Exclusive: Elite Hiring, Disparities, and Solutions

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This paper studies how socioeconomically biased screening practices impact access to elite firms and what policies might effectively reduce bias. Using administrative data on job search from an elite Indian college, I document large caste disparities in earnings. I show that these disparities arise in the final round of screening, comprising non-technical personal interviews that inquire about characteristics correlated with socioeconomic status. Other job search stages do not explain disparities, including: job applications, application reading, written aptitude tests, large group debates that test for socio-emotional skills, and job choices. Through a novel model of the job placement process, I show that employer willingness to pay for an advantaged caste is as large as that for a full standard deviation increase in college GPA. A hiring subsidy that eliminates the caste penalty would be more cost-effective in diversifying elite hiring than other policies, such as those that equalize the caste distribution of pre-college test scores or enforce hiring quotas.

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1 Introduction

Socioeconomically biased screening practices commonly determine access to elite jobs and educational institutions (Stevens, 2009; Rivera, 2015). Such screening practices are often outwardly blind to race, gender, ethnicity, or class. However, they can implicitly penalize certain groups by screening on culture fit, personal hobbies, legacy and athlete preferences, and subjective impressions of personality (Rivera, 2012; SFFA v. Harvard, 2021; Arcidiacono et al., 2021). Thus, screening practices that emphasize such qualities can create barriers to elite jobs and schools (henceforth, “elite attainment”).

The pivotal socioeconomic role of elite attainment has led many governments, firms, and educational institutions around the world to advance policies to improve access to such opportunities (McArthur, 2021). Despite progress, substantial disparities persist. In India, most elite educational institutions have caste-based quotas that set aside 50% of college seats for disadvantaged castes. Yet stark caste disparities remain a feature of elite jobs: nearly 95% of board members in India’s top 1,000 businesses belong to advantaged castes, which make up about 30% of the overall population (Dayanandan et al., 2019). The pipelines leading to the highest positions in elite firms are important to examine, as such opportunities shape not only an individual’s economic trajectory but also broader societal inequalities (Rivera, 2015).

This paper uses insights from the screening practices of elite firms in the Indian private sector to isolate the sources of and evaluate potential solutions to caste disparities. Such jobs lack compensatory hiring policies for disadvantaged castes. There is also little empirical evidence on the sources of caste disparities in elite hiring (Madheswaran, 2008). Moreover, hiring practices of elite firms are often non-transparent, making it challenging to understand why inequalities arise and persist (Rivera, 2015).

I have two main findings. First, caste disparities in hiring are primarily due to non-technical personal interviews that inquire about characteristics correlated with socioeconomic status in order to assess culture fit, trustworthiness, long-term professional behavior, and attrition. Second, hiring subsidies are more cost-effective in diversifying elite hiring than other policies, such as those that equalize the distribution of pre-college test scores across castes or enforce hiring quotas.

My paper proceeds in two parts. In the first part, I uncover the mechanisms driving the caste gap in earnings. To do so, I employ novel administrative data on each stage of the job placement process from an elite Indian college. I combine this data with evidence on common questions asked by Human Resources (HR) managers in personal interviews. My paper offers a representative window into how elite college graduates transition into “elite entry-level jobs,” defined as the top 1% paying entry-level jobs in the Indian private sector.
These jobs are primarily in foreign-based multinational corporations (MNCs) that hire for their Indian locations (Section 3).

Despite the elite college setting aside nearly 50% of the seats for disadvantaged castes, there are large disparities in labor market outcomes. The unconditional caste gap in earnings among graduates from the elite college 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 is reduced to 11%. There are no caste differences in pay for a given job, so the earnings gap is due to differences in job composition across castes.

I further decompose the 11% caste gap in earnings into components attributable to each successive stage of the job placement process. In my setting, firms post uniform job-specific (not match-specific) wages that are non-negotiable over the course of job search. This feature allows the earnings gap to be further decomposed by comparing the caste difference in the composition of jobs at each stage of the placement process. The composition of job applications does not explain the earnings gap. After applications are submitted, firms conduct three pre-interview screening stages: application reading, written aptitude tests comprising either coding or case exams (also called “technicals”), and large group debates that test for socio-emotional skills. Together, these three stages contribute to only about one-tenth of the 11% earnings gap. The composition of job choices over offered jobs also does not contribute to the earnings gap. Therefore, almost nine-tenths of the 11% earnings gap emerges between non-technical personal interviews and job offers, suggesting that policies informing applicants about job opportunities, modifying student preferences, or improving performance at university are unlikely to close the earnings gap for this population.

