makes firms indifferent between an observably identical advantaged or disadvantaged caste. The subsidy is similar in spirit to the incentive-based Diversity Index proposed by the Ministry of Minority Affairs (Sachar Committee, 2006; Report of the Expert Group on Diversity Index, 2008).

> The implementation of the [diversity] index prepared by this Expert Group could be operationalised either on the principle of (a) incentive (reward) or disincentive (punishment) or (b) a lucrative incen-

> tive(s) (reward) and the lack of it (the denial of reward to be construed as penalty). Obviously, the former could be resented, may even lead to legal entanglements, while the latter, though slower to implement, could initially be used by enthusiastic States and institutions for incentives, while the others may just ignore it. But eventually, the Expert Group feels, it would catch up.

To calculate this subsidy, I use one of the key model estimates which shows that firms discount the value of disadvantaged castes at the equivalent of 4.8% of average annual salary, holding other student attributes constant. This amount is a one-time common payment to each firm. In the second policy, I consider a "pre-college intervention" which equalizes the distribution of pre-college skills (college entrance exam scores) across castes, holding the caste composition of the college constant. This assumption is tenable because, by design, affirmative action policies equalize the caste composition of admits within this college. My results show that firms put a very small weight on pre-college test scores, equivalent to a model-implied subsidy of only 0.6% of average annual salary ($337). Indeed, the weights on pre-college test scores are so small that even lower bounds of displacement effects under hiring subsidies are larger than upper bounds of displacement effects under the "pre-college intervention" policy. Therefore, hiring subsidies increase job assignments and earnings of disadvantaged castes by substantially more, in absolute terms, than the "pre-college intervention" policy.

To evaluate cost-effectiveness, I compare the model-implied subsidy equivalent of the "pre-college intervention" policy to the direct costs of changing test scores. For this purpose, I use estimates from a meta-analysis documenting the costs of pre-college intervention policies which changed test scores of primary and secondary school students in India (Asim et al., 2015). These policies span nearly two decades and include interventions like hiring tutors, bonuses to teachers, redesigning school curricula etc. To extrapolate costs of the "pre-college intervention" policy, I make two extremely conservative assumptions: 1) costs scale linearly with test score changes and, 2) students can be perfectly targeted i.e. the test score of a given student can be changed by any desired amount. Even under these assumptions, subsidies to hire disadvantaged castes are twice as cost-effective in promoting diversity. The lower cost-effectiveness of the "pre-college intervention" policy is primarily driven by the modest roles of test scores in firm hiring, relative to caste.

The third, and final, counterfactual policy for diversity is a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes. While compensatory hiring practices do not exist in the Indian private sector, quotas or reservation-based policies have been extensively used to improve the representation of disadvantaged castes in government jobs and educational institutions (Madheswaran, 2008; Newman and Thorat, 2010; Verma, 2012). In my setting, the penalty on disadvantaged castes is large enough to make the average marginal utility of filling two slots lower than the average marginal cost. Therefore, firms counteract the quota policy by making fewer job offers. In particular, unlike the previous two policies, quotas mirror a hiring tax and decrease university recruitment by 7%.

The paper contributes to several strands of the economics literature, especially in labor economics. The paper presents unique descriptive facts on the decomposition of earnings differentials which helps us go beyond what one can learn from traditional resume-based correspondence studies. Unlike those studies, this paper accounts for rounds beyond the initial resume screening (first round), which is especially relevant since discrimination occurs during later stages in this setting. Another well-known drawback of resume-based correspondence studies is that they typically cannot document impacts on actual labor market outcomes, like job offers, job choices or earnings (Bertrand and Duflo, 2016). This drawback is not just technical. For example, lower callback rates for historically disadvantaged students may be either because firms are discriminating or because such students are more likely to accept lower paying jobs which offer better non-pecuniary amenities, leading firms to respond to differential worker preferences in equilibrium. (Kroft et al., 2013; Nunley et al., 2017; Farber et al., 2018). In the absence of information on job choices conditional on job offers, resume-based correspondence studies conflate the economic interpretation of differences in callback rates across groups and, therefore, limit the implications of their findings for redressive policies.

My policy proposals to improve the share of disadvantaged castes in the private sector can help assess the equity-efficiency tradeoff of affirmative action policies. Pre-college interventions, like changes in test scores, can arguably raise both efficiency as well as promote equity. My estimates show that firms put only modest weights on pre-college test score improvements. Hence, efficiency gains from such policies are likely to be small. Moreover, leaning towards equity through interventions in later stages, like hiring subsidies, might not necessarily sacrifice efficiency given growing evidence that disadvantaged groups are likely to benefit the most from selective education or job opportunities whereas displaced advantaged groups are likely to be not much worse off (Holzer and Neumark, 2000a,b; Holzer, 2007; Durlauf, 2008; Black et al., 2020). Similar legal arguments have been made recently in the U.S. in favor of redistributive policies in later stages, especially in college admissions (Grutter v. Bollinger, 2003; Fisher v. University of Texas, 2013, 2016).

The paper also contributes to the personnel economics literature. To my knowledge, this is the first paper to model and quantify the determinants of job recruitment in an elite college. My structural model of the job placement process can also serve as a prototype for studies of the placement processes used by engineering schools, business schools, law schools, and other institutions that use formal job placement mechanisms. While the details vary, it is an open question as to how best to efficiently match students to firms while also addressing concerns about equity.

This paper proceeds as follows. Section 2 provides a brief overview of the origin of caste-based affirmative action policies in India. Section 3 describes the setting and the data. Section 4 establishes key descriptive facts. Section 5 describes the model. Section 6 discusses identification and estimation. Section 7 discusses parameter estimates. Section 8 evaluates counterfactuals. Section 9 concludes.

2 Caste and Affirmative Action in India

In present-day India, 49.5% of seats in government jobs and government educational institutions are reserved for disadvantaged castes. This section provides a brief overview of the origin and limitations of caste-based affirmative action policies in India.

The first provisions for uplifting "depressed" or socio-economically disadvantaged classes of Indian society were passed under the Government of India Act, 1919, which established self-governing institutions i.e. provincial assemblies and central legislative assemblies. The depressed classes, under the leadership of Dr. B.R. Ambedkar, demanded reservation of seats (quotas) in legislative bodies, special educational concessions and recruitment in public sector jobs. B.R. Ambedkar also wanted a separate electorate for depressed classes but faced opposition, most notably by Mahatma Gandhi. A compromise was reached between Mahatma Gandhi and B.R. Ambedkar under the Poona Pact of 1932, which agreed upon a single general electorate to govern British India and the new central legislatures. The Poona Pact also reserved 18% of the seats in central legislatures for depressed classes. The Government of India, Act, 1935 ratified the Poona Pact and replaced the words "depressed classes" with "Scheduled Castes" (Bayly, 2008; Lee, 2020; Jenkins, 2003).

From 1942-1946, B.R. Ambedkar served as a member of the British Viceroy's Executive Council as a Minister for Labour. He used this position to further the interests of depressed classes (or, Scheduled Castes) and demanded reservations in government educational institutions, in addition to government jobs. His demands became the foundation of affirmative action policies for depressed classes in independent India (Ambedkar, 2016). These demands were formally accepted in 1946 during deliberations of the first Constituent Assembly, which was tasked with drafting the constitution for independent India.

Many articles of the Constitution of India, ratified in 1949, formalized reservation-based affirmative action policies in legislatures, higher educational institutions and government jobs for the so-called "backward" classes. "Backward " classes were intended to include not only members of Scheduled Castes (SCs) and Scheduled Tribes (STs) but also those from the Other Backward Classes (OBCs). These provisions begged an obvious question: what determines "backwardness"? In *M.R. Balaji v. State of Mysore* (1963), the Supreme Court ruled that "backwardness" should be classified on the basis of caste, although social and educational disparities should also be considered. Moreover, the Court ruled that "backwardness" of OBCs should be comparable to that of the SCs and STs (Khosla, 2020).

In 1979, the Mandal Commission was set up with a mandate to "identify the socially and educationally backward classes in India" (Mandal Commission Report, 1980). The Mandal Commission recommended caste as the basis for reservation. In particular, it recommended a 27% reservation (quota) in central and state services, public undertakings and educational institutions for OBCs. Given the already existing 22.5% reservation for SCs and STs, the fraction of reserved seats for disadvantaged castes (SCs, STs and OBCs) was brought up to 49.5%.

Interestingly, none of the current constitutional provisions extend to providing compensatory hiring policies for disadvantaged castes in private sector jobs (Panandiker, 1997; Madheswaran, 2008). The focus of this paper is to assess the potential of such policies in promoting hiring diversity.

3 Setting and Data

In this section, I describe the job recruitment process under study as well as the data used in the paper.

3.1 The Job Recruitment Process

The job recruitment process involves the following steps: 1) the career office invites firms, 2) invited firms post their job positions and compensation packages, 3) students apply for jobs, 4) firms make the "first cut" after skimming through applications and invite students for additional screening, 5) firms conduct written and verbal tests to determine eligibility for on-campus interviews, 6) firms interview students, 7) firms make job offers, and 8) students make final job choices.

3.2 Data Overview

The administrative dataset collected by the career office of the post-secondary educational institution has detailed information on both students and firms. The sections below describe sample selection followed by some key descriptive facts for both students and firms.

3.2.1 Sample Selection

I omit students pursuing the Master of Science (M.Sc.) degree and those in other smaller degree programs. Such students are also much less likely to make use of the career office in their job search.

I also omit firms belonging to the public sector. Such firms comprise less than 4% of all jobs available to students in the degree programs included in the sample. Public sector firms are also quite different from their private sector counterparts, especially in salary structure, job stability etc. For example, public sector firms have pay-scales for different job ranks with a substantial portion of the perks in the form of allowances for transportation, phone bills, medical needs and so on.

3.2.2 Students

Appendix Table D.1 shows the total number of students belonging to each caste in each college degree.

There are 4207 students in the sample. Quota-based admissions policies are imposed at the college major level. Therefore, there are nearly 50% disadvantaged castes in each college degree, except in one out of the four college degrees in the sample (see, Section 2). Both Bachelor of Technology (B.Tech.)

and Dual degree students are admitted to the institution through a common entrance exam. A Dual degree integrates undergraduate and post-graduate studies and is completed a year after the conventional four-year B.Tech. degree. Master of Technology (M.Tech.) and Master of Science (M.S.) degree students are also admitted through a common entrance exam. The M.S. degree has a substantially larger proportion of advantaged castes indicating that despite admissions quotas, some college degrees may not be able to fill up all college seats reserved for disadvantaged castes.

3.2.3 Differences in Baseline Characteristics Across Castes

In this section, I document differences in baseline characteristics across castes. The largest differences are concentrated in pre-college skills, especially in college entrance exam scores. There are also large differences in college GPA. However, I find only modest differences in previous labor market experience and employer-relevant skills.

3.2.3.1 Pre-college Skills

There are substantial differences in pre-college skills across castes, especially in college entrance exam scores. Appendix Table D.2 reports differences in pre-college skills across castes. The largest differences are in college entrance exam scores. Appendix Figure D.1 shows common support for caste within each entrance exam score decile.

The differences in 10th and 12th grade national level examination scores are substantially smaller. This is because college entrance exams for elite colleges differentiate at the top of the test-taking ability distribution whereas 10th and 12th grade exams do not.

3.2.3.2 Within-College Academic Performance

There are also large differences across castes in college GPA. Appendix Table D.3 reports caste differences in college GPA for each degree. The differences are largest in the B.Tech. and Dual degrees. Appendix Figure D.1 shows common support for caste within each college GPA decile.

Appendix Tables D.5, D.6, D.7 and D.8 show that college GPA and entrance exam scores are negatively correlated. The effect is most concentrated among selective majors who, on average, have higher entrance exam scores.[2] The differential effects at the top and bottom of the distribution could be explained by random variation in entrance exam scores, conditional on ability. Students at the top are likely to have more positive error in their entrance exam scores. This will be less true for students in the lower range. However, the overall effect is likely much stronger at the top because the pool of students entering the college is truncated at relatively high entrance exam scores.

[2] In Appendix Table D.4, I show that student characteristics, like entrance exam scores and caste, are almost perfectly predictive of major assignments.

3.2.3.3 Previous Labor Market Experience

I find only modest differences across castes in previous labor market experience. Appendix Table D.9 reports caste differences in some key measures of previous labor market experience. Previous labor market experience includes detailed information on both summer and winter internships, including duration of internship employment, duration of part-time or full-time employment, total pay during internships, total pay during part-time or full-time employment, sector of internship employment and employment in startups. Internship descriptions typically include application eligibility criterion, desired skills and expectations on the job etc.

3.2.3.4 Other Employer-Relevant Skills

Admissions quotas coupled with fairly rigid engineering curricula lead to almost no caste differences on many measures of employer-relevant skills. These include college major, college degree and coursework. For Master's degree holders, the dataset has additional information on undergraduate institution, undergraduate degree, undergraduate major and degree specialization (e.g. computational fluid mechanics, solid mechanics, aircraft propulsion etc.). Most Master's degree students choose to write senior projects pertaining to their specialization. The dataset contains information on the main focus of their senior projects ("experimental fluid mechanics with a focus on interfacial phenomena"), keywords from their senior projects ("surface phenomena contact, angle hysteresis, wetting angle characterization"), whether the projects were experimental or analytical or both ("experimental and analytical") and their software programming skills ("Fortran and MATLAB"). The dataset does not have measures of degree specialization or software programming skills for Bachelor's degree holders. However, one can proxy for other employer-relevant skills by including dummies for getting past the various stages of job search (see, Section 3.2.4).

3.2.4 Firms

The dataset also has detailed information on various job characteristics, including job descriptions, job designations, sector, salaries, non-pecuniary amenities, and even job application eligibility criterion, desired skills, expectations on the job etc. In addition, the dataset comprises firm-level information on all stages of the job search, including job applications, pre-interview screening, job interviews, job offers and job choices.

3.2.4.1 Salaries and Non-Pecuniary Amenities

In the sample, a job designation (henceforth, a "job") means a job title within a firm. For example, a firm can hire a Product Manager and a Software Engineer. Conditional on college degree, job salaries do not vary across major, caste or gender.

Appendix Table D.10 shows the distribution of firms by sector and the average salary across all jobs by sector. 52% of all firms belong to the technology sector, 20% belong to the consulting sector and 28% belong to the manufacturing sector. Average salaries across all jobs in the technology, consulting and manufacturing sectors are $67,302.64 (PPP), $63,544.02 (PPP) and $43,525.25 (PPP), respectively.

In addition to salaries, firms offer over 50 different types of non-pecuniary amenities, including stock options, signing bonuses, performance bonuses, relocation allowances, medical insurance etc.[3] Therefore, firms horizontally differentiate themselves along many characteristics to attract their favorite candidates. Like salaries, these other forms of compensation vary across but not within college degrees. Almost all firms hire only for domestic locations. Appendix Table D.11 shows the fraction of firms in each sector offering a select subset of non-pecuniary amenities.

Finally, firms pre-commit to advertised wages and non-pecuniary amenities per job designation. Bargaining over wages or amenities is disallowed and compensation bundles are verified ex-post by the college's placement office.

3.2.4.2 Job Applications

The administrative dataset has detailed information on job applications. Students apply for jobs through a centralized job application portal, like JOE for economists. Applying to a job only involves clicking on the name of the job in the application portal and does not require additional cover letters or other statements. Employers only request student resumes which are automatically made available to them when the student "clicks" against the name of a company to apply. Resumes are written in a standardized format prescribed by the placement office. I do not have access to student resumes. Application eligibility depends upon a combination of major, degree and GPA, information which the dataset contains.

3.2.4.3 Screening, Job Offers and Job Choices

The data comprises job-level information regarding the number of students who qualified for each round of screening, received job offers and decided to accept. Each firm typically conducts four rounds of screening before making job offers. The first round is the application reading stage. This "first cut" is typically made on a GPA cutoff to select students for the next round. The second round is a written aptitude test. These tests are mostly conducted online. The third round is a large group debate, usually comprising 25-30 students. At the third round, employers observe students for the first time, but do *not* extensively interact with them. In this round, students discuss a topic with some speaking for or against the motion. Meanwhile, recruiters behave like passive observers, their only active role being to start and end the discussion on time, ensure decorum etc. Discussion moderators organically "emerge" from the group

[3] In my dataset, I categorize some fringe benefits as "non-pecuniary" amenities since, for a substantial portion of the sample, I do not have information on direct cash-equivalents of such benefits.

of students participating in the discussion. The fourth round is a one-on-one (personal) interview featuring the only extensive interactions between the students and recruiters during the job search process. Fourth round interviews are not technical or case-based interviews: they are typically a combination of small talk, employers advertising their job, assessing "culture fit" and asking potential employees about competing firms.

4 Descriptive Facts

In this section, I establish key descriptive facts specific to my institutional setting. I document large earnings disparities across castes upon graduation, argue that the earnings gap is conservative and show that the earnings drop off is concentrated between one-on-one interviews (fourth round) and job offers.

4.1 Large Earnings Gap Between Castes

The unconditional earnings gap across castes is -0.174 (0.016) log points, or about 17%, where the number in parenthesis denotes the standard error. In the presence of detailed controls for pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills, the gap reduces to 0.113 (0.014) log points, or about 11%. These results are robust to many different specifications (see, Appendix Tables D.14, D.15 and D.16; Section 4.1).

The reported earnings gap is conservative. Appendix Tables D.14, D.15 and D.16 only include those students who got jobs through the formal placement process. Appendix Tables D.17 and D.18 show that among the sample of non-job getters, disadvantaged castes are much more negatively selected on college GPA and entrance exam scores. Since average earnings are increasing in college GPA and entrance exam scores (not shown), the reported earnings gap is conservative.

The magnitude of caste disparities differs across sectors and job types. For example, the earnings gap among firms in the consulting sector is -0.102 (0.033) log points, whereas it is -0.071 (0.033) log points among technology firms. These sectors comprise nearly three-quarters of all firms. The earnings gap is -0.041 (0.033) log points among manufacturing firms. Non-client facing and client facing jobs have substantially different earnings gaps. The earnings gap is -0.071 (0.022) among non-client facing jobs, which comprise 85% of all advertised jobs, and rises to -0.123 (0.031) log points among client facing jobs (see, Appendix Tables D.27-D.31). Almost all advertised jobs hire only for domestic locations.

4.2 Almost All of the Earnings Gap is at the Offer Stage

In this section, I lay out one of the key contributions of the paper. I offer the first quantitative decomposition of the residual earnings drop off at each step of job search: application reading (first round), written aptitude tests (second round), large group debates (third round), one-on-one interviews (fourth round), job offers and job choices.