Personal interviews, also known as HR interviews, are a widely employed screening practice in the Indian private sector and are not technical or case-study-based. Rather, they are typically a combination of small talk and employers advertising their jobs, assessing culture fit, and asking potential employees about their interest in competing firms (Deshpande, 2011; Jodkha, 2017; Fernandez, 2018). Through analysis of the kinds of questions HR managers ask in such interviews, I argue that caste disparities in earnings are primarily due to employers screening on background characteristics that are correlated with socioeconomic status (Deshpande and Newman, 2007; Jodkha, 2017).¹ These characteristics include educational qualifications of family members, neighborhood of residence, family background, father’s job, cosmopolitan attitudes, upbringing, personal hobbies, and desire for traveling (Section 4.3).

¹Naukri.com, India’s leading job search portal with a market share over 60%, 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).
Survey responses of HR managers have also documented unanimous agreement on the importance of screening on background characteristics in personal interviews. HR managers in elite firms see little contradiction in judging a candidate’s individual merit through background characteristics. Instead, they argue that decision-relevant unobservables, such as culture fit, trustworthiness to potential clients, long-term professional behavior, and attrition could be reasonably gleaned through such inquiries (Jodhka and Newman, 2007). Free-form or unstructured interviews that screen on conversations related to shared experiences, aspects of culture fit, and personal hobbies are not unique to India. Such practices are commonly employed in the recruitment practices of elite U.S. colleges and corporate America (Stevens, 2009; Rivera, 2015).

The emergence of earnings disparities due to non-technical personal interviews closely parallels caste revelation. Caste in elite, urban-educated India is more likely to be signaled through background characteristics correlated with socioeconomic status than surface-level cues observed by employers during the application reading, written aptitude test, and group debate rounds. These cues include last names, skin color, facial features, accents, and dialects (Section 6.1). Thus, personal interviews are more likely to reveal caste leading to direct discrimination and, even if not, exacerbate caste disparities due to indirect discrimination on background characteristics.

The paper’s descriptive facts advance the literature on the detection and measurement of labor market disparities. Caste disparities due to discretionary screening practices that value background characteristics are unlikely to be detected through traditional correspondence studies. In addition, recent works studying the role of hiring discretion have either exclusively focused on low-skilled jobs or provided correlational evidence between callback disparities and HR practices being more subjective (Hoffman et al., 2018; Kline et al., 2021). By collecting data on all steps of the placement process, my paper is the first to decompose the earnings drop-off at successive stages of job search and quantify the role of a widely employed

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2 Surnames like “Singh,” “Sinha,” “Verma,” “Chaudhary,” “Mishra,” and “Das” are shared across castes (Anthropological Survey of India, 2009). 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.” Naming conventions also differ significantly across regions. For example, South Indians typically do not have conventional last names. Rather, for them, personal (first) names often perform the role of traditional “surnames” (Jayaraman, 2005).

3 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).

4 Among educated elites, like those in my sample, English has emerged as a caste-neutral language with no remnants of caste dialects (Ambedkar, 2002; Kothari, 2013; Ransubhe, 2018). Rather, perception of accent variation among young, English-speaking university graduates in India is linked to broad regional factors (Wiltshire, 2020).
subjective screening practice—non-technical personal interviews—in determining access to elite jobs.

I also consider other alternative explanations and argue that none of them are likely to explain the earnings drop-off. These explanations include differences in socio-emotional skills, outside options, negotiation abilities, the possibility that employers may be “playing along” at earlier rounds due to government audits or internal institutional pressure, competition from the government sector, employers casting a wider net at earlier screening stages, and employee preference for living in a metropolitan city (Section 6.3).

In the second part of the paper, I propose and evaluate the effectiveness of policies to diversify hiring in elite entry-level jobs. For this purpose, I calculate employer willingness to pay for key characteristics, such as pre-college test scores and caste. These estimates are obtained from a model of the hiring process. The model incorporates the economically relevant stages of job search in my setting: firm hiring and final job choices. Estimation takes advantage of rich micro-level data on job search, a highly regulated job placement process, and national wage setting—i.e., firms offering about the same job-specific wage across all locations in India (Section 7). Using the model estimates, I propose and evaluate three counterfactual policies to diversify elite hiring.

The employer willingness to pay for caste is calculated through a reduced-form caste coefficient in the employer’s utility function. As mentioned previously, background characteristics are almost perfectly predictive of caste in urban-educated India. Therefore, the reduced-form coefficient representing the caste penalty could capture discrimination due to employers valuing direct (caste) in addition to indirect characteristics (family background, neighborhood of residence, and upbringing) revealed during personal interviews. Such discrimination could stem from either taste-based or statistical motivations and the reduced-form caste coefficient embeds a mechanism for both. In other words, the magnitude of the caste penalty, and therefore, the employer willingness to pay for caste is invariant to the underlying motivations for caste disparities.

My empirical approach to model the caste penalty through a reduced-form caste coefficient that captures both direct and indirect sources of disparities helps advance recent research that argues for a constructivist understanding of group identities, instead of treating them as immutable facts (Bohren et al., 2022; Rose, 2022; Sarsons, 2022). Such an approach is crucial to better understand “caste,” classifications of which are rooted in the economic, political, and material history of India (Beteille, 1965, 1969). In addition, perceptions of caste in urban-educated India are guided by a myriad of socioeconomic cues, paralleling the impressions of social class in other contexts, especially Britain (Deshpande, 2011; Mamidi, 2011; Savage, 2015; Jodkha, 2017).
The model estimate of the caste penalty shows that firms discount the value of disadvantaged castes at the equivalent of 4.8% of average annual salary, holding other student attributes constant. Employer willingness to pay for an advantaged caste is as large as that for a full standard deviation increase in college GPA. In addition, eliminating the caste gap in each pre-college test score quantile closes only about 10% of the model-implied caste penalty, suggesting the need for policies that directly mitigate caste disparities.

In the first counterfactual exercise, I consider one such policy: a hiring subsidy that eliminates the caste penalty by making firms indifferent between observably identical applicants across castes. Therefore, the subsidy is equivalent to the amount employers discount the value of disadvantaged castes—i.e., 4.8% of average annual salary. This amount is a one-time common payment to each elite entry-level job, per disadvantaged caste hired, and 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). Note that, in principle, the hiring subsidy reimburses the employer for a stream of costs incurred in the future and not just the cost of hiring a disadvantaged caste over a single year. In the second policy, I consider a “pre-college intervention” that equalizes the distribution of pre-college skills (college entrance exam scores) across castes. In the third, and final, counterfactual policy, I consider a hiring quota that requires firms to hire an equal proportion of applicants from advantaged and disadvantaged castes: a policy that mirrors reservation-based compensatory policies in government jobs (Madheswaran, 2008).

I evaluate the cost-effectiveness of the above three policies in improving both the absolute and relative caste hires at elite firms, holding other aspects such as wage setting, reallocation to elite entry-level jobs, the share of disadvantaged castes applying to such jobs, and firm entry as given. Omitting these equilibrium effects is not a major limitation for this population (Section 10.3).

To evaluate the cost-effectiveness of subsidies and pre-college interventions, I compare the model-implied subsidy equivalent of the pre-college intervention policy to the direct costs of changing test scores. My estimates show that elite firms put modest weights on pre-college test scores, suggesting that the efficiency gains from pre-college interventions (which my cost-effectiveness analysis omits) are likely small. The model-implied subsidy equivalent of the pre-college intervention policy is about 0.6% of average annual salary, which is only about 10% of the caste penalty. To calculate the direct costs of changing pre-college test scores, I use estimates from a meta-analysis of education-focused impact evaluations that documents the costs of changing test scores of primary and secondary school students in India (Asim et al., 2015). Even under extremely conservative assumptions to extrapolate the direct costs of test score changes, subsidies to hire applicants from disadvantaged castes are twice as
cost-effective in diversifying elite hiring.

Finally, I discuss results from a hiring quota policy that requires firms to hire an equal proportion of applicants across castes, mirroring the caste shares in the elite college. While more disadvantaged castes are hired, the caste penalty is large enough to eventually make the average marginal utility of filling two slots lower than the average marginal cost. This happens well before firms can achieve baseline levels of hiring. Firms counteract the quota policy by making fewer job offers and decrease overall recruitment from the university by 7%.

Discrimination based on socioeconomic cues in elite, urban-educated settings is likely to become more salient as the world becomes increasingly multi-ethnic and diverse and standard characteristics by which to differentiate groups become less perceptible (Loury, 2002; Freeman et al., 2011; Gaddis, 2017). I provide an important example of the kinds of data future researchers may have to collect in such settings to better detect disparities from outwardly neutral screening practices. By connecting how perceptions of socioeconomic cues determine barriers to elite attainment, this paper also helps advance how to conceptualize, quantify, and address racial, class, or caste disparities in such opportunities, most of which are situated in a rapidly diversifying urban landscape.

2 Caste and Affirmative Action in India

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 socioeconomically disadvantaged classes of Indian society were made possible after the Government of India Act of 1919 established self-governing institutions (i.e., provisional assemblies and central legislative assemblies), which introduced limited self-government to a majority British-controlled India. The depressed classes represented in these institutions, 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. The Government of India Act of 1935 replaced the words “depressed classes” with “Scheduled Castes” (Bayly, 2008).