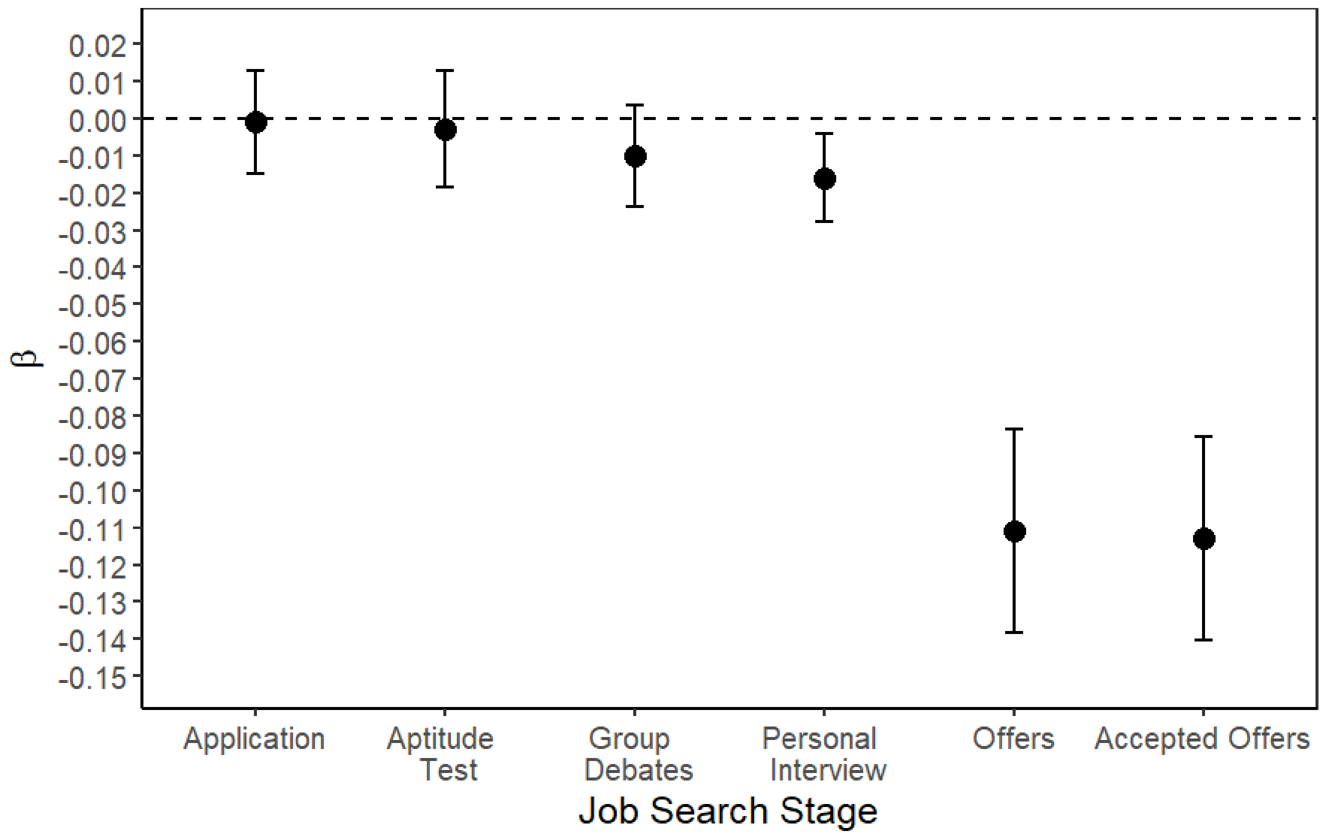

Figure 1: Earnings Gap Across Castes at Each Job Search Stage

Notes: Figure 1 shows the coefficient β corresponding to the regression in Equation 1. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

I show that almost all of the earnings drop off occurs between one-on-one interviews (fourth round) and job offers. To do so, I run different specifications of the following regression:

$$\log(\text{Avg. Job Salary}_i^{\text{Search Stage}}) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \tag{1}$$

where Search Stage $\in$ {Application, Aptitude Test, Group Debates (GD), Personal Interview, Offers, Accepted Offers}. The coefficient of interest is β, which is shown in Figure 1 for each successive stage of job search.

Figure 1 shows that almost all of the earnings gap is at the offer stage i.e. between one-on-one interviews (fourth round) and job offers. As reported in Appendix Tables D.19, D.20 and D.21, disadvantaged and advantaged castes apply to similar jobs since the streamlined job application process makes the marginal cost of application effectively zero (see also, Appendix Figure D.2). Three-rounds of screening — application reading, written aptitude tests and large group debates — account for only 14% of overall earnings gap. The remaining 86% of the earnings gap is concentrated between one-on-one interviews (fourth round) and job offers.[4]

The drop off is more concentrated for technology and non-client facing jobs. The entire earnings drop off among these jobs occurs after one-on-one interviews (see, Appendix Figures D.4 and D.7).

4.2.1 When Does Caste get Revealed to Employers?

The earnings decomposition shown in Figure 1 begs the question: when does caste get revealed to employers? In this section, I argue based on the institutional context of my study and related research that caste identity is plausibly revealed or strongly signaled during one-on-one interviews (fourth round), while prior job search stages are most likely to offer noisy signals that obfuscate caste identification.

It is unlikely that caste status is known during the application reading stage (first round) given enormous regional variation, different naming conventions, migration etc. For example, surnames like "Singh", "Sinha", "Verma", "Chaudhary", "Mishra", "Das" etc. are shared across castes (Anthropological Survey of India, 2009).[5] It is also unlikely that caste status is known during written aptitude tests (second round) since these tests are typically conducted online.

Caste identification is also unlikely to be reliable in group debates (third round). Recall, these debates are conducted among large groups, typically comprising 25-30 students, who either argue for or against a given topic. In the data, students at group debates are about evenly split between castes. At this round, employers finally get to observe, but do *not* extensively interact with students after an initial setup. They also become privy to additional information like facial features, skin tone, accent, language, demeanor etc. Scholars have argued that there is no association between skin color and caste, especially since Indian skin color is influenced mostly by geographic location rather than caste status (Mishra, 2015; Parameswaran and Cardoza, 2015). Among educated elites, like those in my sample, English has emerged as a caste-neutral language with no memory of caste dialects, which plague most Indian languages (Ambedkar, 2002; Kothari, 2013; The New Polis, 2018; Ransubhe, 2018). Instead, perception of accent variation among young, English-speaking, university graduates in India is linked to broad regional factors (Wiltshire, 2020).[6]

[4]There is a substantial winnowing down in the number of jobs available at each successive stage of job search. The number of jobs available to each student reduces by about 35% between any two stages, except between job interviews and job offers where the drop off is much sharper due to the rules of the job placement process (see, Section 3.1).

[5]In a recent audit study based on firms in the New Delhi area, Banerjee et al. (2009) state that the "enormous regional variations [in last names] mean that the precise coding of a particular last name is unlikely to be familiar to people from a different linguistic region of India."

[6]The overwhelming influence of regionality in common parlance is perhaps most clearly expressed in Gumperz (1961) which states that a "high-caste villager may speak the same form of urban Hindi as his untouchable neighbor."

It is quite plausible that conversations in one-on-one interviews provide information that is not captured by written test ability or interpersonal skills, but are caste-correlated. One-on-one interviews (fourth round) are not technical or case-based interviews: they are usually a combination of small talk, employers advertising their job, assessing "culture fit", and asking potential employees about competing firms.[7] Moreover, recent survey responses of elite H.R. managers and students regarding hiring practises suggest that questions on "family background" during one-on-one interviews, such as educational status of family members, schooling, neighborhood of residence etc., are considered par for the course (Jodhka and Newman, 2007; Deshpande and Newman, 2007).

It must be noted that I do not put a label on the "caste penalty" quantified through the earnings gap decomposition. Statistical discrimination seems most plausible given that 85% of the jobs are non-client facing and, especially, given the survey evidence documented by Jodhka and Newman (2007) and Deshpande and Newman (2007). Moreover, even if one were to grant the unlikely scenario that caste is strongly signaled at the rounds prior to one-on-one interviews, as I argue against in this section, it only shifts the interpretation of the "caste penalty" as one most plausibly stemming from statistical discrimination.

4.2.2 Alternative Explanations

In this section, I discuss some alternative explanations that could explain the earnings drop off observed in Figure 1. I argue below that none of these are likely to explain the earnings gap.

1. **Differences in socio-emotional skills across castes:** The drop off in earnings occurs primarily *after* one-on-one interviews (fourth round) and not due to performance in large group debates (third round). Moreover, in this setting, nearly 85% of the jobs are non-client facing (see, Section 3.2.4), which suggests that employers may not have a substantial preference for students at the right tail of the socio-emotional skills distribution compared to those closer to the mean.[8]

2. **Better "outside options" for advantaged castes:** For example, such "outside options" may represent aspects of broader discrimination, like better job offers procured from outside of the centralized placement process. However, nearly 99% of all graduating students in this college participate in searching for jobs through the help of the placement office. Moreover, if students are discovered searching for jobs "offline" i.e. outside of the centralized placement process, they risk being debarred from the services of the placement office in their on-campus job search. Hence, the lack of "offline" job opportunities limits the possibility of advantaged castes leveraging employers for high paying jobs.

[7] Assessing "culture fit" may itself involve assessing caste status and lead to self-perpetuating inequalities. For example, see Goldin (2015) which proposes a "pollution theory" of hiring as a way to explain high segregated occupations by sex.

[8] Detailed job descriptions (particularly, job titles and job functions) were used to categorize jobs as client facing versus non-client facing. Typically, a software engineering role would be considered as non-client facing whereas a consulting or managerial role would be considered as client facing.

3. **Advantaged castes can bargain better over salaries and amenities:** Differences in negotiation ability have been a well documented source of labor market disparities in other contexts, especially across gender (Babcock and Laschever, 2003; Gneezy and Croson, 2009; Bertrand, 2011; Blau and Kahn, 2017; Recalde and Vesterlund, 2020). However, in this setting, firms are required by the placement office to commit to the compensation bundles they advertise for each job *before* the start of the job search process i.e. before students start applying. Therefore, salaries and non-pecuniary amenities posted by jobs are non-negotiable. Moreover, the placement office requires students to submit copies of their job offer letters and matches its details against what was previously advertised by employers. Ex-ante commitment and ex-post verification of compensation bundles rules out differences in negotiation skills as a potential source of disparities across castes.

4. **Employers are "playing along" at rounds prior to one-on-interviews due to possibility of government audits or internal institutional pressure:** India lacks a formal auditing mechanism like an EEO office. Informal government-led discussions have also found support from the private sector wanting, even for voluntary adoptions of basic codes of conduct for affirmative action in hiring (Jodhka, 2008; The Wall Street Journal, 2011; The Wire, 2019). However, in the absence of an EEO-like ombudsman, government pressure has been weak.

   Overtly expressed attitudes by private sector employers suggest lack of support for compensatory hiring policies, even absent formal government pressure. As mentioned previously, a survey of H.R. managers from elite private sector firms in the New Delhi area, employing a total of nearly two million workers, found unanimous opposition toward compensatory hiring policies. Some respondents even suggested that being caste-conscious is synonymous with being "anti-merit" (Jodhka and Newman, 2007). Such opinions have not only been stated in private but also publicly, with some insisting that hiring processes in the private sector are "caste-blind" (Jodhka, 2008; The Wall Street Journal, 2011). Perhaps unsurprisingly then, only 3 of the top 100 firms listed on India's premier stock exchange claimed to maintain caste data for internal H.R. purposes, as recently as 2018 (BusinessLine, 2018). Diversity practices in multinational firms employing Indians are overwhelmingly influenced by considerations of the West, where caste is not a protected category (The Times of India, 2020; The New York Times, 2021).

   Finally, if internal institutional pressure on employers to "appear fair" is particularly pressing, it seems reasonable for these constraints to also be present at the offer stage where, paradoxically, almost all caste disparities arise in my setting. Final hires are more visible to the broader public than shortlists from initial screening rounds.

5 A Model of the Job Placement Process

Guided by the sequential decomposition of the earnings gap, I build a model of the job placement process. This is the first empirically estimated model of the entire job recruitment process of an elite college. Given that most students apply everywhere conditional on eligibility, I omit job applications from the model (see, Appendix Tables D.19, D.20, D.21).[9] The model therefore incorporates the most economically relevant stages of job search: firm hiring and final job choices. Firms evaluate student characteristics and make job offers subject to bounds on their hiring size. Under certain assumptions, firms follow cutoff hiring rules, or reservation utilities, which are allowed to change in response to counterfactual hiring policies. Once job offers have been made, students make final job choices by evaluating job characteristics, which include salaries and other non-pecuniary amenities.

The model serves four main purposes: it allows us to assess displacement effects of counterfactual hiring policies, evaluate cost-effectiveness of policies, calculate willingness-to-pay for non-pecuniary amenities, and quantify the role of unobservables in jointly determining observed choices.

5.1 Additional Institutional Details

During job recruitment season, each firm is allotted one interview day to conduct one-on-one interviews (fourth round) on campus. Unlike job recruitment in U.S. colleges, there are no further "onsite" interviews. A particular rule of the job placement process states that conditional on getting a job offer on a given interview day, a student can no longer participate in interviews on future interview days. At best, a student can receive multiple job offers within a given interview day. If a student does not get any job offer on a particular interview day, he can participate in interviews on future interview days.[10] All job offers are announced within a short interval of time at the end of the interview day, typically late in the evening to prevent firms from coordinating on whom to hire.

The placement rule above could potentially affect strategic behavior of firms to compete for better slots. However, I argue that it is reasonable to take interview days allotted to firms as exogenous. Past interview day allocations and job characteristics are almost perfectly predictive of current interview day allocations (see, Appendix Tables D.32 and D.33). Among these job characteristics, job salaries are the only significant determinants of interview day assignments. A one standard deviation increase in salary increases the probability of getting assigned the first interview slot (first interview day) by 8%.

However, I also take job salaries as exogenous due to three reasons. First, the data allows us to account for over 50 unique non-pecuniary amenities per job designation. Second, firms pre-commit to ad-

[9] In Appendix Section C, I show how the model can be extended to incorporate job application behavior, which may be important in other settings.

[10] Having applied, students cannot "reject" firms midway by either skipping any of the pre-interview screening rounds or the sequence of scheduled interviews.

vertised wages and non-pecuniary amenities per job designation. Bargaining over wages or amenities is disallowed and compensation bundles are verified ex-post by the college's placement office. Finally, comparing salaries for the same job designation in my setting to those on Glassdoor suggest modest differences, averaging to only about 2% (see, Appendix Table D.34). Since job salaries in my institutional setting — the only significant determinants of interview day assignments — are transparent, regulated and representative, it is plausible to assume wage setting, and therefore, interviews day allocations as exogenous.

5.2 Stage 2: Job Choice by Students

The model is solved backwards starting from final job choices followed by job offers. At the job choice stage, students know their job offers and there is no uncertainty about preferences. The set of job options for student i denoted by $\mathcal{O}(Z_i)$ is

$$\mathcal{O}(Z_i) = \{0\} \cup \{j : Z_{ij} = 1\}. \tag{2}$$

where the outside option, which is indistinguishable from unemployment, is denoted by $j = 0$. The vector $Z_i = (Z_{i1}, \ldots, Z_{iJ})$ collects all job offers for student i, where Z_{ij} is an indicator variable which takes the value 1 if student i receives an offer from job j and 0 otherwise.

Let U_{ij} be the utility of student i from job j. U_{ij} depends upon student and job characteristics, econometrician-unobserved random effect q_i and a job offer acceptance shock, ϵ^1_{ij}, realized after job offers are known but before final job choices are made. Mathematically,

$$U_{ij} = X'_{ij}\beta + \mathrm{NP}'_j\Psi + w_j\tau + q_i + q_i \times \sum_{m=1}^{M} \gamma_m \mathrm{NP}_{jm} + \epsilon^1_{ij}. \tag{3}$$

where X_{ij} includes student and job characteristics, especially interactions between student caste and non-pecuniary amenities. The vector $\mathrm{NP}_j = (\mathrm{NP}_{j1}, \ldots, \mathrm{NP}_{jM})$ is a vector of over 50 unique non-pecuniary amenities for job j and w_j is the (log) salary offered by job j.[11] For identification, econometrician-unobserved q_i does not enter the utility for the outside option i.e. q_i shifts the value of all jobs uniformly relative to the value of unemployment. Furthermore, interacting q_i with non-pecuniary amenities like stocks, signing bonuses, relocation allowances etc. allows random marginal effects for non-pecuniary amenities and drives preferential selection over job offers. Each element in the vector $\epsilon^1_i = (\{\epsilon^1_{ij}\}_{j\in J}, \epsilon^1_{i0})$ is drawn from an independent, identically distributed Type-1 extreme value distribution and $q_i \sim \mathcal{N}(0, \sigma^2_q)$.

[11] Recall that I categorize some fringe benefits as "non-pecuniary" amenities since, for a substantial portion of the sample, I do not have information on direct cash-equivalents of such benefits.

We normalize the value of the outside option for identification.[12] This value is given by

$$U_{i0} = \epsilon^1_{i0}. \tag{4}$$

Student i's optimal choice of job j given his set of job offers $\mathcal{O}(Z_i)$ solves the following problem:

$$C^*_i = \arg \max_{j \in \mathcal{O}(Z_i)} U_{ij} - U_{i0}. \tag{5}$$

5.3 Stage 1: Student Choice by Jobs

I assume that a firm allotted interview day k makes job offers independently of any other firm allotted the *same* interview day. This assumption is plausible since the career office requires all firms conducting interviews on the same interview day to announce job offers within a very short interval of time at the end of the interview day, typically late in the evening to prevent firms from coordinating on whom to hire (see, Section 3.1).

Let the binary variable A_{ij} indicate whether student i applies to job j. The vector $A_i = (A_{i1}, \ldots, A_{iJ})$ collects these indicators for all jobs. Taking student applications as given, job j accepts student i on interview day k with probability π^i_j, which depends upon both student and job characteristics. Let $f(Z_i|A_i)$ denote the probability of realizing a job offer vector Z_i given an application vector A_i. The formula for $f(Z_i|A_i)$ is shown in Appendix Section A.

In the following paragraphs, I describe how jobs choose students in more detail. Motivated by the earnings decomposition shown in Figure 1, I model firm hiring as a one stage process. Each job chooses an incoming cohort of students to maximize expected utility.[13] For a job j, the utility from student i is given by

$$V_{ij} = S'_{ij}\alpha + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta + \mu_{ij}. \tag{6}$$

where S_{ij} includes student and job characteristics. Student characteristics include controls for pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills, including dummies for whether or not the student qualified for various stages of job search. Job characteristics include dummies for the job sector and the entire set of over 50 non-pecuniary amenities, as applicable. The term w_j denotes the (log) salary offered by job j, q_i is econometrician-unobserved student-level attributes and μ_{ij} is an idiosyncratic match term, which is unobservable to student i but observable

[12] Disadvantaged castes are more negatively selected among non-job getters (see, Section 4.1). However, caste differences in average welfare may be modest within this sample. This is because the broader option set for disadvantaged castes includes government jobs, which have caste-specific quotas. These jobs are lower paying but provide very stable tenure. Recall that I do not include public sector jobs in my sample as they comprise less than 4% of all advertised jobs.

[13] Recall, a "job" means a job-designation within a firm.

to job j. We will assume that each μ_{ij} follows a standard logistic distribution and is independent across all students and jobs.[14]

Let $C(j)$ denote the set of applicants who accept an offer from job j. We will assume that the utility of job j from cohort $C(j)$ is given by

$$\overline{V}_j(C(j)) = \sum_{i \in C(j)} V_{ij}. \tag{7}$$

An economic interpretation of Equation 7 is that jobs do not focus on complementarities or team-building during hiring. The assumption is plausible since the university comprises a small fraction of a job's overall incoming cohort i.e. a job does not coordinate hiring across universities. Moreover, jobs select students for interviews based on screening tests which are general in scope. The assumption of firms not focusing on complementarities or team-building during hiring is also common in the firm-worker matching literature (Chade et al., 2006).

In Equation 7 above, the utility of job j is defined for a *given* cohort $C(j)$. $C(j)$ is random from the perspective of job j when it is deciding which students to extend offers to. Accepting an offer from job j depends upon students' preferences over other jobs (through ϵ_{ij} in Equation 3) while getting other jobs depends upon idiosyncratic match terms not observed by job j (through $\mu_{ij'}$ in Equation 6). While job j does not observe $\mu_{ij'}$ for $j' \neq j$, it observes $(S_{ij}, w_j, q_i, \mu_{ij})$ for each student i. Job j solves

$$Z^*(j) = \arg \max_{Z(j) \in \{0,1\}^{|A(j)|}} \mathbb{E}\left[\overline{V}_j(C(j))\right]. \tag{8}$$

$$\text{s.t. } \mathbb{E}(C(j)) \leq \overline{M_j}. \tag{9}$$

where the above expectation is taken over unknowns from the perspective of job j, $A(j)$ is the set of applicants to job j, $Z(j)$ is the set of applicants who receive offers from job j and Equation 9 is the ex-ante hiring constraint faced by job j. The left-hand side of Equation 9 is the expected size of the incoming cohort $C(j)$ for job j. We will assume that each job j has an ex-ante hiring cap which we denote by $\overline{M_j}$.