B.R. Ambedkar’s demands were formally accepted in 1946 during deliberations of the first Constituent Assembly, which was tasked with drafting the constitution for independent India (Bayly, 2008). 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 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%.

None of the current constitutional provisions extend to advancing compensatory hiring policies for disadvantaged castes in private-sector jobs. One of the goals of this paper is to assess the potential of such policies to diversify hiring in elite jobs in the Indian private sector.

3 Institutional Setting

In this section, I define a few key terms and elaborate on some important features of my institutional setting.

1) Defining elite colleges and elite entry-level jobs. An “elite entry-level job” is defined as an entry-level job in the Indian private sector among the top 1% of entry-level salaries (The State of Inequality in India Report, 2022). I define “elite colleges” as those consistently ranked in the top 10 in their respective fields—such as science, engineering, humanities, commerce, or law—by India Today, which is the Indian equivalent of U.S. News & World Report. Nearly all elite Indian colleges are public institutions.

2) Elite colleges have similar job placement processes. Elite Indian colleges have similar job placement processes primarily due to an extended process of historical imitation. Post independence, the earliest elite Indian colleges were built in the early 1950s and were closely modeled on elite U.S. universities, particularly MIT and Stanford. These colleges served as role models for later elite Indian colleges, closely imitating key aspects such as academic calendars, faculty-to-student ratios, and job placement processes. Hence, almost all elite Indian colleges today have similar mechanisms for selectively placing graduates into elite entry-level jobs (Altbach, 2012; Datta, 2017).

Examples of elite Indian colleges sharing common placement processes. These include 23 Indian Institute of Technologies, 20 Indian Institute of Managements, and 91 colleges under the ambit of the prestigious Delhi University.5

5See All IITs Placement Committee Brochure and Central Placement Cell (Delhi University).
3) Elite college graduates primarily work in elite entry-level jobs. Almost 96% of elite college graduates work in elite entry-level jobs (Newman and Thorat, 2012; Jodhka and Naudet, 2019; Subramanian, 2019).

4) Elite entry-level jobs almost exclusively hire from elite colleges. Graduates from elite Indian colleges account for more than 95% of the hires in elite entry-level jobs (Newman and Thorat, 2012; Jodhka and Naudet, 2019; Subramanian, 2019).

5) Elite entry-level companies recruiting from the elite college recruit representatively. Scarping data from the placement websites of colleges, I find that about 94% of the firms that recruit students from this elite college also visit other elite colleges for their on-campus job fairs.

Together, the facts presented in 2), 3), 4), and 5) above imply that the job placement process from the college I examine in the paper offers a representative window into how elite college graduates transition into elite entry-level jobs in the Indian private sector.

6) Elite entry-level jobs are in the Indian offices of foreign-based MNCs. In this setting, about 97% of elite entry-level companies that recruit from this elite college are foreign-based MNCs. These jobs hire overwhelmingly for their Indian offices (see Online Appendix Table OA.1).

A negligible proportion of firms recruiting from elite Indian colleges are India-based startups. Such firms—officially recognized by the Department for Promotion of Industry and Internal Trade—comprised less than 0.5% of elite entry-level firms in the Indian economy over the years spanned by the data i.e., from 2012-2015 (Economic Survey, 2021-22). Startups are typically not given an opportunity to recruit from elite Indian colleges, as such firms do not pay as much as other well-established MNCs. In addition, placement officers consider such firms as risky, especially after many instances of startups reneging on job offers (Rao, 2016).

7) Most of the offices and entry-level labor force of foreign-based MNCs are outside of India. In this setting, almost 97% of the offices and 96% of the entry-level labor force of foreign-based MNCs are outside of India (see Online Appendix Table OA.2).

8) Job placement process of an elite public college. Every year, job recruitment at the elite public college takes place entirely on campus. The job recruitment process can be divided into two broad phases: 1) pre-placement phase, and 2) placement phase.

1. Pre-Placement phase. The pre-placement phase can be further subdivided into the following steps. First, the placement office invites firms prior to June. Second, between June to mid-August, firms visit the college campus and conduct pre-placement talks to
advertise job profiles and gauge student interest. Third, firms make return offers from summer internships by late August. These offers are also called PPOs, which stands for pre-placement offers. Students who accept their PPOs are disallowed from participating in the formal placement process for full-time jobs. Fourth, students register for the formal on-campus job placement process by late August. Fifth, by early September, firms submit employer registration forms to the placement office; these forms list details including job positions, compensation packages, and the probable number of slots (vacancies) they want to fill from the college that year (see Online Appendix Section A). Sixth, after these forms are submitted, advertised job profiles are considered “locked.” They cannot be changed by firms during the course of the placement cycle. Moreover, students are prohibited by the placement office from bargaining over compensation bundles. The placement office verifies advertised compensation bundles by requiring students to submit copies of their job offer letters.

2. Placement phase. The placement phase can be further subdivided into the following steps. First, students start applying for jobs in mid-September. Second, firms make the “first cut” after skimming through applications and invite students for additional screening. Third, firms conduct written and verbal tests to determine eligibility for on-campus interviews. Fourth, firms conduct interviews. Fifth, firms make job offers. Sixth, students make final job choices and the placement process concludes around early January. Below are some key rules of the placement process set by the elite college’s placement office:

   a) Interview day allotment. Each firm is allotted one interview day by the college’s placement office to conduct personal interviews on campus. Unlike job recruitment at U.S. colleges, there are no further “onsite” interviews. A particular rule of the job placement process is 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 offers on a particular interview day, he can participate in interviews on future interview days.

   b) Students cannot “reject” firms midway nor can they accept offers too early. Per placement office rules, students cannot “reject” firms midway by either skipping any of the pre-interview screening rounds or the sequence of scheduled interviews, typically spread over multiple days. Neither can students accept offers “early” in the process (e.g., by negotiating with firms midway before job offers are officially announced for everyone else).
c) All job offers are announced at the end of the interview day. Per placement office rules, all job offers are announced within a short interval of time at the end of the interview day to prevent firms that are allotted the same interview day from coordinating on offers.

I defer the discussion of how the process of interview day allotment affects strategic behaviors of firms (if at all) to Section 7, where I discuss the model of the job placement process.

4 Data Overview

The sections below present some key descriptive facts for both students and firms.

4.1 Students

The administrative data belong to the job placement cycles corresponding to four years: 2012, 2013, 2014, and 2015. Online Appendix Table OA.3 shows the total number of students belonging to each caste for each college degree. There are 4207 students in the sample. Male students comprise about 90% of the sample. Caste in the data is self-declared by students and is used as the basis for quota-based policies in admissions. These policies equalize the share of both disadvantaged and advantaged castes within each college major. Therefore, nearly 50% of the students are from disadvantaged castes for three of the four college degrees in the sample (see Section 2).6

There are four college degrees in the sample. They are the Bachelor of Technology (B.Tech.), Dual, Master of Technology (M.Tech.) and Master of Science (M.S.) degrees. A Dual degree integrates undergraduate and post-graduate studies and is completed a year after the conventional four-year degree (B.Tech.). These students are admitted to the elite college through entrance exams based on caste-major-specific cutoffs that comprise the only criteria for college admission. I omit students pursuing a different Master of Science (also called M.Sc.) degree, as they comprise about 2% of the student population and typically do not make use of the career office in their job search.7

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6The Master of Science (M.S.) degree has a substantially larger proportion of advantaged castes. This indicates that despite admissions quotas, some college degrees may not be able to fill all of the college seats reserved for disadvantaged castes. Frisancho Robles and Krishna (2015) also document similar patterns.

7There are two different Master of Science degrees offered at the college. M.S., which is included in the sample, has an industry focus. M.Sc., which is not included in the sample, is a much smaller program with a research focus.
4.2 Differences in Baseline Characteristics across Castes

In this section, I discuss differences in baseline characteristics across castes.

Differences in pre-college skills across castes. There are substantial differences in college entrance exam scores, averaging about 0.6 standard deviations across college degrees (Online Appendix Table OA.4). Entrance exam scores in the data are originally ranks, which have been renormalized so that larger numbers are better. However, differences in 10th and 12th grade national examination scores are modest and not statistically significant, likely because such tests do not distinguish at the top of the test-taking ability distribution. Importantly, there are students from both castes (common support) within each entrance exam score decile (Online Appendix Figure OA.1).

Differences in college GPA across castes. As with entrance exam scores, there are substantial differences in college GPA across castes but students from both castes within each GPA decile (Online Appendix Table OA.5; Online Appendix Figure OA.1).

Differences in previous labor market experience across castes. I find only modest differences in previous labor market experience across castes. 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 (Online Appendix Table OA.6).

Differences in other employer-relevant skills across castes. Admissions quotas coupled with fairly rigid engineering curricula lead to almost no caste differences on many measures of other employer-relevant skills. These measures include college major, college degree, and coursework. The dataset can also proxy for other employer-relevant skills by including indicators for getting past the various stages of job search, as will be elaborated upon in Section 4.3 below.

4.3 Firms

Below, I provide some key definitions and an overview of firms recruiting from the college.

Definition of a job, the location of advertised jobs, and the number of years each firm recruits from the elite college. In the sample, a “job” means a job designation within a firm. For example, Google can hire a product manager and a software engineer.
These are two different jobs. Each firm included in my sample spanning four placement cycles arrives on the college’s campus for each of the four years to conduct recruitment.