Note also that econometrician-unobserved q enters the utility functions of both students and jobs. An economic interpretation of such a specification is that jobs may choose students either because they like high q students (see, Equation 6) or because high q students are more likely to accept an offer conditional on getting one (see, Equations 3 and 9). Hence, q acts as a productivity term while also affecting preferences

[14] As shown in Equation 6, the probability of getting an offer from job j depends upon econometrician-unobserved q_i which is observable to student i. Therefore, from the student's perspective, job offer probabilities on a given interview day are independent based on the information available to him. However, job offer probabilities on a given interview day are not independent from the econometrician's perspective as they are all functions of q_i.

over jobs.[15,16]

In Appendix Section D.22, I show that each job j follows a cutoff hiring rule denoted by $\underline{k}_j^*$ and hires a student i iff $V_{ij} > \underline{k}_j^*$. The result relies on the assumption that the information observed by job j, $(S_{ij}, w_j, q_i, \mu_{ij})$, is sufficient for its valuation of V_{ij}. In other words, observing decisions of other jobs does not affect job j's best estimate of V_{ij}. Note also that $\underline{k}_j^*$ is not a structural parameter and will be allowed to change under counterfactuals. In fact, cutoff hiring rules will allow us to bound displacement effects of counterfactual policies which explicitly improve employers' valuation of disadvantaged castes (see, Section 8.1.1).

5.4 Equilibrium

An equilibrium is a tuple

$$\{\underline{k}_j^*, C_i^*\}_{i=1,\ldots,I, j=1,\ldots,J}$$

where $i \in \{1, \ldots, I\}$ indexes the student and $j \in \{1, \ldots, J\}$ indexes the job such that:

1. At the final stage, student i's optimal choice of job j given his set of job offers $\mathcal{O}(Z_i)$ solves

$$C_i^* = \arg \max_{j \in \mathcal{O}(Z_i)} U_{ij} - U_{i0}. \tag{10}$$

   where U_{ij} and U_{i0} are given by Equations 3 and 4 respectively.

2. Given the application vector A_i of student i, each job j solves

$$Z^*(j) = \arg \max_{Z(j) \in \{0,1\}^{|A(j)|}} \mathbb{E}\left[\overline{V}_j(C(j))\right]. \tag{11}$$

$$\text{s.t. } \mathbb{E}(C(j)) \leq \overline{M_j}. \tag{12}$$

   where the expectation above is taken over unknowns from the perspective of job j, $C(j)$ is the incoming cohort for job j, $A(j)$ is the set of applicants to job j, $Z(j)$ is the set of applicants who receive offers from job j, Equation 12 is the ex-ante hiring constraint faced by job j and $\overline{M_j}$ is the ex-ante hiring cap for job j.

[15]See, Howell (2010) for a similar treatment of unobserved heterogeneity.

[16]One might wonder if instead of the same q entering the utilities of students and jobs, it would be more reasonable to allow for two different, but correlated, sources of unobserved heterogeneity: one that affects how students value jobs and vice-versa. However, in a world where most students apply to all eligible jobs, such a correlation will be difficult to identify in practice. For example, if we consider such a correlation to represent the "quality" of the private information observed by the student about his employer-observed q, then the ideal data should have observably identical students with better signals applying more "aggressively". However, with little variation in student application behavior conditional on observables, such a correlation will be difficult to identify.

6 Identification and Estimation

I assume that characteristics like caste, salaries, non-pecuniary amenities etc. entering the utility function of students are exogenous. Similarly, exogenous characteristics entering the utility functions of jobs include salaries, sector, caste, major and degree etc. Identification of student preference parameters in Equation 3 comes from cross-student variation in job choices and other exogenous characteristics. Similarly, identification of job preference parameters in Equation 6 comes from cross-job variation in offer rates and other exogenous characteristics.

Differences in job choices and job offers among observationally equivalent students and jobs identify the distributional parameters of unobservable preferences entering their utility functions. Conditional on observables, highly correlated job offer outcomes within a student's job application portfolio imply that econometrician-unobserved q plays an important role in job hiring.

Identification of the caste parameter entering Equation 6 is crucial as counterfactual policies will aim to mitigate the "caste penalty" imposed by firms on disadvantaged castes. I assume that the caste coefficient entering the utility functions of jobs is causal. I also do not distinguish between taste-based, statistical or client-based discrimination. To address concerns regarding potential differences in unobservable ability by caste, Equation 6 includes detailed measures of pre-college skills, within-college academic performance, previous labor market experience, other employer-relevant skills, including dummies for whether or not the student qualified for various stages of job search.

I estimate the parameters by maximum simulated likelihood (MSL) and compute standard errors using the information identity. See Appendix Section B for details.

7 Parameter Estimates

In this section, I quantify the willingness-to-pay measures for key characteristics entering the utility function of students and firms. To do so, I scale the coefficients of interest by the coefficient on wage and express utility in wage units.

Recall that to credibly calculate WTP measures, I take advantage of rich data on job characteristics, a highly regulated placement process and representative wage setting (see, Sections 5.1 for details).

7.1 Student Preferences Over Job Characteristics

Table 1 shows select parameter estimates entering the utility functions of students. Unless otherwise stated, all compensation measures are interpreted for a student with mean q_i. All dollar amounts are in purchasing power parity (PPP) terms.

Table 1: Select Parameter Estimates (Student Utility)

Parameter	Estimate	Std. Error	Compensation ($)	Std. Error ($)	Compensation (%)	Std. Error (%)
Salary (log), τ	2.482***	0.008	—	—	—	—
Signing Bonus	0.156***	0.005	+3683.111***	120.058	+6.489***	0.211
Performance Bonus	0.049***	0.008	+1132.033***	199.491	+1.994***	0.351
Medical Insurance	0.046***	0.010	+1062.080***	233.872	+1.871***	0.412
Relocation Allowance	0.078***	0.010	+1812.616***	246.859	+3.193***	0.434
Restricted Stock Units	0.124***	0.002	+2908.609***	50.599	+5.123***	0.089
Getting a Job in Technology	0.078***	0.005	+1812.616***	115.655	+3.193***	0.204
Getting a Job in Consulting	0.087***	0.006	+2025.454***	143.100	+3.567***	0.252
Disadv. Caste × Salary (log)	−0.013	0.099	—	—	—	—
Disadv. Caste × Signing Bonus	−0.026	0.061	−591.654	1380.824	−1.042	2.432
Disadv. Caste × Performance Bonus	−0.011	0.117	−251.072	2664.572	−0.442	4.693
Disadv. Caste × Medical Insurance	−0.013	0.134	−296.602	3049.280	−0.522	5.371
Disadv. Caste × Relocation Allowance	−0.039	0.131	−885.165	2949.910	−1.559	5.196
Disadv. Caste × Restricted Stock Units	−0.012	0.127	−273.842	2891.160	−0.482	5.093
Disadv. Caste × Technology	−0.046	0.065	−1042.574	1459.487	−1.836	2.571
Disadv. Caste × Consulting	0.016	0.079	+367.188	1818.833	+0.647	3.204

Average Salary = $56,767.29 (PPP), N = 4207 (no. of students), J = 644 (no. of jobs).
Notes: Table 1 includes estimates for select student preference parameters over job characteristics. The compensation terms are calculated for a person with average unobserved heterogeneity (q) in units of dollars (PPP). Full estimation tables are available upon request.
* significant at 10%, ** significant at 5%, *** significant at 1%.

Stock options and signing bonuses are the most valuable non-pecuniary amenities.[17] All things the same, a student needs to be compensated 5.1% of average salary ($2909) to remain indifferent between a job that offers stock options versus one that does not. Similarly, the willingness-to-pay for signing bonuses is 6.5% of average salary ($3683). Other non-pecuniary amenities like relocation allowance, medical insurance and performance bonuses are not valued as highly as stock options or signing bonuses.

Jobs in the consulting sector are more preferred than comparable ones in either the technology or manufacturing sector. However, since first jobs may continue and disparities in starting salaries may have long term effects, these compensation measures may not fully capture the true willingness-to-pay to remain indifferent across sectors.

The model confirms a key result intimated in Figure 1: there are no average differences between castes in preferences over job characteristics, including non-pecuniary amenities and job sectors. Therefore, student preferences over jobs do not explain caste disparities. The absence between demographic groups in preferences over job characteristics is in contrast to those found in similar studies on labor market disparities, especially across gender (Altonji and Blank, 1999; Buser et al., 2014; Flory et al., 2014; Goldin, 2014; Mas and Pallais, 2017; Zafar and Wiswall, 2018).

7.2 Job Preferences Over Student Characteristics

Table 2 shows select parameter estimates entering the utility functions of jobs. All dollar amounts are in purchasing power parity (PPP) terms.

Overall, firms discount the value of disadvantaged castes at the equivalent of 4.8% of average annual salary ($2721), holding other student attributes constant.[18] This "caste penalty" imposed by firms for disadvantaged castes is consistent with descriptive facts which show the adverse effect of caste on firm hiring. The compensation required for employers to remain indifferent between an observably identical disadvantaged or advantaged castes is much higher than the amount required to offset a one standard deviation decrease in college entrance exam scores and on par with the amount required to offset a one standard deviation decrease in college GPA.

7.3 Modelled Unobservables

The model also allows us to learn about unobservables which jointly affect observed choices. Econometrician-unobserved q_i plays only a modest role in the utility functions of students. Consider a job that does not offer any non-pecuniary amenities. To get the same utility from that job as a student with one

[17] As mentioned before, in my dataset, I categorize some fringe benefits as "non-pecuniary" amenities since, for a substantial portion of the sample, I do not have information on direct cash-equivalents of such benefits.

[18] Recall that I do not distinguish between taste-based, statistical or client-based discrimination.

Table 2: Select Parameter Estimates (Job Utility)

Parameter	Estimate	Std. Error	Employer Subsidy ($)	Std. Error ($)	Employer Subsidy (%)	Std. Error (%)
Salary (log), ϕ	1.893***	0.074	—	—	—	—
Disadv. Caste, η	−0.093***	0.030	+2721.486***	863.231	+4.794***	1.521
			B.Tech. Degree			
College GPA	0.077***	0.023	+2262.744***	667.570	+3.986***	1.175
College GPA × Consulting	0.018**	0.010	+537.226**	299.516	+0.946**	0.522
College GPA × Technology	0.028**	0.012	+833.485**	357.073	+1.468**	0.630
Entrance Exam Score	0.022**	0.011	+655.917**	326.920	+1.155**	0.576
			Dual Degree			
College Degree	0.039	0.033	+1157.567	972.072	+2.039	1.712
College GPA	0.121***	0.021	+3515.013***	604.677	+6.192***	1.065
College GPA × Consulting	0.012	0.076	+358.718	2264.842	+0.632	3.990
College GPA × Technology	0.014	0.052	+418.283	1548.101	+0.737	2.727
Entrance Exam Score	0.019**	0.010	+566.922**	297.577	+0.998**	0.524
			M.Tech. Degree			
College Degree	0.203***	0.041	+5772.520***	1130.359	+10.169***	1.991
College GPA	0.123***	0.028	+3571.245***	796.479	+6.291***	1.403
College GPA × Consulting	0.038**	0.017	+1128.183**	503.132	+1.987**	0.886
College GPA × Technology	0.048	0.052	+1421.328	1521.945	+2.504	2.681
Entrance Exam Score	0.003***	0.001	+89.893***	29.988	+0.158***	0.053
			M.S. Degree			
College Degree	0.182***	0.063	+5203.660***	1727.431	+9.167***	3.043
College GPA	0.090***	0.022	+2635.767***	636.632	+4.643***	1.121
College GPA × Consulting	0.023	0.057	+685.550	1689.161	+1.207	2.976
College GPA × Technology	0.078	0.051	+2291.530	1472.316	+4.036	2.593
Entrance Exam Score	0.003***	0.001	+89.893***	29.998	+0.158***	0.053

Average Salary = $56,767.29 (PPP), N = 4207 (no. of students), J = 644 (no. of jobs).
Notes: Table 2 includes estimates for the preference parameters of jobs over student characteristics. Employer subsidy measures for entrance exam scores (GPA) are calculated for a unit standard deviation decrease in entrance exam score (GPA). College entrance exam scores (ranks) have been re-normalized so that higher numbers are better. The standard errors for the employer subsidy terms are calculated through the delta method. Degree fixed effects are shown relative to the Bachelor's degree. College GPA and sector interactions are shown relative to manufacturing sector. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%.

standard deviation higher q_i, a student with mean q_i needs to be compensated 1.7% ($969) of average salary.

Table 3: Modelled Unobservables

Parameter	Estimate	Std. Error
Standard deviation of q, σ_q	0.042^{***}	0.004
Parameter on σ_q, δ	0.512^{***}	0.024
$\gamma_{\text{Signing Bonus}}$	0.217^{***}	0.053
$\gamma_{\text{Performance Bonus}}$	0.526^{***}	0.049
$\gamma_{\text{Medical Insurance}}$	0.017	0.079
$\gamma_{\text{Relocation Allowance}}$	0.286^{***}	0.051
$\gamma_{\text{Restricted Stock Units}}$	0.487^{***}	0.104

Notes: Table 3 includes estimates of the standard deviation of econometrician-unobserved q, the factor loading $\$delta$ in Equation 6, and factor loadings (γ_m) in Equation 3, where m indexes non-pecuniary amenities or fringe benefits. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 3 shows random marginal effects over non-pecuniary amenities. To get the same utility as a student with one standard deviation higher q_i, a student with mean q_i needs to be compensated 6% of average salary ($3400) for the removal of stock options, 6.9% of average salary ($3906) for the removal of signing bonus, 3.7% of average salary ($3209) for the removal of relocation allowance and 2.9% of average salary ($1652) for the removal of performance bonus. Therefore, q_i not only shifts the value of all jobs relative to that unemployment but also drives preferential selection over job offers by making high q_i students value non-pecuniary amenities more than low q_i students (see, Equation 3).

As with job choices, econometrician-unobserved q_i plays only a modest role in firm hiring. A firm needs to be subsidized 1.1% of average salary ($623) to offset a one standard deviation decrease in econometrician-unobserved q_i.

Finally, Appendix Table D.35 shows model fit on job offers, job choices, unemployment and the earnings gap. The model matches these moments quite well. Job cutoff estimates are shown in Appendix Table D.36. These align with lay intuition. For example, the top 25% paying jobs have the highest cutoffs whereas the bottom 25% paying jobs have the lowest cutoffs.

8 Counterfactuals

As shown in Section 7.2, caste has a significant impact on firm hiring. To mitigate the role of caste on firm hiring, I propose and evaluate the effects of three counterfactual policies. First, I consider a policy in which firms are subsidized by the cash-equivalent amount that makes them indifferent between hiring an observably identical advantaged or disadvantaged caste. As mentioned previously, the subsidy is similar in spirit to the incentive-based Diversity Index proposed by the Ministry of Minority Affairs (Sachar Committee, 2006; Report of the Expert Group on Diversity Index, 2008). Next, I consider a "pre-college intervention" which equalizes the distribution of pre-college skills (college entrance exam scores) across castes. Finally, I consider a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes.

The hiring subsidy is a one-time payment amounting to 4.8% of average annual salary (see, Section 7.2).[19] The "pre-college intervention" policy encompasses different interventions — usually RCTs — including hiring tutors, bonuses to teachers, redesigning school curricula etc., which are evaluated through their impact on educational outcomes, especially test scores (Asim et al., 2015). Hiring quotas policies have been extensively used in government jobs and educational institutions, but not in the private sector (see, Section 2).

I assume that the composition of advantaged and disadvantaged castes remains fixed under all counterfactual policies. This assumption is tenable since admission quotas in the elite college equalize the distribution of castes within each major, and, therefore, within each cohort. I also keep GPA fixed in the counterfactuals. This assumption *overestimates* the effects of the "pre-college intervention" policy since entrance exam scores and college GPA are negatively correlated (see, Section 3.2.3.2 and Appendix Table D.5, D.6, D.7 and D.8).

8.1 Hiring Subsidies and Pre-College Intervention

In this section, I first discuss how the model can bound displacement effects under hiring subsidies and the "pre-college intervention" policy. I then compare absolute effects and discuss cost-effectiveness.

8.1.1 Bounding Displacement Effects

Note that both of these counterfactual policies explicitly improve employers' valuation of disadvantaged castes (see, Equation 6). The bounds depend upon the elasticity of labor demand.

[19] Estimating differing weights on caste by firm characteristics, like sector, is more of a theoretical curiosity, since subsidizing firms in proportion to the magnitudes of their discrimination may lead to perverse incentives, especially since my model does not distinguish between taste-based or statistical discrimination. For example, seen through the lens of my model, it would not be inconsistent to view a higher subsidy for consulting firms, compared to firms in technology, as a compensation for their higher animus toward disadvantaged groups.

When labor demand is perfectly elastic, jobs do not adjust cutoffs (reservation utilities) and hire everyone who qualifies. This scenario is schematically represented in Appendix Figure D.8. Disadvantaged caste hires are at least as large as in the baseline. There is also no displacement of advantaged castes. When labor demand is perfectly inelastic, jobs do not relax their employment targets, raise their reservation utility levels, and displace advantaged castes in favor of disadvantaged castes. The scenario is schematically represented in Appendix Figure D.9.

Under both scenarios, the number of disadvantaged caste hires is at least as large as in the baseline. However, it is bounded above by the number of hires when labor demand is perfectly elastic. Similarly, the number of advantaged caste hires is bounded below (above) by the number of hires when labor demand is perfectly inelastic (elastic).

The viewpoint above is a natural way to consider plausible responses under counterfactual policies which explicitly improve employers' valuation of disadvantaged castes. If firms start deriving higher utility from a proportion of the population, they would typically do a combination of increasing the hiring threshold a little and hiring a few more people.

8.1.2 Absolute Effects

The hiring subsidy is a one-time payment amounting to 4.8% of average annual salary. Firms put a very small weight on pre-college test scores, equivalent to a model-implied subsidy of only 0.6% of average annual salary ($337). Indeed, the weights on pre-college test scores are so small that even lower bounds of displacement effects under hiring subsidies are larger than upper bounds of displacement effects under the "pre-college intervention" policy. Basically, a rise in cutoffs offsets some of the positive effects of either policy.[20] However, the net effect of the subsidy policy is still larger than the full effect the "pre-college intervention" policy. Therefore, employer cash-subsidies increase job assignments and earnings of disadvantaged castes by substantially more, in absolute terms, than the "pre-college intervention" policy.

Lower and upper bound effects under both policies are shown for job offers, job choices, unemployment and earnings in Appendix Sections Appendix Tables D.39, D.40, D.41, D.42, D.43 and D.44.

8.1.3 Cost-Effectiveness

To evaluate cost-effectiveness, I compare the model-implied subsidy equivalent of the "pre-college intervention" policy to the direct costs of changing test scores. I use estimates from a meta-analysis documenting the costs of pre-college intervention policies — hiring tutors, paying bonuses to teachers, redesigning curricula etc. — which changed test scores of primary and secondary school students in India. These policies span nearly two decades (Asim et al., 2015). To extrapolate costs, I make two extremely con-

[20] Job cutoffs under hiring subsidies and the "pre-college intervention" policy are shown in Appendix Tables D.37 and D.38, respectively.

servative assumptions: 1) costs scale linearly with test score changes and, 2) students can be perfectly targeted i.e. the test score of a given student can be changed by any desired amount. Even under these assumptions, subsidies to hire disadvantaged castes are twice as cost-effective in promoting diversity than the "pre-college intervention" policy. he lower cost-effectiveness of the "pre-college intervention" policy is primarily driven by the modest effects of test scores in firm hiring, relative to caste.

8.1.4 Discussion

Policies, active or proposed, to subsidize employers to hire members of disadvantaged groups has many examples, particularly in India, U.S. and the E.U. For example, the Ministry of Minority Affairs in India recently proposed an incentive-based Diversity Index for all private sector firms. The Diversity Index is similar in spirit to the hiring subsidy studied in this paper. The government proposal mentions incentives (subsidies) to firms for promoting diversity, while denying rewards (implicit taxes) to those who fall below a certain threshold (Report of the Expert Group on Diversity Index, 2008, pg. 47). In early 2020, the government of Kerala, a large southern state in India, announced a hiring subsidy to promote women employment in new industries (ET Bureau, 2020). In the U.S., the federally mandated Work Opportunity Tax Credit (WOTC) subsidizes employers to hire welfare recipients, young food stamp recipients, poor veterans and youth from disadvantaged geographic areas (Hamersma, 2005). Similarly, 11 U.S. states currently provide hiring subsidies to encourage job creation (Neumark, 2013). Evidence from the U.S. shows that hiring subsidies typically outperform other active labor market policies, like public job creation programs, in improving post-program employability (Brown, 2015). In the E.U., hiring subsidies have been the most cost-effective methods to improve net employment, employee retention, and skill development. For example, in both Sweden and Switzerland, employers used subsidized hiring to screen workers as an alternative to work experience. As a consequence, employers were able to obtain direct information about on-the-job performance and correct stereotypes regarding the supposed low productivity of previously unemployed workers. This indirectly led to better labor market matching and, as a consequence, improved long-term employment prospects of targeted workers (Martin and Grubb, 2001; Kluve et al., 2008). In Germany, hiring subsidies helped previously unemployed workers in regaining human capital and readily transferable work-specific skills, hence improving labor market attachment (Neubäumer, 2012).

The equity-efficiency tradeoff is also of fundamental importance in assessing the potential of affirmative action policies. Pre-college interventions, like changes in test scores, can arguably raise both efficiency as well as promote equity. In this setting, I show that the direct productivity offset of test scores is quite small. Hence, efficiency gains from such policies are likely to be modest. Moreover, leaning towards equity through interventions in later stages, like hiring subsidies, might not necessarily sacrifice efficiency given growing evidence that disadvantaged groups are likely to benefit the most from selective education or job opportunities whereas displaced advantaged groups are likely to be not much worse off (Holzer and Neumark, 2000a,b; Holzer, 2007; Durlauf, 2008; Black et al., 2020). Similar legal arguments have been made recently in the U.S. in favor of redistributive policies in later stages, especially in college admissions (Grutter v. Bollinger, 2003; Fisher v. University of Texas, 2013, 2016). Improvements in pre-college skills might also be a consequence of incentivizing firms to hire more disadvantaged castes (Khanna, 2018; Akhtari et al., 2018).

Finally, while I do not discuss financing, hiring subsidies may raise tax receipts by increasing employment and also reduce expenditure on unemployment assistance. Recent studies of hiring subsidies in Germany and France have even found them to be self-financing (Brown and Snower, 2011; Cahuc et al., 2014).

8.2 Hiring Quotas

In this section, I evaluate the effects of a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes. Since the proportion of final hires are balanced on caste, I only evaluate the aggregate displacement effects (if any) of hiring quotas at the university.

8.2.1 Implementation

My model of the job placement process can readily accommodate hiring quotas. In contrast to firm responses to other hiring policies considered in this paper, firms now explicitly decide on two hiring thresholds: one for the advantaged castes and vice-versa.[21]

Solving for two cutoffs per job, instead of just one, introduces additional computational complexity. The computational challenge can be overcome by leveraging a key institutional feature of the job placement process. Recall that patterns borne out by the data allow us to assume interview day allocation as exogenous (see, Section 5.1). Additionally, students are prevented from attending interviews on future interview days conditional on receiving job offers on the current interview day (also see, Section 5.1) Hence, firms allotted the first interview day can ignore firms allotted the second interview day onward as legitimate competition. Firms allotted the second interview day can, therefore, take the decisions of firms allotted the first interview day as given, and can ignore firms allotted the third interview day onward as legitimate competition, and so on.[22]

Appendix Table D.45 shows the hiring cutoffs for advantaged and disadvantaged castes under the quota policy for each pay category, job sector and job title.

[21] I use the word "explicitly" because, under previous counterfactual policies, firms implicitly solved for two hiring thresholds. The cutoffs for disadvantaged castes were shifted up by the common intercept term ("caste penalty") in Equation 6.

[22] Of course, one could resort to a brute force calculation of alternative cutoffs, although the institutional features of the job placement process significantly enhance computational tractability.

8.2.2 Results

Unlike hiring subsidies or the "pre-college intervention" policy, quotas lead to a substantial *increase* in overall unemployment at the university as firms counteract the policy by making fewer job offers in total.[23]

The following elucidates the economic reasoning driving the result above. Under the quota policy, a firm needs to balance hiring of advantaged and disadvantaged castes. All things equal, if a firm derives substantially lower utility from disadvantaged castes, then it may be willing to hire an additional disadvantaged caste only if the accompanying advantaged caste hire gives it sufficiently high utility. Conversely, hiring an additional advantaged caste comes at the price of going further to the left of the skill distribution of disadvantaged castes (see, Equation 6; Figures D.8, D.9). A job slot is no longer filled if marginal utility of filling it exceeds marginal cost, but instead if the average marginal utility of filling two job slots — one filled by an advantaged caste and the other by a disadvantaged caste — exceeds the average marginal cost. It is worth noting that if a firm does not have a hard constraint on its hiring size, then quotas may either increase or decrease the fraction of students who are not recruited through the formal placement process.[24] If the penalty on disadvantaged castes is large enough to make the average marginal utility lower than the average marginal cost, a firm will counteract the quota policy by reducing aggregate hiring, even though the composition of total hires is balanced on caste.

Appendix Table D.46 shows the effect of hiring quotas on unemployment of advantaged and disadvantaged castes. As expected, more disadvantaged castes find jobs under quotas. The proportion of unemployed disadvantaged castes falls from 36% to 31%. However, the displacement effects of quotas on advantaged castes are severe. On average, nearly two advantaged castes become unemployed for a newly employed disadvantaged caste. The proportion of unemployed advantaged castes increases from 25% to 35%. Overall, quotas mirror a hiring tax and decrease university recruitment by 7%.[25]

9 Conclusion

To my knowledge, this is the first paper to formally study the entire job recruitment process of an elite college. Job recruitment processes moderated by college career offices serve as a critical segue between college and that first job. Therefore, a detailed study of such processes offers a unique window into the mechanisms which drive the sorting patterns in job search and, as a consequence, have implications for a richer understanding of the initial determinants of career trajectories and earnings growth.

Despite widespread and effective quota-based college admissions policies in India, there are large caste

[23] In my model, job salaries are taken as given (see, Section 5) so firms do not respond on the intensive margin by exerting wage discrimination under quota policies.

[24] In my model, a firm's hiring cap is denoted by $\overline{M_j}$ (see, Equation 9), which is *not* treated as a parameter.

[25] This result could also explain the prevalence of hiring backlogs in public sector jobs in India despite a similar government-mandated hiring quota policy (The Hindustan Times, 2006; The Economic Times, 2019; The Print, 2021).

disparities among private sector jobs. Still, the Indian private sector does not have compensatory hiring policies for disadvantaged castes. To address this gap, this paper employs novel administrative data on the job search from an elite college and evaluates policies to promote hiring diversity. I show that application reading (first round), written aptitude tests (second round), large group debates (third round), and job choices do not explain caste disparities. Disparities arise primarily between one-on-one interviews (fourth round) and job offers, the emergence closely paralleling caste revelation. These findings suggest that policies which provide information about jobs, modify preferences or improve performance at university are unlikely to close the earnings gap. Finally, I assess the potential of policies in promoting diversity. For promoting diversity, I show that hiring subsidies are twice as cost-effective as improving pre-college achievement. In contrast, government-mandated quotas mirror a hiring tax and reduce university recruitment by 7%.

While this paper does not directly quantify benefits due to diversity on firm profits or attitudes toward minorities, such changes have been documented in other studies. The mechanisms vary. Diverse teams may perform better by incorporating different viewpoints, often with little negative effects due to communication costs created by "language barriers" in diverse groups (Hoogendorn and Van Praag, 2012; Hoogendoorn et al., 2013). Non-homogeneous groups may also prevent corruption by reducing in-group favoritism (Prendergast and Topel, 1996; Banerjee et al., 2010; Beaman et al., 2010). Successful leaders in business, academia and politics from minority groups might help in changing attitudes regarding minorities, either directly by serving as role models for those in the minority group or indirectly by correcting previously held stereotypes of those in the majority group (Beaman et al., 2010; Cheryan et al., 2011; Betz and Sekaquaptewa, 2012). Recent works studying the effects of affirmative action policies in education or hiring have also argued that leaning towards diversity might be efficient since disadvantaged groups are likely to benefit the most from selective education or job opportunities whereas displaced advantaged groups are likely to be not much worse off (Holzer and Neumark, 2000a,b; Holzer, 2007; Durlauf, 2008; Black et al., 2020).

This paper also opens up many avenues for further research. For example, one could ask what the optimal job placement mechanism would be. Theoretical first-best mechanisms, like the one proposed by Kelso and Crawford (1982), may not be well-suited for distributional welfare (or, equity). However, ad-hoc job placement processes might sacrifice substantial aggregate welfare (or, efficiency) for modest improvements in distributional welfare. An ideal job placement process would, therefore, balance considerations of both equity and efficiency. Given the earnings drop off after personal interviews in my setting, future research could investigate how and why social differences manifest themselves as status differences, like "competence" on a given task. Research into better understanding the role of implicit bias in determining labor market outcomes could also be a promising area of future exploration. While there are examples of such works in sociology (Correll and Ridgeway, 2006; Ridgeway et al., 2009), economists have, thus far, paid relatively little attention to such endeavors. Experimenting with different recruitment formats, like using standardized interview questions, have also showed early promise (The New York Times, 2019). In future work, I plan to pursue these and other related avenues of research.

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A Calculation of Job Offer Probabilities

In this section, I show how to calculate job offer probabilities, which take into account the key features of the job placement process.

Let A_i^k be a vector of indicators which takes the value 1 if student i applies to a job allotted interview day k.[26] Similarly, let Z_i^k be a vector of indicators which takes the value 1 if student i gets accepted from a job allotted interview day k. Taking student applications as given, job j accepts student i on interview day k with probability π_j^i, which depends upon both student and job characteristics.

For a given interview day allotment to firms, define the probability of interview day k job offers given interview day k job applications, conditional on being eligible for an interview day k job offer, by

$$f_k(Z_i^k|A_i^k) = \prod_{j=1}^{J} \left(A_{ij}^k \left[\pi_j^i Z_{ij}^k + (1-\pi_j^i)(1-Z_{ij}^k) \right] + (1-A_{ij}^k)(1-Z_{ij}^k) \right). \tag{A.1}$$

From Section 5.1, it is reasonable to assume interview day allotments to jobs as exogenous. However, for the purposes of the illustration of the formula for job offer probabilities, it will be easier to also assign probabilities to interview day allotments.

Recall that Z_i is the offer vector for student i and A_i is the application vector for student i. Let $f(Z_i|A_i)$ denote the probability of realizing Z_i given A_i. Then, $f(Z_i|A_i)$ is defined as

$$f(Z_i|A_i) = \begin{cases} \prod_{l=0,1,\ldots,K} \widetilde{f}_l(\underbrace{(0,0,\ldots,0)}_{J}|A_i) & \text{if } Z_{ij}=0\ \forall j \\ \sum_{k=1}^{K} \left(\prod_{l=0,1,\ldots,k-1} \widetilde{f}_l(\underbrace{(0,0,\ldots,0)}_{J}|A_i) \right) \widetilde{f}_k(Z_i|A_i) & \text{else.} \end{cases} \tag{A.2}$$

where $\widetilde{f}_l(Z_i|A_i) = \sum_{\{m: Z_i \times D_m^l = Z_i\}} \Pr(D_m^l) f_l(Z_i^l|A_i^l)$ is the probability of realizing the offer vector Z_i on interview day l, D_m^l is a collection of indicator variables denoting a possible interview day assignment for day l and $m = 1, \ldots, 2^{|\{1,\ldots,J\}|}$. For completeness,

(1) Let $\widetilde{f}_0(\underbrace{(0,0,\ldots,0)}_{J}|A_i) = 1$.

[26] Recall, a "job" means a job-designation within a firm.

(2) If, for a given k, there is no such m such that $Z_i \times D_m^k = Z_i^k$, then set $\sum_{\{m: Z_i \times D_m^k = Z_i^k\}} \Pr(D_m^k) f_k(Z_i^k | A_i^k) = 0$.

The term $\prod_{l=0,1,\ldots,k-1} \widetilde{f}_l(\underbrace{(0,0,\ldots,0)}_{J} | A_i)$ is the probability that student i is eligible for a job offer on interview day k.

B Estimation Details and Standard Errors

I describe each of the choice probabilities below, the likelihood function to be estimated and the estimation method.

B.1 Job Choice by Students

Conditional on $q_i \sim N(0, \sigma_q^2)$ and given the assumption that each element in the vector of job acceptance shocks, ϵ_i^1, follows independent Type-1 extreme value distributions, the probability of student i choosing job j at the job choice stage is

$$\Pr(C_i^* = j | X_{ij}, w_j, \mathrm{NP}_j, q_i) = \frac{\exp(u_{ij})}{\sum_{k \in \mathcal{O}(Z_i)} \exp(u_{ik})}. \tag{B.1}$$

where $\mathcal{O}(Z_i)$ denotes offer set of student i, X_{ij} is the vector of student and firm characteristics, w_j is the (log) salary, NP_j is the vector of non-pecuniary amenities and $u_{ij} = X_{ij}'\beta + \mathrm{NP}_j'\Psi + w_j\tau + q_i + q_i \times \sum_{m=1}^{M} \gamma_m \mathrm{NP}_{jm}$.

B.2 Student Choice by Jobs

Conditional on $q_i \sim N(0, \sigma_q^2)$ and given the assumption that the idiosyncratic match specific term μ_{ij} between student i and job j follows a standard logistic distribution, the probability of student i getting accepted from job j is

$$\pi_j^i(S_{ij}, w_j, q_i, \underline{k_j^*}) = \frac{\exp(S_{ij}'\alpha + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta - \underline{k_j^*})}{1 + \exp(S_{ij}'\alpha + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta - \underline{k_j^*})}. \tag{B.2}$$

where S_{ij} is the vector of student and job characteristics, w_j is the (log) salary offered by job j and $\underline{k_j^*}$ is the cutoff hiring rule followed by job j. Let $f(Z_i|A_i)$ denote the the probability of realizing a job offer vector Z_i given an application vector A_i. The formula for $f(Z_i|A_i)$ is shown in Appendix Section A.

B.3 Likelihood

Let θ denote the parameters to be estimated. The complete likelihood contribution of student i with endogenous job offers and job choices, (Z_i^*, C_i^*), is given by

$$\mathcal{L}_i(Z_i^*, C_i^* | A_i, \overline{X_i}, \theta) = \int_q f(Z_i^* | A_i, \overline{X_i}, q, \theta) \times \Pr(C_i^* = j | Z_i^*, \overline{X_i}, q, \theta) \, dF(q|\theta). \tag{B.3}$$

where A_i is the application vector for student i and $\overline{X_i}$ is the vector of all other exogenous characteristics entering the likelihood function of student i.

Let $\mathcal{L}_i^r(\theta)$ be the likelihood for individual i in simulation r. Define

$$\widehat{\mathcal{L}}_i(\theta) = \frac{1}{R} \sum_{r=1}^{R} \mathcal{L}_i^r(\theta). \tag{B.4}$$

where R is the total number of simulation draws. The maximum simulated likelihood (MSL) estimator is then defined by

$$\widehat{\theta}_{MSL} = \arg\max_{\theta} \frac{1}{N} \sum_{i=1}^{N} \log \widehat{\mathcal{L}}_i(\theta) = \arg\max_{\theta} \left(\frac{1}{N} \sum_{i=1}^{N} \log \left[\frac{1}{R} \sum_{r=1}^{R} \mathcal{L}_i^r(\theta) \right] \right). \tag{B.5}$$

If R rises at any rate with N, the MSL estimator is consistent (Train, 2003).

I calculate standard errors using the information identity. By the information identity, the sample hessian, $\widehat{H}$, can be computed by the average outer product of the gradient of simulated likelihood evaluated at $\widehat{\theta}_{MSL}$ i.e.

$$\widehat{H} = \frac{1}{N} \sum_{i=1}^{N} \nabla_{\theta} \log \widehat{\mathcal{L}}_i(\widehat{\theta}_{MSL}) \nabla_{\theta} \log \widehat{\mathcal{L}}_i(\widehat{\theta}_{MSL})'. \tag{B.6}$$

Then, $\widehat{H}^{-1}$ is a consistent estimate of the variance of $\sqrt{N}(\widehat{\theta}_{MSL} - \theta^*)$, where θ^* is the vector of true parameter values.

C Modeling Job Applications

The difference in composition of job applications across castes is not economically significant in my setting. However, I show below that the model can be extended to incorporate job application behavior. Therefore, the decision to omit job applications is not a restriction on the generality of my model of the job placement process.

C.1 Choosing Jobs Instead of Job Portfolios

The key trick in modeling job application behavior is to convert the student's search from one over potential *job application portfolios* to one over *jobs*. The intuition is simple: for any job a student applied to, the expected marginal benefit from adding the job to his application vector should exceed the cost of applying to the job.

Let A_i denote the application vector of student i. Following the notation in Howell (2010), define

$$A_{i/k} = \begin{cases} \{m|m \in A_i, m \neq k\} & \text{if } k \in A_i \\ \{m|m \in A_i\} \cup \{k\} & \text{if } k \notin A_i \end{cases} \tag{C.1}$$

Then, it must be true that

$$MV_{i/k} > 0 \quad \forall k \in A_i \tag{C.2}$$

$$MV_{i/p} < 0 \quad \forall p \notin A_i \tag{C.3}$$

$MV_{i/k} = V(A_i) - V(A_{i/k})$ denotes the marginal value from modifying the application vector according to Equation C.1 above. To make the computation tractable, one proceeds by reducing the search space by eliminating dominated strategies. Following Howell (2010), we categorize strategies into four main categories: adjacent, non-adjacent, single-swap and multiple-swap strategies.

Consider an application vector, $A_i = \{\text{Goldman Sachs}, \text{Microsoft}, \text{Google}\}$. Removing "Goldman Sachs" from the application vector is an *adjacent strategy*. Removing both "Goldman Sachs" and "Google" from the application vector is a *non-adjacent strategy*. Replacing "Goldman Sachs" with "Facebook" in the application vector is a *single-swap strategy*. Replacing "Goldman Sachs" and "Microsoft" with "Facebook" and "Uber" in the application vector is a *multiple-swap strategy*.

Howell (2010) shows that if a student's application strategy is preferred to all adjacent and single-swap strategies, then it will also be preferred to all non-adjacent and multiple-swap strategies. Hence, to begin with, a student only needs to examine J application patterns and find the first job to apply to. Next, he needs to evaluate $J-1$ applications and find the second job to apply to and so on. At most, he needs to evaluate a total of $J + (J-1) + \cdots + 2 + 1 = \frac{J(J+1)}{2}$ applications. The complexity of the problem is reduced dramatically. When searching over *job portfolios*, the complexity of the problem is $\mathcal{O}(2^J)$, where J is the number of jobs. However, when searching over *jobs*, the complexity of the problem is only $\mathcal{O}(J)$, where J is the number of jobs. A similar idea is used in the Marginal Improvement Algorithm (MIA) studied by Chade and Smith (2006).

The cost of job applications can then be modelled in a manner similar to Howell (2010). Finally, a logit kernel smoother is used to obtain closed form solutions (Train, 2003).

D Appendix V: Tables and Figures

D.1 Students

Table D.1: Distribution of Students by Caste in Each College Degree

Degree	Adv. Caste	Disadv. Caste	Total
Bachelor of Technology	579	710	1289
Dual Degree	622	617	1239
Master of Technology	616	586	1202
Master of Science	350	127	477
N	2167	2040	4207
Fraction	0.51	0.49	1

Notes: Appendix Table D.1 includes the total number of students belonging to each caste in each college degree. The college degrees included are Bachelor of Technology (B.Tech.), Dual Degree (a five year integrated Bachelor's and Master's degree), Master of Technology (M.Tech.) and Master of Science (M.S.). Adv. Caste stands for advantaged caste and Disadv. Caste stands for disadvantaged caste.