**Omitting public-sector jobs.** I omit such jobs for four reasons. First, such firms comprise less than 4% of all jobs available to students in the degree programs included in the sample. Second, public-sector firms are quite different from their private-sector counterparts, especially in areas like salary structure and job stability.\(^8\) Third, the probability of transitioning from elite public-sector jobs to elite private-sector jobs is less than 2.5% and vice versa (see Online Appendix Table OA.7; Section 10.3). Fourth, such firms already have strong government-mandated hiring quotas for disadvantaged castes (Madheswaran, 2008).

**Distribution of salaries and firms by sector and job types.** Online Appendix Table OA.8 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. Non-client-facing jobs comprise almost 85% of all available jobs.\(^9\)

Conditional on college degree, job salaries do not vary across major, caste, or gender. See Online Appendix Section A for how firms declare salaries for job profiles. 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.

**Declaration of job descriptions, non-pecuniary amenities, and vacancies per job.** Firms declare job details in the employer registration forms made available to them by the placement office. These details include information on various job characteristics, including job descriptions, job designations, sector, salaries, non-pecuniary amenities, desired skills, expectations on the job, the expected number of slots (vacancies) a job wants to fill from the college, and even job application eligibility criterion. The number of advertised non-pecuniary amenities is high and ranges between 40-50 per job (see “Pre-Placement Phase” in Section 3; Online Appendix Section A, Online Appendix Table OA.9).

**Return offers from internships.** These usually have a deadline of late August. Students who accept them are not allowed to participate in the regular placement cycle for full-time jobs (see “Pre-Placement Phase” in Section 3). Therefore, a typical student who applies to a firm during the regular placement season would not have completed a summer internship in his junior year at the same firm. I discuss selection in Section 5.1.

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\(^8\)See the report of the Seventh Central Pay Commission, 2016.

\(^9\)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 non-client-facing, whereas a consulting or managerial role would be considered client-facing.
Data on multiple stages of job search. The administrative dataset also has detailed information on job applications, pre-interview screening, job offers, and job choices. Students apply for jobs through a centralized job application portal, like Job Openings 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 that are automatically made available to them when the student “clicks” on 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 that the dataset contains.

The data also comprise job-level information regarding the number of students who qualified for each round of screening, received job offers, and decided to accept jobs. All jobs conduct 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, also called “technicals,” are mostly conducted online. Technicals differ by roles and include coding tests for manufacturing or technology firms and case-study-based tests for consulting firms. The third round is a large group debate, usually comprising 25 to 30 students. In the third round, employers come face-to-face with 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 consisting of duties such as starting and ending the discussion on time and ensuring decorum. Discussion moderators organically “emerge” from the group of students participating in the discussion. The fourth round is a personal interview featuring the only extensive interactions between students and recruiters during the job search process.

More on personal interviews. Personal interviews, also called HR interviews, are not technical or case-study-based. Rather they are typically a combination of small talk and employers advertising their jobs, assessing culture fit, and asking potential employees about their interest in competing firms. Such interviews, which screen on background characteristics (e.g., educational qualifications of family members, father’s job, neighborhood of residence, preference for living in a cosmopolitan city, and desire for traveling), are commonly used in recruitment for elite private- and public-sector jobs in India.

In a detailed survey of HR managers in the Indian offices of elite MNCs, employing a total of nearly 2 million workers worldwide, Jodhka and Newman (2007) 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 background characteristics in personal interviews. Interestingly, HR managers saw little contradiction in
judging a candidate’s individual merit through background characteristics, arguing instead that trustworthiness of potential clients, attrition, and culture fit could be reasonably gleaned through such inquiries. One HR manager at a large MNC expressed what he looks for in personal interviews:

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].

Another HR manager expressed the signaling value of background characteristics by mentioning that conversations about family background and upbringing are useful in forming impressions about trustworthiness of potential clients, culture fit, attrition, and long-term professional behavior:

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 behavior, 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 colleges in New Delhi, Deshpande and Newman (2007) found that almost all of them were asked about their family background and upbringing 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.
Recent research based on Likert scale ratings also supports the above evidence on the role of family background in candidate screening. Mamgain (2019) shows that HR managers in elite firms value family background almost as much as candidate experience, quality of the institution of education, aptitude, and technical skills.

These prevailing personal interview conventions have also influenced the advice provided to job seekers by online employment platforms. For example, Naukri.com, India’s leading job search portal with a market share over 60%, 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 traveling and meeting people if [they] are appearing for a client-meeting role” (Naukri.com, 2019).