D.2 Differences in Pre-College Skills Across Castes

Table D.2: Differences in Pre-College Skills Across Castes

	B.Tech. Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. entrance exam score	0.41	-0.37	0.78***
Avg. 10th grade score	0.07	-0.06	0.13
Avg. 12th grade score	0.04	-0.03	0.07
	Dual Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. entrance exam score	0.34	-0.38	0.72***
Avg. 10th grade score	0.03	-0.03	0.06
Avg. 12th grade score	-0.03	0.03	−0.06
	M.Tech. Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. entrance exam score	0.26	-0.28	0.54***
Avg. 10th grade score	0.04	-0.04	0.08
Avg. 12th grade score	0.02	-0.02	0.04
	M.S. Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. entrance exam score	-0.02	0.07	−0.09
Avg. 10th grade score	0.001	-0.001	0.002
Avg. 12th grade score	0.01	-0.02	0.03

Notes: Appendix Table D.2 documents differences in pre-college skills across castes. Pre-college skills include scores in 10th grade national level examinations, 12th grade national level examinations and college entrance exam scores. All scores are pooled and normalized to have zero mean and unit standard deviation. College entrance exam scores have been re-normalized so that higher numbers are better. The difference across castes is reported in standard deviation units. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.3 Differences in College GPA Across Castes

Table D.3: Differences in Average Overall GPA (Not Adjusted for Major) Across Castes

	B.Tech. Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. Overall GPA	0.51	-0.42	0.93***
	Dual Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. Overall GPA	0.43	-0.43	0.86***
	M.Tech. Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. Overall GPA	0.33	-0.35	0.68***
	M.S. Degree		
	Adv. Caste	Disadv. Caste	Difference (S.D.)
Avg. Overall GPA	0.05	-0.13	0.18**

Notes: Appendix Table D.3 documents differences in average college GPA (not adjusted for major) across castes. All scores are pooled and normalized to have zero mean and unit standard deviation. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

D.4 Predicting Major Assignments with Student Characteristics

Table D.4: Predicting Major Choice using Student Characteristics

	Dependent Variable: Assigned a Selective Major			
Coefficient	B.Tech.	Dual Degree	M.Tech. Degree	M.S. Degree
Accuracy	0.904	0.948	0.932	0.929
95% CI	[0.841, 0.948]	[0.896, 0.979]	[0.875, 0.969]	[0.841, 0.976]
Kappa	0.768	0.892	0.841	0.852

Notes: Appendix Table D.4 includes measures of predictive accuracy of major assignments given student characteristics. Dependent variable is whether or not a student was assigned a selective major. Controls include caste, college entrance exam scores, scores on 10th and 12th grade national level examinations. Bachelor of Technology (B.Tech.) and Dual degree students are admitted through a common entrance exam. Master of Technology (M.Tech.) and Master of Science (M.S.) degree students are admitted through a separate common entrance exam. Selective majors are Computer Science, Electrical Engineering, Mechanical Engineering, Civil Engineering and Chemical Engineering. Both columns report estimates from separate logistic regressions. Accuracy is the total number of correct predictions divided by the total number of observations. The Kappa statistic, which lies between 0 and 1, measures how classification results compare to values assigned by chance. A higher Kappa statistic is better. Full regression results are available on request.

D.5 College GPA and Entrance Exam Scores (B.Tech. Degree)

Table D.5: GPA for B.Tech. Degree Students and Entrance Exam Scores

	Dependent Variable: (log) GPA		
Coefficient	All	Non-Selective Majors	Selective Majors
Disadv. Caste	-0.171^{***} (0.010)	-0.162^{***} (0.011)	-0.187^{***} (0.020)
Entrance Exam Score	-0.025^{***} (0.006)	-0.008 (0.007)	-0.060^{***} (0.010)
N	1289	902	387
R^2	0.237	0.232	0.264
Adjusted R^2	0.230	0.225	0.249

Notes: Appendix Table D.5 includes estimates from a regression of grade point averages (GPA) of B.Tech. degree holders on student characteristics. Dependent variable is log GPA. Controls include college major, entrance exam score (standardized), grades in 10th and 12th grade national level examinations (standardized) and caste. College major includes dummies for each major. College entrance exam scores have been re-normalized so that higher numbers are better. In column (1), I report results for all students. In column (2), I report results only for students in non-selective majors. In column (3), I report results only for students in selective majors. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.6 College GPA and Entrance Exam Scores (Dual Degree)

Table D.6: GPA for Dual Degree Students and Entrance Exam Scores

	Dependent Variable: (log) GPA		
Coefficient	All	Non-Selective Majors	Selective Majors
Disadv. Caste	-0.147^{***} (0.009)	-0.140^{***} (0.012)	-0.155^{***} (0.014)
Entrance Exam Score	-0.029^{***} (0.006)	-0.021^{**} (0.010)	-0.036^{***} (0.007)
N	1239	780	459
R^2	0.221	0.190	0.276
Adjusted R^2	0.212	0.182	0.262

Notes: Appendix Table D.6 includes estimates from a regression of grade point averages (GPA) of Dual degree holders on student characteristics. Dependent variable is log GPA. Controls include college major, entrance exam score (standardized), grades in 10th and 12th grade national level examinations (standardized) and caste. College major includes dummies for each major. College entrance exam scores (ranks) have been re-normalized so that higher numbers are better. In column (1), I report results for all students. In column (2), I report results only for students in non-selective majors. In column (3), I report results only for students in selective majors. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.7 College GPA and Entrance Exam Scores (M.Tech. Degree)

Table D.7: GPA for M.Tech. Degree Students and Entrance Exam Scores

	Dependent Variable: (log) GPA		
Coefficient	All	Non-Selective Majors	Selective Majors
Disadv. Caste	-0.071^{***} (0.007)	-0.078^{***} (0.010)	-0.048^{***} (0.013)
Entrance Exam Score	-0.033^{***} (0.006)	-0.042^{***} (0.011)	-0.022^{***} (0.004)
N	1202	840	362
R^2	0.245	0.271	0.206
Adjusted R^2	0.236	0.264	0.183

Notes: Appendix Table D.7 includes estimates from a regression of grade point averages (GPA) of M.Tech. degree holders on student characteristics. Dependent variable is log GPA. Controls include college major, entrance exam score (standardized), grades in 10th and 12th grade national level examinations (standardized) and caste. College major includes dummies for each major. College entrance exam scores (ranks) have been re-normalized so that higher numbers are better. In column (1), I report results for all students. In column (2), I report results only for students in non-selective majors. In column (3), I report results only for students in selective majors. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.8 College GPA and Entrance Exam Scores (M.S. Degree)

Table D.8: GPA for M.S. Degree Students and Entrance Exam Scores

	Dependent Variable: (log) GPA		
Coefficient	All	Non-Selective Majors	Selective Majors
Disadv. Caste	-0.011^{*} (0.056)	-0.019^{**} (0.008)	0.003 (0.011)
Entrance Exam Score	-0.004^{***} (0.001)	-0.004 (0.010)	-0.005^{***} (0.001)
N	477	322	155
R^2	0.076	0.055	0.157
Adjusted R^2	0.046	0.031	0.098

Notes: Appendix Table D.8 includes estimates from a regression of grade point averages (GPA) of Master of Science (M.S.) degree holders on student characteristics. Dependent variable is log GPA. Controls include college major, entrance exam score (standardized), grades in 10th and 12th grade national level examinations (standardized) and caste. College major includes dummies for each major. College entrance exam scores (ranks) have been re-normalized so that higher numbers are better. In column (1), I report results for all students. In column (2), I report results only for students in non-selective majors. In column (3), I report results only for students in selective majors. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.9 Previous Labor Market Experience Across Castes

Table D.9: Differences in Previous Labor Market Experience Across Castes

	B.Tech. and Dual Degrees		
	Adv. Caste	Disadv. Caste	Difference
Avg. Internship Duration (Weeks)	8.00 (0.06)	7.81 (0.07)	0.19**
Fraction worked in the IT sector	0.22 (0.05)	0.22 (0.04)	0.00
Fraction worked in the Consulting Sector	0.35 (0.05)	0.37 (0.05)	−0.02
Fraction worked in the Manufacturing Sector	0.43 (0.05)	0.41 (0.06)	0.02
Fraction worked in a startup	0.34 (0.05)	0.30 (0.05)	0.04
Total Internship Pay ($)	3042.24 (249.40)	2877.28 (220.89)	164.96
	M.Tech. and M.S. Degrees		
	Adv. Caste	Disadv. Caste	Difference
Avg. Part-Time/Full-Time Employment Duration (Weeks)	68.48 (4.52)	68.93 (6.96)	−0.45
Fraction worked in the IT sector	0.36 (0.04)	0.18 (0.07)	0.18***
Fraction worked in the Consulting Sector	0.19 (0.04)	0.15 (0.06)	0.04
Fraction worked in the Manufacturing Sector	0.45 (0.05)	0.67 (0.08)	−0.12***
Total Part-Time/Full-Time Employment Pay ($)	22523.80 (1458.03)	19645.89 (1390.32)	2877.91

Notes: Appendix Table D.9 documents differences in previous labor market experience across castes. Previous labor market experience includes internship duration (weeks), part-time or full-time employment duration (weeks), total pay during internships, total pay during part-time or full-time employment, sectors of employment and employment in startups. Standard errors are reported in parenthesis. All dollar amounts are in puchasing power parity (PPP) units. T-tests are conducted for differences in overall means. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.10 Firms

Table D.10: Total Number of Firms and Average Salary by Sector

Sector	Total (Fraction)	Avg. Salary ($)
Technology	335 (0.52)	67302.64
Consulting	129 (0.20)	63544.02
Manufacturing	180 (0.28)	43525.25

Notes: Appendix Table D.10 shows the distribution of firms by sector and the average salary across all jobs by sector. Column (1) shows the number of firms in each sector with their proportions in parenthesis. Column (2) shows the average salary of all jobs in a given sector. All dollar amounts are in purchasing power parity (PPP) terms.

D.11 Non-Pecuniary Amenities by Sector

Table D.11: Select Non-Pecuniary Amenities by Job Sector

Non-Pecuniary Amenity	Technology	Consulting	Manufacturing
Stock Options	29.52	27.00	17.85
Signing Bonus	25.58	24.77	22.08
Medical Insurance	18.00	15.75	20.28
Relocation Allowance	36.78	40.95	28.80
401 Benefits/EPF	26.01	34.24	23.80
Retention Bonus	32.76	22.50	36.60
Travel Allowance	37.26	46.80	43.02
Annual Bonus	37.83	36.04	34.35
Performance Bonus	30.60	36.45	29.80

Notes: Appendix Table D.11 shows the fraction of firms in each sector offering a select subset of non-pecuniary amenities. EPF stands for Employees' Provident Fund. Retention Bonus is the extra amount paid for staying one additional year in the firm.

Table D.12: Non-Pecuniary Amenities

Row Number	Non-Pecuniary Amenity	Additional Details
1.	Variable Annual Pay?	
2.	Is the Variable Compensation Taxable?	
3.	Restricted Stock Units?	
4.	Paid Leave?	Non-personal, non-educational purposes leave
5.	Sickness or Disability Leave?	
6.	Signing Bonus?	
7.	Bonus for spending 1 year in the firm?	
8.	Bonus for spending 2 years in the firm?	
9.	Bonus for spending 3 years in the firm?	
10.	Bonus for spending 4 years in the firm?	
11.	Annual Bonus?	
12.	Variable Bonus?	In addition to fixed bonus
13.	Performance Bonus?	Could be project specific
14.	Stakeholder Bonus?	
15.	Festival Bonus?	
16.	Loyalty Bonus?	Might vary by job tenure
17.	ELRP Bonus?	Also called deferred compensation
18.	Probation Completion Bonus?	
19.	Relocation Bonus?	
20.	Relocation Assistance?	Arranging moving company
21.	Employees' Provident Fund (EPF)?	Similar to a 401k benefit
22.	Voluntary Provident Fund?	Voluntary employee contribution over and above EPF
23.	Medical Insurance?	
24.	Dental Insurance?	
25.	Eye Insurance?	
26.	Life Insurance?	
27.	Food Allowance?	
28.	Temporary Accommodation?	
29.	Stipend during temporary accommodation?	
30.	Travel Allowance?	Air, rail and road travel
31.	Leave Travel Concession (LTC)?	Non-work related travel

Notes: Appendix Table D.12 shows the complete list of unique non-pecuniary amenities in the data along with an added description of the perks, unless self-explanatory. In the data, amenities vary within job title i.e. job designation within a firm.

Table D.13: Non-Pecuniary Amenities (Contd.)

Row Number	Non-Pecuniary Amenity	Additional Details
32.	House Rent Allowance (HRA)?	
33.	Telephone/Mobile Phone Allowance?	
34.	Conveyance Allowance?	Covers travel between work and residence
35.	Night Shift Allowance?	
36.	Counseling Services?	
37.	Option to work from home?	
38.	Paid Maternity Leave?	
39.	Sodexo Coupons?	Tax-free vouchers for restaurants, grocery stores etc.
40.	Flexible working hours?	
41.	Paid day care for kids?	
42.	Happy Fridays?	
43.	Gym subsidies?	
44.	Lunch on company campus?	
45.	Child Psychology Services?	
46.	Personal development classes?	Yoga, cooking, dancing etc.
47.	Family days?	
48.	Smoking Zones?	
49.	Telemedicine?	
50.	Parental Day Care?	
51.	Financial Literacy classes?	
52.	Employee Assistance Program?	
53.	Subsidized personal leave?	Usually upto 6 months
54.	Subsidized educational leave?	
55.	Subsidized high-school education for kids?	
56.	Subsidized Housing?	
57.	Gratuity?	Lump sum payment after 4 years 8 months of service
58.	Leave Encashments?	Unused paid leave reimbursed as part of salary
59.	Option to return after sabbatical?	

Notes: Appendix Table D.13 shows the complete list of unique non-pecuniary amenities in the data along with an added description of the perks, unless self-explanatory. In the data, amenities vary within job title i.e. job designation within a firm.

D.12 Employer Registration form

Step 1: After the invitation, companies should register basic details using the online portal.

Step 2: Register basic details on online portal:

A) Company Details:

- Company Name* :
- Password* :
- Confirm Password* :
- Website* :

B) Contact Details:

- Name* :
- Designation* :
- Contact Number* :
- Address* :

Step 3: After registering basic details, companies should enter job details, select majors who qualify to apply etc.

A) Job Details:

- Job Designation* :
- Offer Types* : Domestic ☐ International ☐
- Startup* : Yes ☐ No ☐
- Job Description* : Job_Details.pdf [details of non-pecuniary amenities here]

B) Select the Majors you wish to recruit from:

- **Bachelor of Technology:**
  All ☐ Electrical Eng. ☐ Aerospace Eng. ☐ Mechanical Eng. ☐
  Metallurgical Eng. ☐ Civil Eng. ☐ Material Eng. ☐
  Ocean Eng. ☐ Computer Science ☐
- **Dual Degree:**
  All ☐ Electrical Eng. ☐ Aerospace Eng. ☐ Mechanical Eng. ☐
  Metallurgical Eng. ☐ Civil Eng. ☐ Material Eng. ☐
  Ocean Eng. ☐ Computer Science ☐

- **Master of Technology:**
  All ☐ Electrical Eng. ☐ Aerospace Eng. ☐ Mechanical Eng. ☐
  Metallurgical Eng. ☐ Civil Eng. ☐ Material Eng. ☐
  Ocean Eng. ☐ Computer Science ☐
- **Master of Science:**
  All ☐ Physics ☐ Chemistry ☐ Mathematics ☐

C) Salary Details:

Degree	Gross Annual Pay	Gross Monthly Pay	Additional Comments
Bachelor of Technology			
Dual Degree			
Master of Technology			
Master of Science			

D.13 Large Earnings Gap Across Castes

Using data on job placements, I document large earnings disparities across castes. I run different specifications of the following regression:

$$\log(\text{earnings}_i) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \tag{C.4}$$

The coefficient of interest is β, which is reported in Appendix Tables D.14, D.16 and D.15 for four alternative specifications. In all of the regression tables below, I include detailed controls on pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2).

Table D.14: Earnings Gap

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Full Interactions
Disadv. Caste	-0.113^{***} (0.014)	-0.115^{***} (0.015)	-0.107^{***} (0.015)	-0.105^{***} (0.017)
N	2927	2927	2927	2927
R^2	0.452	0.455	0.459	0.532
Adjusted R^2	0.447	0.448	0.450	0.486

Notes: Appendix Table D.14 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), GPA and entrance exam scores enter as quadratic polynomials while other controls enter linearly. In column (3), GPA and entrance exam scores enter as cubic polynomials while other controls enter linearly. In column (4), estimates are reported from a fully-flexible quadratic polynomial regression with all possible interactions between controls. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table D.15: Earnings Gap with Score Quantiles

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Rank Quartile	Rank Quintile	Rank Decile
Disadv. Caste	-0.113^{***} (0.014)	-0.111^{***} (0.015)	-0.112^{***} (0.015)	-0.106^{***} (0.015)
N	2927	2927	2927	2927
R^2	0.452	0.448	0.449	0.452
Adjusted R^2	0.447	0.442	0.443	0.445

Notes: Appendix Table D.15 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), dummies for entrance exam score quartiles are included. In column (3), dummies for entrance exam score quintiles are included. In column (4), dummies for entrance exam score deciles are included. Full regression results are available on request. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table D.16: Earnings Gap with Fully-Flexible Polynomials

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.113^{***} (0.014)	-0.105^{***} (0.017)	-0.104^{***} (0.019)	-0.104^{***} (0.024)
N	2927	2927	2927	2927
R^2	0.452	0.532	0.553	0.578
Adjusted R^2	0.447	0.486	0.490	0.497

Notes: Appendix Table D.16 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a natural cubic spline regression with three degrees of freedom is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available on request. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.14 The Earnings Gap is Conservative

Table D.17: Average GPA of Students vs. those of Students Without Jobs

B.Tech. Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
8.08	7.00	7.97	6.58***
Dual Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
8.05	7.15	8.02	6.86**
M.Tech. Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
8.33	7.62	8.00***	7.35***
M.S. Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
8.49	8.42	8.46	8.23*

Notes: Appendix Table D.17 compares the average GPA of students versus those of students without jobs. T-tests are conducted for differences in overall means versus means of students without jobs within each caste. Significance denoted by asterisks are shown in the third and fourth columns. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table D.18: Average Entrance Exam Scores of Students vs. those of Students Without Jobs

		B.Tech. Degree	
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-1617.89	-3707.45	-1879.32^{*}	-4315.18^{**}
		Dual Degree	
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-2096.60	-4067.13	-2602.79^{***}	-5743.80^{***}
		M.Tech. Degree	
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-653.94	-2445.64	-1052.61^{***}	-3310.677^{**}
		M.S. Degree	
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-558.94	-1416.09	-642.18	-1411.26

Notes: Appendix Table D.18 compares the average entrance exam scores (ranks) of students versus those of students without jobs. Ranks have been re-normalized so that higher numbers are better. T-tests are conducted for differences in overall means versus means of students without jobs within each caste. Significance denoted by asterisks are shown in the third and fourth columns. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.15 Job Applications Do Not Explain the Earnings Gap

Using data on job applications, I show that the composition of job applications does not explain the earnings gap reported in Appendix Table D.14. Appendix Figure D.2 shows the raw distribution of salaries of jobs to which students applied.

Even without any controls, the distribution of salaries of jobs to which students applied is strikingly similar across castes. These similarities are largely explained by the presence of a centralized job application portal (like, JOE, EconJobMarket etc.), which makes the marginal cost of an additional application effectively zero. The difference between castes in the unconditional mean salary of jobs to which students applied is only -0.04 (0.001) log points, or 4%. To see if this difference remains salient in the presence of controls, I run different specifications of the following regression:

$$\log(\text{Avg. Salary of Jobs Applied to}_i) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \tag{C.5}$$

Table D.19: Salaries of Jobs to Which Students Applied

	Dependent Variable: Log Avg. Salary of Jobs Applied To (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Full Interactions
Disadv. Caste	−0.001 (0.007)	−0.001 (0.008)	−0.001 (0.007)	−0.001 (0.007)
N	4207	4207	4207	4207
R^2	0.554	0.556	0.557	0.613
Adjusted R^2	0.551	0.553	0.553	0.585

Notes: Appendix Table D.19 includes estimates from a regression run on the sample of all students who applied for jobs. Dependent variable is log average salary of jobs to which students applied. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), GPA and entrance exam score enter as quadratic polynomials while other controls enter linearly. In column (3), GPA and entrance exam score enter as cubic polynomials while other controls enter linearly. In column (4), estimates are reported from a fully-flexible quadratic polynomial regression with all possible interactions between controls. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The coefficient of interest is β, which is reported in Appendix Table D.19 for four alternative specifications. Appendix Table D.19 shows that the difference between castes in the average salary of jobs to which students applied is only -0.001 (0.007) log points, or 0.1%. The difference is economically very small, and statistically insignificant. Therefore, the composition of job applications does not explain the earnings gap across castes. The results are robust to many different specifications (see, Appendix Table D.20).

Appendix Table D.21 shows that disadvantaged and advantaged castes submit, on average, the same number of job applications.

Table D.20: Salaries of Jobs to Which Students Applied with Fully-Flexible Polynomials

	Dependent Variable: Log Avg. Salary of Jobs Applied to (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.001 (0.007)	-0.001 (0.007)	-0.001 (0.008)	-0.001 (0.007)
N	4207	4207	4207	4207
R^2	0.554	0.613	0.631	0.625
Adjusted R^2	0.551	0.585	0.587	0.395

Notes: Appendix Table D.20 includes estimates from a regression run on the sample of all students who applied for jobs. Dependent variable is log average salary of jobs to which students applied. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), estimates from a natural cubic spline with three degrees of freedom are reported. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available on request. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table D.21: No. of Jobs to Which Students Applied with Fully-Flexible Polynomials

	Dependent Variable: Log No. of Jobs Applied to			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.012 (0.033)	-0.034 (0.034)	-0.038 (0.037)	-0.034 (0.033)
N	4207	4207	4207	4207
R^2	0.248	0.427	0.443	0.446
Adjusted R^2	0.244	0.385	0.388	0.395

Notes: Appendix Table D.21 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log number of firms to which students applied. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), estimates from a natural cubic spline with three degrees of freedom are reported. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available on request. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.16 Differential Impact of Group Discussions by Sector

Figure 1 shows that the initial drop off in earnings across castes occurs at the group discussion stage (third round). On average, disadvantaged castes perform similarly to advantaged castes in written aptitude tests (second round). The drop off at the group discussion stage raises the possibility that disadvantaged castes have worse communication skills, on average, than advantaged castes. Alternatively, it is possible that while differences in communication skills across castes are not substantial, these skills are valued differently in different sectors. For example, firms in the consulting sector may place a large weight on communication skills while making interview decisions and exacerbate small initial differences in communication skills across castes.

In this section, I study whether the drop off in earnings across castes at the group discussion stage shown in Figure 1 varies by sector. I find that the drop off in earnings across castes at the group discussion stage occurs only among consulting jobs and not among jobs in either technology or manufacturing.

Appendix Figure D.3 shows the decomposition of the earnings gap in the manufacturing sector. There is no drop off in earnings across castes at the group discussion stage. The point estimate of the earnings gap across castes among manufacturing jobs is about 4%, and the upper bound of the 95% confidence interview is slightly above zero (see also, Appendix Table D.27).

Appendix Figure D.4 shows the decomposition of the earnings gap in the technology sector. Notably, there is still no drop off in earnings across castes at the group discussion stage. However, the point estimate of the earnings gap across castes among jobs in technology is about 8% (see also, Appendix Table D.28).

Appendix Figure D.5 shows the decomposition of the earnings gap in the consulting sector. Unlike in manufacturing or technology jobs, there is a drop off in earnings across castes at the group discussion stage among consulting jobs. The point estimate of the earnings gap across castes among jobs in consulting is about 10% (see also, Appendix Table D.29).

Overall, these findings indicate that the drop off in earnings across castes at the group discussion stage, shown in Figure 1, is exclusively driven by the consulting sector. These results suggest the possibility that communication skills are valued differently by consulting jobs. However, based on the absence of an earnings drop off at the group discussion stage among jobs in technology and manufacturing, it seems unlikely that average differences in communication skills across castes are prohibitively large. After all, verbal skills are part of the screening mechanisms of most jobs in technology and manufacturing. Therefore, it is reasonable to assume such firms value communication skills to some degree. Still, it is challenging to formally disentangle differences in communications skills across castes from the weights placed on them by firms in different sectors.

It is also challenging to formally separate the role of caste in firm hiring from differences in communication skills across castes. One could identify a random effect on the odds of getting through different types of interviews, with factor loadings that depend on job sectors. However, the random effect may not be communication skills. Moreover, by definition, such a specification would be uninformative regarding caste-related differences in the distribution of communication skills.

D.17 Differences in Job Assignments Are Most Pronounced in the Consulting Sector and in Client Facing Jobs

Motivated by the differential impact on castes by sector (particularly, at the group discussion stage), I examine whether there are characteristics of a job, besides pay, that predict a disadvantaged caste hire. I find that, even unconditional on pay, consulting jobs and client-facing jobs are less likely to hire disadvantaged castes. These findings are consistent with a Beckerian framework of labor market sorting in which job assignments might be driven by the affinity of clients in some sectors, like consulting, to work with advantaged castes (Becker, 1971).

I first show that, even unconditional on pay, jobs in the consulting sector are less likely to hire disadvantaged castes. To do so, I run different specifications of the following regression:

$$1\{i \text{ hired in the } j \text{ sector}\} = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \tag{C.6}$$

where $j \in \{\text{Technology, Consulting, Manufacturing}\}$. The coefficient of interest is β. These regressions include only those students who submitted at least one job application in a given sector.

Table D.22: Offer Probabilities for Jobs in the Technology Sector

	Dependent Variable: Got an Offer		
Coefficient	LPM	Logit	Probit
Disadv. Caste	0.039** (0.016)	0.037** (0.016)	0.036** (0.015)
N	3974	3974	3974
R^2	0.187	0.156	0.157
Adjusted R^2	0.182	0.146	0.146

Notes: Appendix Table D.22 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got an offer from a job in the technology sector. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The differences in job assignments between advantaged and disadvantaged castes are most pronounced in the consulting sector. On average, disadvantaged castes are 8 percentage points less likely to get consulting jobs than advantaged castes.

The trends are reversed in the manufacturing and technology sectors. Disadvantaged castes are as likely as advantaged castes to get jobs in manufacturing. Disadvantaged castes are 4 percentage points more likely to get jobs in technology than advantaged castes (see, Appendix Tables D.22, D.23 and D.24).

Table D.23: Offer Probabilities for Jobs in the Manufacturing Sector

Coefficient	Dependent Variable: Got an Offer LPM	Logit	Probit
Disadv. Caste	0.015 (0.015)	0.016 (0.015)	0.015 (0.015)
N	3563	3563	3563
R^2	0.114	0.122	0.122
Adjusted R^2	0.108	0.108	0.108

Notes: Appendix Table D.23 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got an offer from a job in the manufacturing sector. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table D.24: Offer Probabilities for Jobs in the Consulting Sector

Coefficient	Dependent Variable: Got an Offer LPM	Logit	Probit
Disadv. Caste	-0.081^{***} (0.014)	-0.087^{***} (0.015)	-0.082^{***} (0.015)
N	3610	3610	3610
R^2	0.142	0.160	0.159
Adjusted R^2	0.136	0.146	0.145

Notes: Appendix Table D.24 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got an offer from a job in the consulting sector. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.18 Job Offer Disparities Largest in Client Facing Jobs

I now show that, even unconditional on pay, client facing jobs are less likely to hire disadvantaged castes. Detailed job descriptions (particularly, job titles and job functions) were used to categorize jobs as client facing versus non-client facing. Typically, a software engineering role would be considered as non-client facing whereas a consulting or managerial role would be considered as client facing. Nearly 85% of the jobs are non-client facing. I run different specifications of the following regression:

$$1\{i \text{ got a } k \text{ job} \mid \text{applying}\} = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \tag{C.7}$$

where $k \in \{\text{Client Facing, Non-Client Facing}\}$. The coefficient of interest is β. These regressions include only those students who submitted at least one job application in a given type of job.

The differences in job assignments between advantaged and disadvantaged castes are most pronounced within client facing jobs. On average, client facing jobs are 8 percentage points less likely to hire disadvantaged castes than advantaged castes. In contrast, non-client facing jobs are 6 percentage points more likely to hire disadvantaged castes than advantaged castes (see, Appendix Tables D.25 and D.26).

Table D.25: Offer Probabilities in Client Facing Jobs

	Dependent Variable: Got an Offer		
Coefficient	LPM	Logit	Probit
Disadv. Caste	-0.083^{***} (0.015)	-0.087^{***} (0.015)	-0.084^{***} (0.015)
N	3751	3751	3751
R^2	0.159	0.171	0.169
Adjusted R^2	0.153	0.159	0.156

Notes: Appendix Table D.25 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got a client facing job. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix Tables D.27-D.31 show that the largest earnings disparities are in the consulting sector and client facing jobs. For example, the earnings gap among firms in the consulting sector is -0.102 (0.033) log points, whereas it is -0.071 (0.033) log points among technology firms and -0.041 (0.033) log points among manufacturing firms.[27] Similarly, the earnings gap among client-facing jobs is -0.123 (0.031) log points, whereas it is -0.071 (0.022) log points among non-client facing jobs.

[27] Recall, firms in the technology and consulting sectors comprise nearly three-quarters of all firms (see, Section 3.2.4).

Table D.26: Offer Probabilities in Non-Client Facing Jobs

	Dependent Variable: Got an Offer		
Coefficient	LPM	Logit	Probit
Disadv. Caste	0.063*** (0.017)	0.058*** (0.016)	0.058*** (0.016)
N	4109	4109	4109
R^2	0.142	0.120	0.120
Adjusted R^2	0.136	0.111	0.111

Notes: Appendix Table D.26 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got a non-client facing job. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

D.19 Earnings Gap Largest in the Consulting Sector

Table D.27: Earnings Gap in the Manufacturing Sector

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.044^{*} (0.023)	-0.037 (0.028)	-0.050 (0.032)	-0.041 (0.033)
N	789	789	789	789
R^2	0.258	0.502	0.593	0.601
Adjusted R^2	0.230	0.312	0.349	0.362

Notes: Appendix Table D.27 includes estimates from an earnings regression run on the sample of all students who graduated with jobs in the technology sector. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table D.28: Earnings Gap in the Technology Sector

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.080^{***} (0.022)	-0.077^{***} (0.028)	-0.061^{*} (0.033)	-0.071^{**} (0.033)
N	1435	1435	1435	1435
R^2	0.418	0.535	0.574	0.575
Adjusted R^2	0.406	0.438	0.443	0.446

Notes: Appendix Table D.28 includes estimates from an earnings regression run on the sample of all students who graduated with jobs in the technology sector. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table D.29: Earnings Gap in the Consulting Sector

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.102^{***} (0.033)	-0.104^{***} (0.033)	-0.102^{***} (0.032)	-0.102^{***} (0.033)
N	703	703	703	703
R^2	0.475	0.613	0.663	0.667
Adjusted R^2	0.454	0.473	0.495	0.498

Notes: Appendix Table D.29 includes estimates from an earnings regression run on the sample of all students who graduated with jobs in the consulting sector. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D.20 Earnings Gap Largest in Client Facing Jobs

Table D.30: Earnings Gap in Client Facing Jobs

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.105^{***} (0.030)	-0.121^{***} (0.037)	-0.126^{***} (0.045)	-0.123^{***} (0.031)
N	822	822	822	822
R^2	0.424	0.554	0.599	0.601
Adjusted R^2	0.404	0.417	0.435	0.436

Notes: Appendix Table D.30 includes estimates from an earnings regression run on the sample of all students who graduated with client facing jobs. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table D.31: Earnings Gap in Non-Client Facing Jobs

	Dependent Variable: Log Earnings (USD PPP)			
Coefficient	Linear	Quadratic	Cubic	Splines
Disadv. Caste	-0.080^{***} (0.016)	-0.070^{***} (0.020)	-0.074^{***} (0.022)	-0.071^{***} (0.022)
N	2105	2105	2105	2105
R^2	0.499	0.581	0.609	0.609
Adjusted R^2	0.492	0.522	0.528	0.528

Notes: Appendix Table D.31 includes estimates from an earnings regression run on the sample of all students who graduated with non-client facing jobs. Dependent variable is log earnings. I include detailed controls including measures of pre-college skills, within-college academic performance, previous labor market experience and other employer-relevant skills (see, Section 3.2). Each column is a separate regression and includes all the controls mentioned above. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

D.21 Interview Days and Firm Characteristics

Table D.32: Predicting Interview Days with Job Characteristics Only

	Dependent Variable: Assigned a Particular Interview Day		
Coefficient	Logistic	Random Forest	Decision Tree
Accuracy	0.734	0.759	0.721
95% CI	[0.690, 0.7745]	[0.716, 0.798]	[0.676, 0.762]
Kappa	0.304	0.366	0.356

Notes: Appendix Table D.32 includes measures of predictive accuracy of interview day assignments given firm characteristics. Dependent variable is the interview day assigned to a firm. Controls include job salaries, job sectors and job titles. In column (1), an ordered logistic model is estimated. In column (2), a random forest model is estimated. In column (3), a decision tree model is estimated. Accuracy is the total number of correct predictions divided by the total number of observations. The Kappa statistic, which lies between 0 and 1, measures how classification results compare to values assigned by chance. A higher Kappa statistic is better. Full regression results are available on request.

Table D.33: Predicting Interview Days with Job Characteristics and "Firm Identity"

	Dependent Variable: Assigned a Particular Interview Day		
Coefficient	Logistic	Random Forest	Decision Tree
Accuracy	0.948	0.951	0.952
95% CI	[0.923, 0.967]	[0.926, 0.969]	[0.929, 0.971]
Kappa	0.879	0.884	0.890

Notes: Appendix Table D.33 includes measures of predictive accuracy of interview day assignments given firm characteristics and measures of "firm identity". "Firm identity" is proxied by previous interview day assignment of the same firm. Other controls include job salaries, job sectors and job titles. Dependent variable is the interview day assigned to a firm. In column (1), an ordered logistic model is estimated. In column (2), a random forest model is estimated. In column (3), a decision tree model is estimated. Accuracy is the total number of correct predictions divided by the total number of observations. The Kappa statistic, which lies between 0 and 1, measures how classification results compare to values assigned by chance. A higher Kappa statistic is better. Full regression results are available on request.

D.22 Each job follows a cutoff hiring rule

Proposition 1. *Each job j follows a cutoff hiring rule denoted by $\underline{k_j^*}$ and hires a student i iff $V_{ij} > \underline{k_j^*}$.*

Proof. The proof follows from Kapor (2020). We prove the proposition above by contradiction. Let $\texttt{Hire}\{j\} : \{1, \ldots, I\} \rightarrow [0, 1]$ be a hiring rule used by job j which satisfies Equation 9. Suppose it is not a cutoff rule. Then there exist two students i and i' such that $V_{ij} > V_{i'j}$ but $\texttt{Hire}\{j\}(i) < 1$ and $\texttt{Hire}\{j\}(i') > 0$. Let P_{ij} and $P_{i'j}$ denote the probabilities that students i and i' accept offers from job j. Then, for some $\epsilon > 0$, it is feasible for job j to increase $\texttt{Hire}\{j\}(i)$ by $\frac{\epsilon}{P_{ij}}$, reduce $\texttt{Hire}\{j\}(i')$ by $\frac{\epsilon}{P_{i'j}}$ and increase overall cohort quality. $\square$

D.23 Model Fit

Table D.35: Model Fit: Job Offer, Job Choice, Unemployment and Earnings

Model Fit		
	Job Offer	
	Data	Model
Consulting	0.25	0.23
Technology	0.48	0.51
Manufacturing	0.27	0.26
	Job Choice	
	Data	Model
Consulting	0.24	0.22
Technology	0.49	0.51
Manufacturing	0.27	0.27
	Unemployed	
	Data	Model
—	0.30	0.31
	Earnings Gap	
	Data	Model
—	-11.3%	-10.6%

Notes: Appendix Table D.35 compares the moments in the data to the corresponding model-simulated moments. Earnings gap reported in the first column corresponds to the regression specification where all controls enter linearly (see, Appendix Table D.14). Model-simulated moments are computed by simulating the model using the MSL estimates 300 times for each observation in the sample, and then averaging over the number of observations and the number of simulation draws.

D.24 Job Cutoffs (Baseline)

Table D.36: Select Job Cutoffs by Pay Category, Job Sector and Job Title

Job Cutoffs (Job Utility)		
	Pay Category	
Parameter	Estimate	Std. Error
Top 25%	-16.300^{***}	0.749
50%-75%	-16.487^{***}	0.765
25%-50%	-16.779^{***}	0.762
Bottom 25%	-17.138^{***}	0.767
	Job Sector	
Parameter	Estimate	Std. Error
Technology	-17.031^{***}	0.788
Consulting	-16.165^{***}	0.734
Manufacturing	-16.274^{***}	0.724
	Job Title	
Parameter	Estimate	Std. Error
Engineer	-16.643^{***}	0.760
Consultant	-16.415^{***}	0.751
Manager	-17.253^{***}	0.782

Average Salary = $56,767.29 (PPP), N = 4207 (no. of students), J = 644 (no. of jobs).

Notes: Appendix Table D.36 includes estimates of the job cutoffs by pay category, job sector and job title for aggregate firms. An "aggregate" firm in a given category (e.g. sector) has the hiring cutoff averaged over all firms in that category. Note that the job cutoff estimates are not structural parameters as they are allowed to change under counterfactual policies. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%.

D.25 Counterfactual Job Cutoffs (Hiring Subsidy)

Table D.37: Select Counterfactual Job Cutoffs by Pay Category, Job Sector and Job Title

Job Cutoffs (Job Utility)		
Pay Category		
Parameter	Baseline	Counterfactual
Top 25%	-16.300	-16.257
50%-75%	-16.487	-16.442
25%-50%	-16.779	-16.712
Bottom 25%	-17.138	-17.067
Job Sector		
Parameter	Baseline	Counterfactual
Technology	-17.031	-16.987
Consulting	-16.165	-16.134
Manufacturing	-16.274	-16.218
Job Title		
Parameter	Baseline	Counterfactual
Engineer	-16.643	-16.598
Consultant	-16.415	-16.373
Manager	-17.253	-17.203

Notes: Appendix Table D.37 includes counterfactual job cutoffs by pay category, job sector and job title under a policy in which employers are given a hiring subsidy which makes them indifferent between an observably identical advantaged or disadvantaged caste.

D.26 Counterfactual Job Cutoffs (Pre-College Intervention)

Table D.38: Select Counterfactual Job Cutoffs by Pay Category, Job Sector and Job Title

Job Cutoffs (Job Utility)		
Pay Category		
Parameter	Baseline	Counterfactual
Top 25%	-16.300	-16.287
50%-75%	-16.487	-16.473
25%-50%	-16.779	-16.764
Bottom 25%	-17.138	-17.121
Job Sector		
Parameter	Baseline	Counterfactual
Technology	-17.031	-17.016
Consulting	-16.165	-16.156
Manufacturing	-16.274	-16.262
Job Title		
Parameter	Baseline	Counterfactual
Engineer	-16.643	-16.632
Consultant	-16.415	-16.408
Manager	-17.253	-17.241

Notes: Appendix Table D.38 includes counterfactual job cutoffs by pay category, job sector and job title under the "pre-college intervention" policy. The "pre-college intervention" policy equalizes the distribution of pre-college skills (entrance exam scores) across caste.

D.27 Job Offers by Pay Category (Subsidy vs. PCI)

Table D.39: Job Offers by Pay Category (Subsidy vs. PCI)

	Job Offers by Pay Category			
	Baseline			
	Adv. Caste	Disadv. Caste	Δ Adv. Caste (%)	Δ Disadv. Caste (%)
Q4	0.68	0.32	—	—
Q3	0.60	0.40	—	—
Q2	0.53	0.47	—	—
Q1	0.40	0.60	—	—
	Employer Cash-Subsidies Perfectly Elastic Labor Demand			
Q4	0.63	0.37	-0%	+27%
Q3	0.55	0.45	-0%	+25%
Q2	0.51	0.49	-0%	+11%
Q1	0.37	0.63	-0%	+16%
	Perfectly Inelastic Labor Demand			
Q4	0.62	0.38	-9%	+20%
Q3	0.55	0.45	-9%	+13%
Q2	0.50	0.50	-6%	+7%
Q1	0.37	0.63	-9%	+6%
	Pre-College Intervention Perfectly Elastic Labor Demand			
Q4	0.66	0.34	-0%	+10%
Q3	0.58	0.42	-0%	+11%
Q2	0.52	0.48	-0%	+4%
Q1	0.39	0.61	-0%	+6%
	Perfectly Inelastic Labor Demand			
Q4	0.66	0.34	-2%	+5%
Q3	0.57	0.43	-5%	+7%
Q2	0.52	0.48	-2%	+2%
Q1	0.38	0.62	-7%	+5%

Notes: Appendix Table D.39 shows the fraction of job offers by each pay category under baseline, hiring subsidies and PCI. "PCI" stands for the pre-college intervention policy.