Personal interviews have also been used for several decades for selection into the elite Indian Administrative Services (IAS). Success in these interviews has historically been influenced by a candidate’s background (Gould, 2010). Such tendencies prompted the Kothari Committee to formally recommend reducing weights on interviews in the recruitment process of IAS officers, which were often “influenced by accidental, and sometimes even trivial factors” (Kothari Committee Report, 1976, p. 62).

Free-form or unstructured interviews that screen on conversations related to shared experiences, aspects of culture fit, and personal hobbies are not unique to India. Such practices are commonly employed in the recruitment practices of elite U.S. colleges and corporate America (Stevens, 2009; Rivera, 2015).

5 Descriptive Facts

In this section, I document large earnings disparities across castes upon graduation, discuss selection, argue that the earnings gap is conservative, and show that the earnings drop-off primarily occurs between personal interviews (fourth round) and job offers.

5.1 Large Earnings Gap across Castes

The unconditional earnings gap across castes is -0.174 (0.016) log points, or about 17%, where the number in parentheses 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 is reduced to -0.113 (0.014) log points, or about 11%. These results are robust to many different specifications (see Online Appendix Table OA.10).
There is modest heterogeneity in the earnings gaps across job sectors and job types. For example, the earnings gap among firms in the consulting sector is -0.119 (0.032) log points, whereas it is -0.080 (0.022) log points among firms in the technology sector and -0.084 (0.022) log points among firms in the manufacturing sector (see Online Appendix Table OA.10).

Non-client-facing and client-facing jobs have modestly different earnings gaps. The earnings gap is -0.080 (0.016) for non-client-facing jobs, which comprise 85% of all advertised jobs, and rises to -0.117 (0.029) log points for client-facing jobs (see Online Appendix Table OA.10).

**Matching with Exit Data.** Exit data is a college-administered survey of students, conducted two months after graduation, that includes their job designations and responses to whether offer terms were negotiated between the conclusion of the placement process (i.e., around early January) and the rollout of the exit survey (i.e., around late July). Most jobs have starting dates around mid-July. The data also include specifics of the negotiated terms and the reasons for doing so. Note that students are restricted from bargaining over advertised compensation bundles only during the course of the placement process and not after its conclusion (see “Pre-Placement Phase” in Section 3). The placement office administers exit surveys to ensure the validity of its employment data.

Exit data is filled by nearly 98% of the graduating cohort, possibly since passing along their current roles and contact information is relevant for students to take advantage of the elite college’s alumni network. Comparable response rates are found in similar exit surveys collected by the career offices of elite U.S. MBA programs (Yale School of Management, 2021).

Reassuringly, exit data show that nearly 99% of job getters began in the same jobs they obtained through the placement process and did not negotiate salaries or non-pecuniary amenities, even two months after graduation or several months after the conclusion of the placement process. Among non-job getters, almost all students indicated that they were still “unemployed” two months after graduation, a catch-all category that may include self-employed students as well as those who are taking gap years.

**Selection and Implications for the Earnings Gap.** I now discuss differential selection by caste among those omitted from the earnings regressions.

1. **About 6% of the student sample deregisters from the job placement process.** Deregistered students are those who either do not sign up to participate in the job placement process for full-time jobs or accept their return offers from summer internships, and therefore, cannot participate in the job placement process for full-time jobs (see “Pre-Placement Phase” in Section 3). Similar proportions of students skip the placement processes of other elite Indian colleges, suggesting that, unlike in the U.S., internships
are exploratory (India Today, 2015).

2. The earnings gap is conservative. In addition to belonging to the deregistered category, students omitted from the earnings regressions could also belong to the “registered” category and comprise those who participate in the full-time job placement process but either do not get full-time jobs or reject all of their job offers.

Comparing characteristics of those who are omitted from the earnings regressions, I find that disadvantaged castes are much more negatively selected on college GPA and entrance exam scores (see Online Appendix Table OA.11). Since average earnings are increasing in college GPA and entrance exam scores (not shown), the reported earnings gap is conservative.

5.2 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 earnings drop-off at each step of job search.

![Figure 1: Earnings Gap across Castes at Each Job Search Stage](image)

Notes: Figure 1 shows the log earnings gap across castes at successive stages of job search. Each coefficient in the figure is represented by a black dot and reports the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. The vertical bars are 95% confidence intervals. These regressions include controls.

Recall, firms post job-specific (not match-specific) wages that are non-negotiable over the course of job search (see “Pre-Placement Phase” in Section 3). Therefore, the earnings
drop-off can be decomposed by comparing the caste difference in the composition of jobs that remain in contention at each stage of the placement process.