D.28 Job Offers by Sector (Subsidy vs. PCI)

Table D.40: Job Offers by Sector (Subsidy vs. PCI)

Job Offers by Sector				
	Baseline			
	Adv. Caste	Disadv. Caste	Δ Adv. Caste (%)	Δ Disadv. Caste (%)
Technology	0.53	0.47	—	—
Consulting	0.63	0.37	—	—
Manufacturing	0.56	0.44	—	—
	Employer Cash-Subsidies Perfectly Elastic Labor Demand			
Technology	0.51	0.49	-0%	+13%
Consulting	0.57	0.43	-0%	+29%
Manufacturing	0.51	0.49	-0%	+21%
	Perfectly Inelastic Labor Demand			
Technology	0.51	0.49	-5%	+5%
Consulting	0.57	0.43	-10%	+18%
Manufacturing	0.49	0.51	-12%	+15%
	Pre-College Intervention Perfectly Elastic Labor Demand			
Technology	0.52	0.48	-0%	+5%
Consulting	0.61	0.39	-0%	+9%
Manufacturing	0.54	0.46	-0%	+10%
	Perfectly Inelastic Labor Demand			
Technology	0.53	0.47	-2%	+2%
Consulting	0.61	0.39	-3%	+6%
Manufacturing	0.53	0.47	-6%	+7%

Notes: Appendix Table D.40 shows the fraction of job offers by caste in each sector under baseline, hiring subsidies and PCI. “PCI” stands for the pre-college intervention policy.

D.29 Job Choices by Pay Category (Subsidy vs. PCI)

Table D.41: Job Choices by Pay Category (Subsidy vs. PCI)

	Job Choices by Pay Category			
	Baseline			
	Adv. Caste	Disadv. Caste	Δ Adv. Caste (%)	Δ Disadv. Caste (%)
Q4	0.67	0.33	—	—
Q3	0.59	0.41	—	—
Q2	0.52	0.48	—	—
Q1	0.41	0.59	—	—
	Employer Cash-Subsidies Perfectly Elastic Labor Demand			
Q4	0.60	0.40	-0%	+37%
Q3	0.54	0.46	-0%	+25%
Q2	0.49	0.51	-0%	+13%
Q1	0.38	0.62	-0%	+15%
	Perfectly Inelastic Labor Demand			
Q4	0.60	0.40	-10%	+25%
Q3	0.53	0.47	-15%	+12%
Q2	0.48	0.52	-6%	+10%
Q1	0.35	0.65	-18%	+6%
	Pre-College Intervention Perfectly Elastic Labor Demand			
Q4	0.65	0.35	-0%	+13%
Q3	0.57	0.43	-0%	+10%
Q2	0.51	0.49	-0%	+6%
Q1	0.39	0.61	-0%	+9%
	Perfectly Inelastic Labor Demand			
Q4	0.66	0.34	-1%	+6%
Q3	0.56	0.44	-5%	+7%
Q2	0.51	0.49	-2%	+4%
Q1	0.38	0.62	-8%	+3%

Notes: Appendix Table D.41 shows the fraction of job choices by each pay category under baseline, hiring subsidies and PCI. "PCI" stands for the pre-college intervention policy.

D.30 Job Choices by Sector (Subsidy vs. PCI)

Table D.42: Job Choices by Sector (Subsidy vs. PCI)

	Job Choices by Sector			
	Baseline			
	Adv. Caste	Disadv. Caste	Δ Adv. Caste (%)	Δ Disadv. Caste (%)
Technology	0.52	0.48	—	—
Consulting	0.63	0.37	—	—
Manufacturing	0.56	0.44	—	—
	Employer Cash-Subsidies Perfectly Elastic Labor Demand			
Technology	0.48	0.52	-0%	+16%
Consulting	0.57	0.43	-0%	+29%
Manufacturing	0.51	0.49	-0%	+22%
	Perfectly Inelastic Labor Demand			
Technology	0.48	0.52	-6%	+9%
Consulting	0.56	0.44	-9%	+22%
Manufacturing	0.48	0.52	-19%	+12%
	Pre-College Intervention Perfectly Elastic Labor Demand			
Technology	0.50	0.50	-0%	+7%
Consulting	0.61	0.39	-0%	+9%
Manufacturing	0.53	0.47	-0%	+10%
	Perfectly Inelastic Labor Demand			
Technology	0.50	0.50	-3%	+5%
Consulting	0.61	0.39	-3%	+5%
Manufacturing	0.54	0.46	-3%	+5%

Notes: Appendix Table D.42 shows the fraction of job choices by caste under baseline, hiring subsidies and PCI. "PCI" stands for the pre-college intervention policy.

D.31 Unemployment (Subsidy vs. PCI)

Table D.43: Unemployment (Subsidy vs. PCI)

	% Unemployed			ΔUnemployed(%)		
	Adv. Caste	Disadv. Caste	Overall	Adv. Caste	Disadv. Caste	Overall
Baseline	25%	36%	31%	—	—	—
	Perfectly Elastic Labor Demand					
Subsidy	25%	24%	28%	-0%	-35%	-20%
PCI	25%	31%	25%	-0%	-15%	-9%
	Perfectly Inelastic Labor Demand					
Subsidy	33%	28%	31%	+31%	-23%	-0%
PCI	28%	33%	31%	+12%	-9%	-0%

Notes: Appendix Table D.43 shows unemployment by caste under baseline, hiring subsidies and PCI. "PCI" stands for the pre-college intervention policy.

D.32 Earnings Gap (Subsidy vs. PCI)

Table D.44: Earnings Gap (Subsidy vs. PCI)

Earnings Gap (%)			
		Perfectly Elastic Labor Demand	
Data	Model Fit	Hiring Subsidy	Pre-College Intervention
-11.3%	-10.6%	-5.5%	-8.9%
		Perfectly Inelastic Labor Demand	
Data	Model Fit	Hiring Subsidy	Pre-College Intervention
-11.3%	-10.6%	-7.6%	-9.5%

Notes: Appendix Table D.44 under hiring subsidies and PCI. "PCI" stands for "pre-college intervention" policy.

D.33 Counterfactual Job Cutoffs (Hiring Quotas)

Table D.45: Select Counterfactual Job Cutoffs by Pay Category, Job Sector and Job Title

Job Cutoffs (Job Utility)			
	Pay Category		
Parameter	Baseline	Counterfactual	
		Adv. Caste	Disadv. Caste
Top 25%	-16.300	-16.247	-16.321
50%-75%	-16.487	-16.412	-16.521
25%-50%	-16.779	-16.702	-16.787
Bottom 25%	-17.138	-17.023	-17.154
	Job Sector		
Parameter	Baseline	Counterfactual	
		Adv. Caste	Disadv. Caste
Technology	-17.031	-16.906	-17.067
Consulting	-16.165	-16.123	-16.186
Manufacturing	-16.274	-16.204	-16.291
	Job Title		
Parameter	Baseline	Counterfactual	
		Adv. Caste	Disadv. Caste
Engineer	-16.643	-16.586	-16.664
Consultant	-16.415	-16.361	-16.437
Manager	-17.253	-17.196	-17.273

Notes: Appendix Table D.45 includes counterfactual job cutoffs by pay category, job sector and job title under hiring quotas. Notice that firms explicitly solve for two hiring cutoffs under quotas, one for the disadvantaged caste and the other for the advantaged caste.

D.34 Unemployment (Hiring Quotas)

Table D.46: Unemployment (Hiring Quotas)

	% Unemployed			ΔUnemployed(%)		
	Adv. Caste	Disadv. Caste	Overall	Adv. Caste	Disadv. Caste	Overall
Baseline	25%	36%	31%	—	—	—
Hiring Quotas	35%	31%	33%	+37%	-16%	+7%

Notes: Appendix Table D.46 shows unemployment by caste under baseline and hiring quotas.

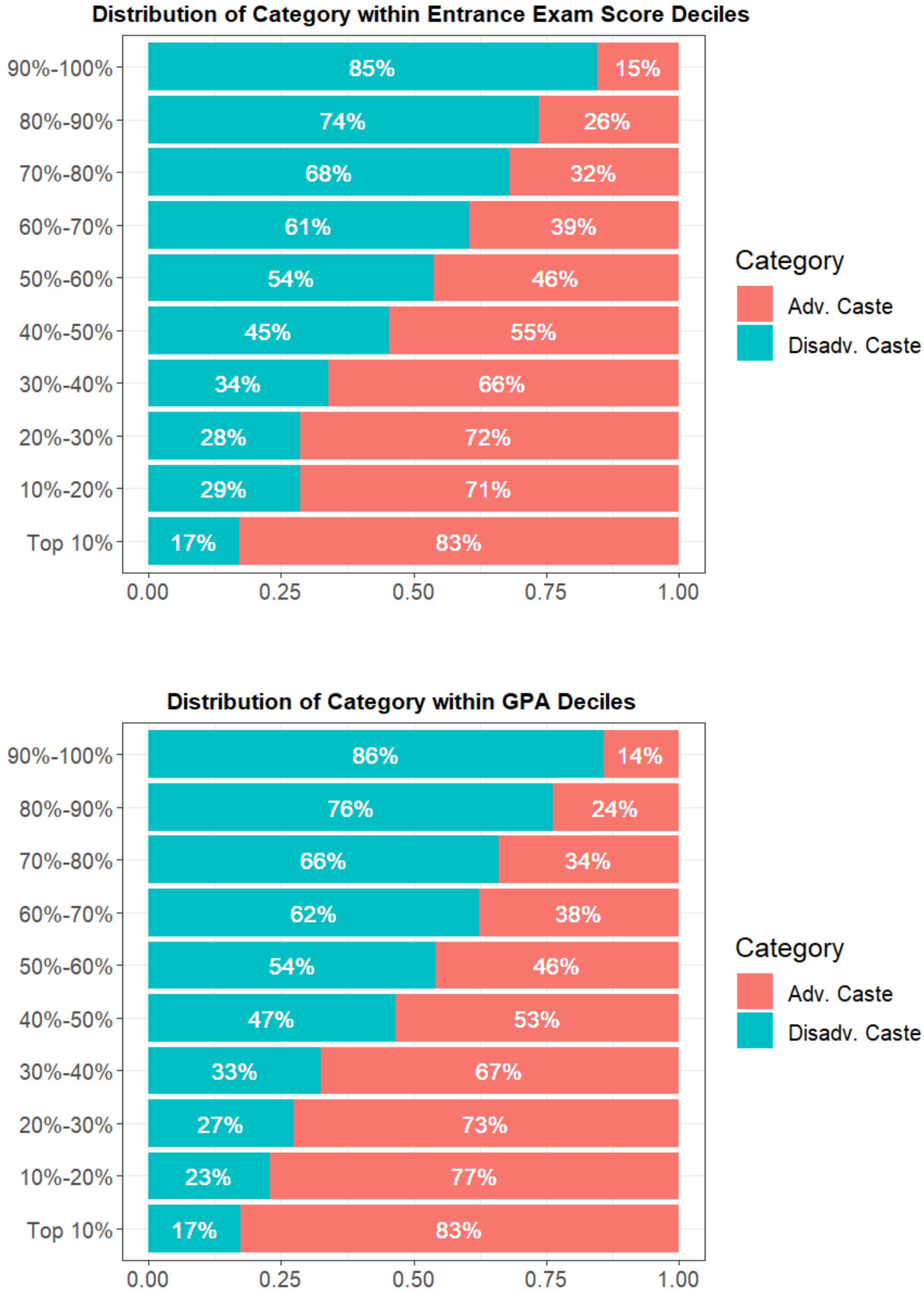

Figure D.1

Notes: Figure D.1 shows full support for students belonging to either disadvantaged or advantaged castes within each entrance exam score or GPA decile.

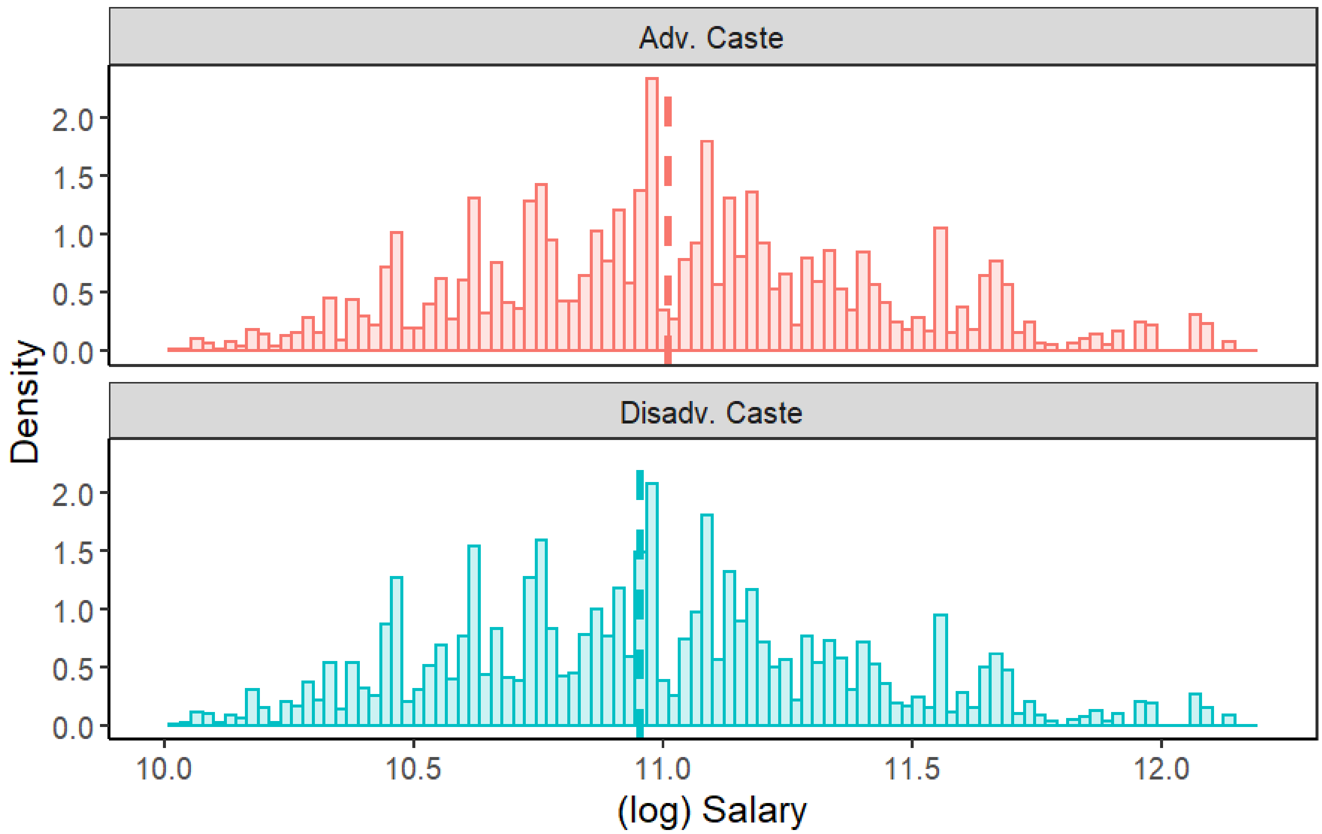

Figure D.2: Distribution of Salaries of Jobs to Which Students Applied

Notes: Figure D.2 shows the raw distribution of job salaries to which students applied by caste. The top panel shows the distribution of job salaries to which advantaged castes applied. The bottom panel shows the distribution of job salaries to which disadvantaged castes applied. The vertical lines denote the average salaries of jobs to which students applied.

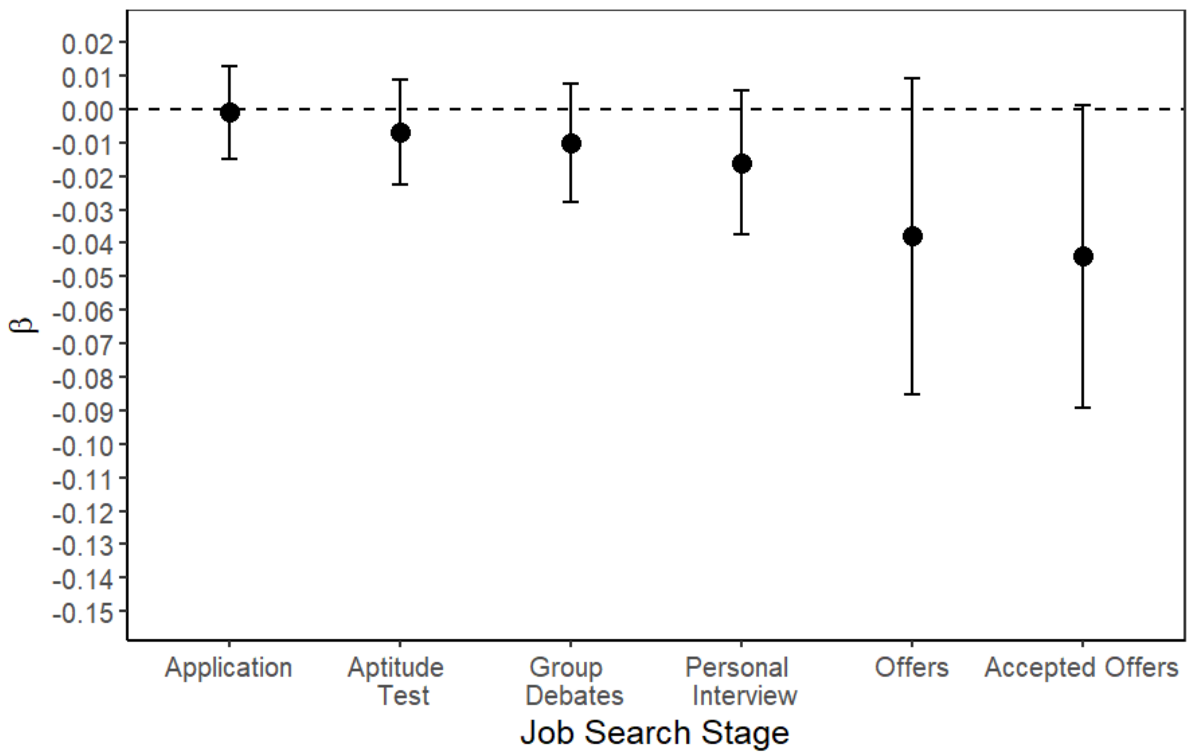

Figure D.3: Earnings Gap Across Castes at Each Job Search Stage in the Manufacturing Sector

Notes: Figures D.3 shows the coefficient β corresponding to the regression in Equation 1 among jobs in the manufacturing sector. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

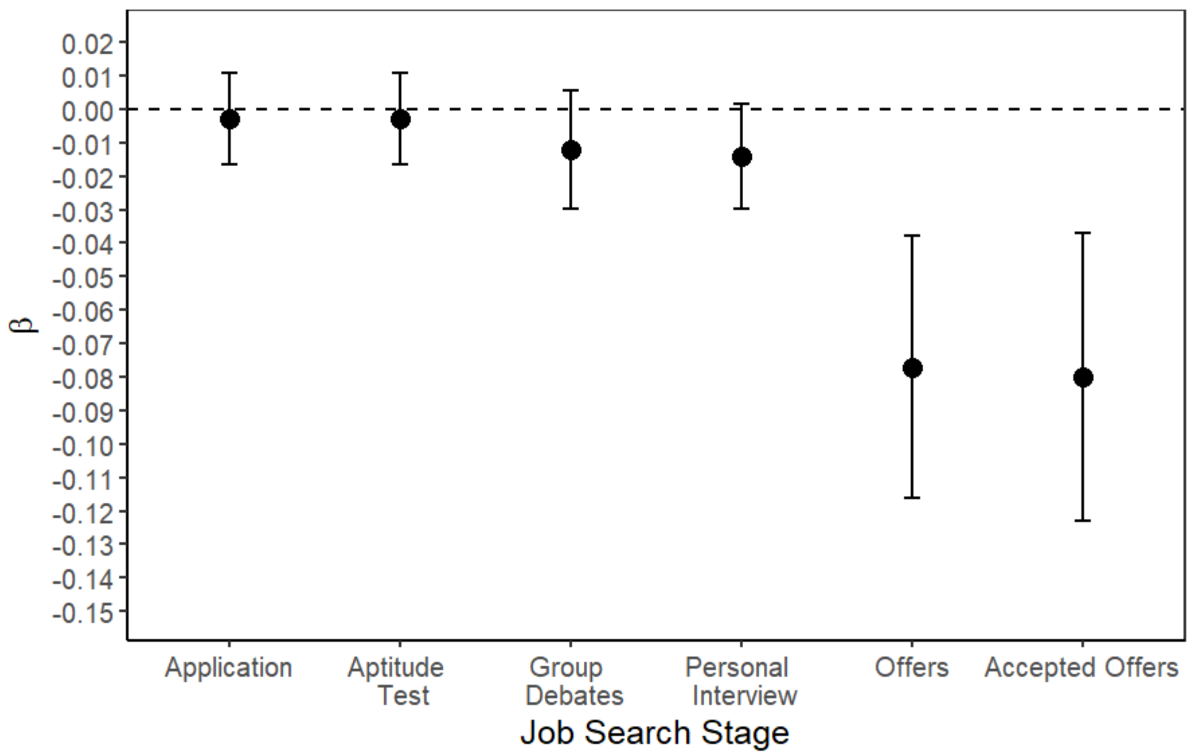

Figure D.4: Earnings Gap Across Castes at Each Job Search Stage in the Technology Sector

Notes: Figures D.4 shows the coefficient β corresponding to the regression in Equation 1 among jobs in the technology sector. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

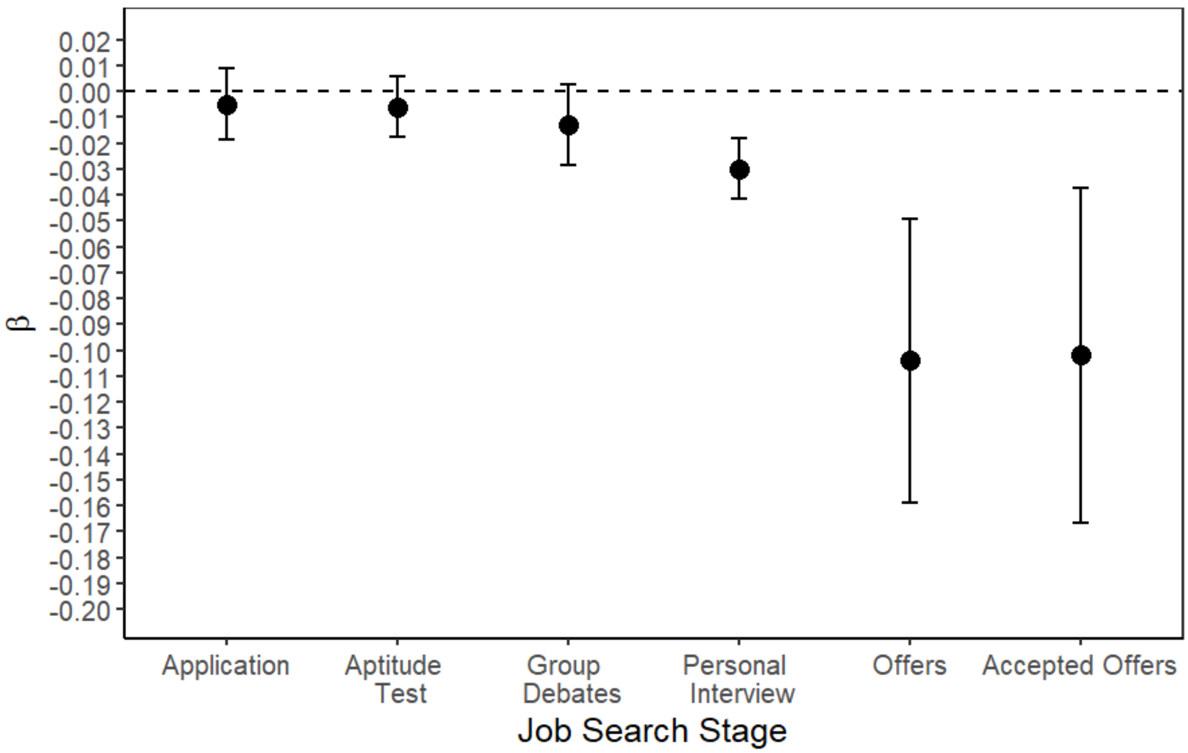

Figure D.5: Earnings Gap Across Castes at Each Job Search Stage in the Consulting Sector

Notes: Figure D.5 shows the coefficient β corresponding to the regression in Equation 1 among jobs in the consulting sector. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

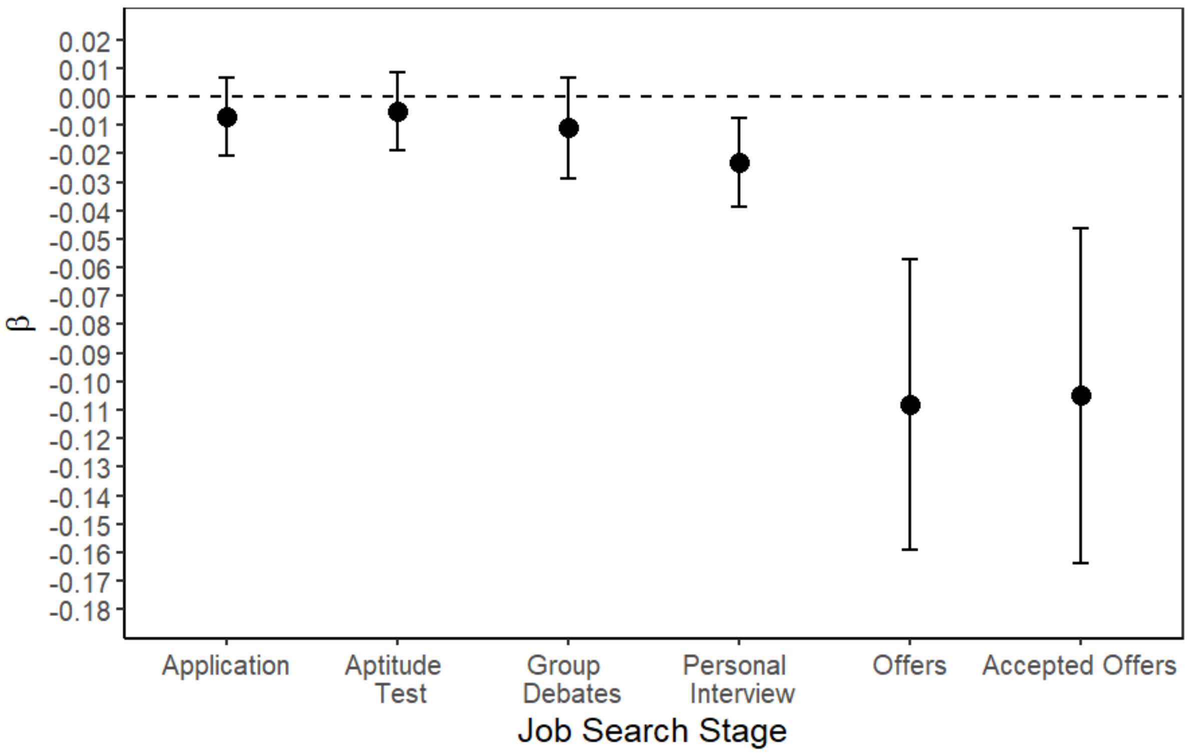

Figure D.6: Earnings Gap Across Castes at Each Job Search Stage in Client Facing Jobs

Notes: Figure D.6 shows the coefficient β corresponding to the regression in Equation 1 among client facing jobs. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

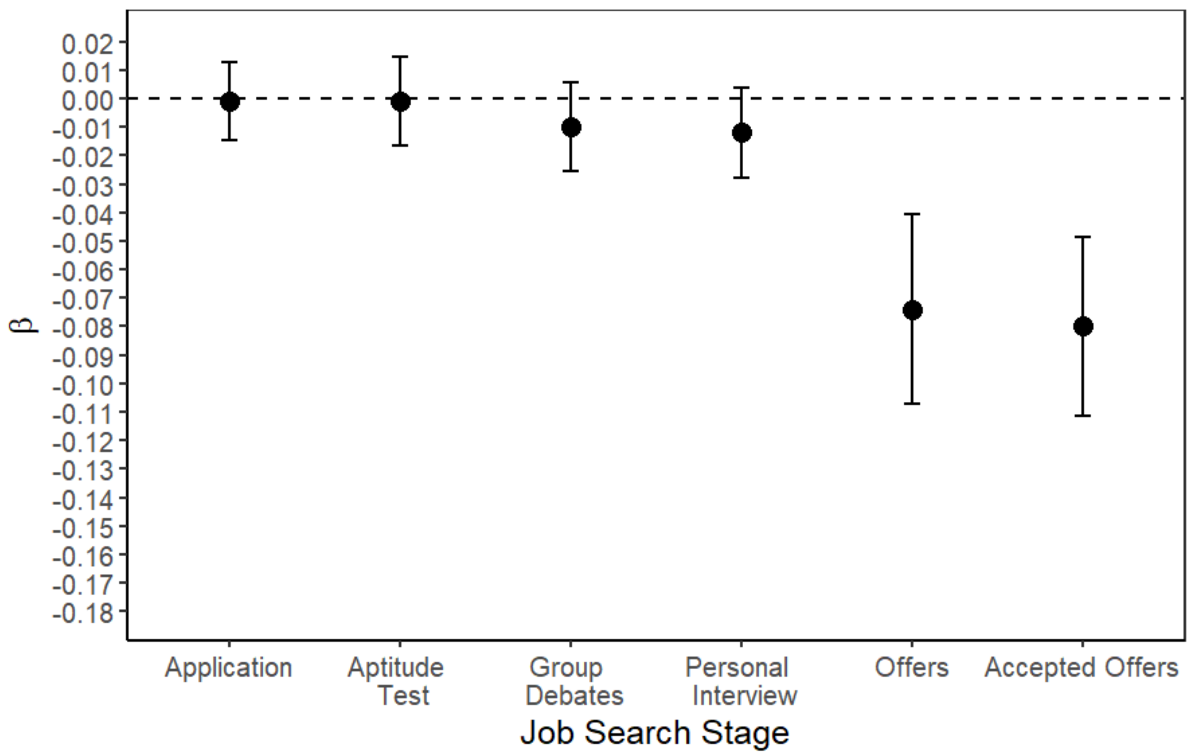

Figure D.7: Earnings Gap Across Castes at Each Job Search Stage in Non-Client Facing Jobs

Notes: Figure D.7 shows the coefficient β corresponding to the regression in Equation 1 among non-client facing jobs. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

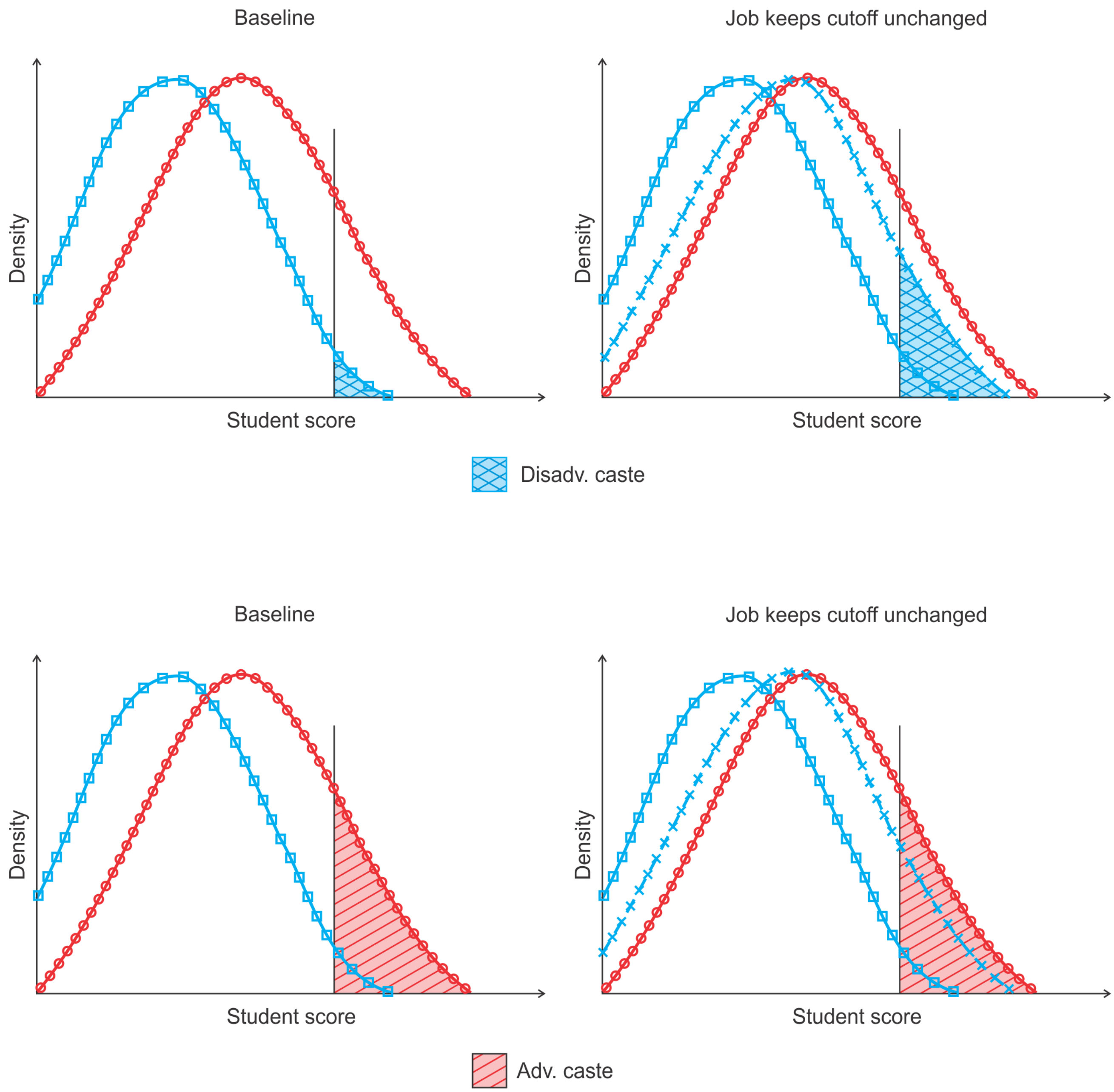

Figure D.8: Disadvantaged Caste Hires under Perfectly Elastic Labor Demand

Notes: In Figure D.8 the distribution of advantaged caste "scores" (red) are to the right of the distributions of disadvantaged caste "scores" (blue). "Scores" can be calculated from Equation 6. As shown in Figure D.8, the distribution of disadvantaged caste "scores" shifts to the right under hiring subsidies and the pre-college intervention policy. In the absence of jobs adjusting cutoffs, disadvantaged caste hires, depicted by the shaded area in the top panel, are at least as large as in the baseline. As shown in Figure D.8, the distribution of advantaged caste "scores" stays the same. In the absence of jobs adjusting cutoffs, advantaged caste hires, depicted by the shaded area in the bottom panel, are the same as in the baseline. When labor demand is perfectly elastic, there is no displacement of advantaged castes from jobs.

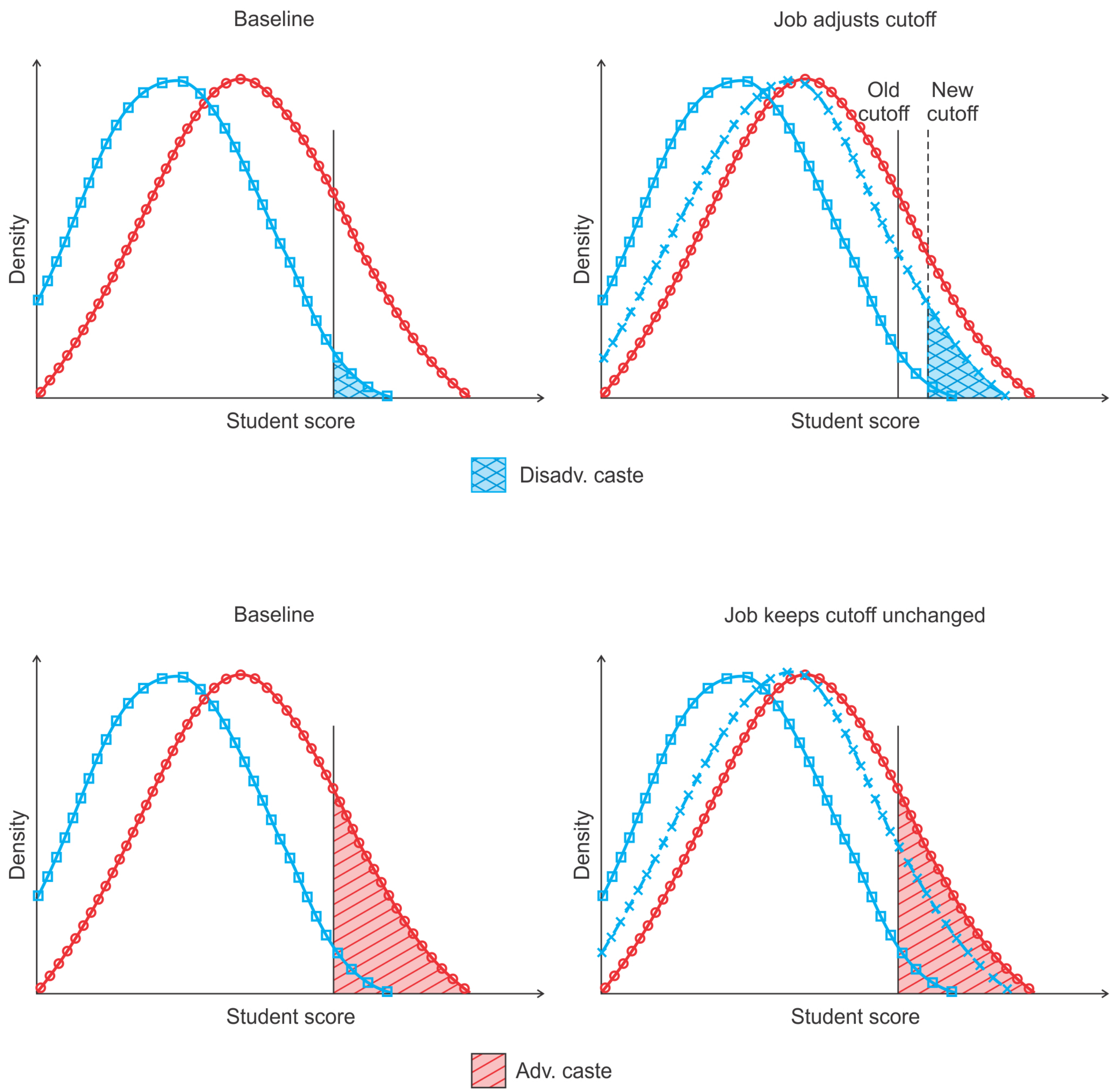

Figure D.9: Disadvantaged Caste Hires under Perfectly Inelastic Labor Demand

Notes: In Figure D.9, the distributions of advantaged caste "scores" (red) are to the right of the distributions of disadvantaged caste "scores" (blue). "Scores" can be calculated from Equation 6. Under both hiring subsidies and the pre-college intervention policy, the distribution of disadvantaged caste "scores" shifts to the right. When jobs adjust cutoffs to hire the same total number of students (in expectation) as in the baseline, the number of disadvantaged caste hires is at least as large as in the baseline. As shown in Figures D.8 and D.9, the number of disadvantaged caste hires when labor demand is perfectly inelastic can be no more than the number disadvantaged caste hires labor demand is perfectly elastic. Therefore, the number of disadvantaged caste hires is bounded above by the number of disadvantaged caste hires when labor demand is perfectly elastic and below by the number of disadvantaged caste hires when labor demand is perfectly inelastic. Hence, when jobs follow cutoff hiring rules, the model bounds the effects of hiring subsidies and the pre-college intervention policy on job placements of disadvantaged castes. The displacement effects on advantaged caste hires are bounded similarly.