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

\[
\log(\text{Avg. Job Salary}_{i}^{\text{Search Stage}}) = \alpha + \beta \times \text{Disadv. Caste}_{i} + \text{Controls}_{i} + \epsilon_{i},
\]  

(1)

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

Figure 1 shows that almost all of the earnings gap emerges between personal interviews (fourth round) and job offers. The composition of job applications does not contribute to the earnings gap plausibly because the streamlined job application process (similar to Job Openings for Economists) makes the marginal cost of an application effectively zero. After applications are submitted, firms conduct three pre-interview screening stages: application reading, written aptitude tests (also called “technicals”), and large group debates that test for socio-emotional skills. Together, these three stages contribute to only about one-tenth of the 11% earnings gap. The composition of job choices over offered jobs also does not contribute to the earnings gap. Therefore, almost nine-tenths of the 11% earnings gap emerges between non-technical personal interviews and job offers.

Interestingly, the earnings drop-off is even more concentrated for technology, manufacturing, and non-client-facing jobs. The entire earnings drop-off among these jobs occurs after personal interviews (see Online Appendix Figures OA.2).

There is a substantial winnowing down in the number of jobs that remain in contention at each successive stage of job search. The number of jobs available to each student is reduced 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 “Placement Phase” in Section 3).

6 Interpreting the Caste Penalty, Key Takeaways, and Alternative Explanations

This section offers a leading explanation for the earnings drop-off shown in Figure 1. I also discuss key takeaways and alternative explanations to the earnings drop-off.
6.1 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 that caste identity is plausibly revealed or strongly signaled during personal interviews (fourth round), whereas 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 in last names, different naming conventions, migration, and other factors. For example, surnames like “Singh,” “Sinha,” “Verma,” “Chaudhary,” “Mishra,” and “Das” are shared across castes (Anthropological Survey of India, 2009).\footnote{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.”}

Naming conventions also differ significantly across regions. For example, South Indians typically do not have conventional last names. Rather, for them, personal (first) names often perform the roles of traditional “surnames” (Jayaraman, 2005). It is also unlikely that caste status is known during written aptitude tests (second round), as these tests are typically conducted online.

Caste identification is also unlikely to be reliable during group debates (third round). Recall, these debates are conducted among large groups, typically comprising 25 to 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 tones, accents, dialects, and demeanor. 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 remnants of caste dialects, which are prevalent in most Indian languages (Ambedkar, 2002; Kothari, 2013; Ransubhe, 2018). Rather, perception of accent variation among young, English-speaking university graduates in India is linked to broad regional factors (Wiltshire, 2020).\footnote{The overwhelming influence of regionality in common parlance is perhaps most clearly expressed by Gumperz (1961), who 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 personal or HR interviews provide information about caste status. As documented in Section 4.3, these interviews primarily ask questions about background characteristics that are correlated with socioeconomic status. Such background characteristics often provide a clear window into caste status in elite, urban-
educated India (Deshpande, 2011; Jodkha, 2017). Recent experimental studies among college educated students in urban-educated India have also shown that background characteristics convey almost perfect signals of caste status relative to surface-level attributes (last names, facial features, and dialects) that are highly evenly shared across castes, and therefore, obfuscate caste identification (Mamidi, 2011).

6.2 Nature of Disparities and Other Key Takeaways

Given the evidence above, the earnings drop-off is due to personal interviews that are more likely to reveal caste leading to direct discrimination and, even if not, worsen caste disparities due to indirect discrimination on background characteristics. HR managers may not be weeding out disadvantaged castes per se but assessing culture fit using “caste-blind” methods that are not caste-neutral.

There are also some other takeaways from the descriptive facts. First, since the earnings drop-off primarily occurs due to non-technical personal interviews, policies informing applicants about job opportunities, modifying student preferences, or improving performance at university are unlikely to close the earnings gap for this population.

Second, the paper’s descriptive facts advance the literature on the detection and measurement of labor market disparities. Caste disparities due to discretionary screening practices that value background characteristics are unlikely to be detected through traditional correspondence studies. In addition, recent works studying the role of hiring discretion have either exclusively focused on low-skilled jobs or provided correlational evidence between callback disparities and HR practices being more subjective (Hoffman et al., 2018; Kline et al., 2021). By collecting data on all steps of the placement process, my paper is the first to decompose the earnings drop-off at successive stages of job search and quantify the role of a widely employed subjective screening practice—non-technical personal interviews—in determining access to elite jobs.

Finally, these descriptive facts provide an important example of the kinds of data future researchers may have to collect in elite, urban-educated settings to better detect disparities from outwardly neutral screening practices. Discrimination based on socioeconomic cues is likely to become more salient in urban-educated settings as they increasingly become more multi-ethnic and diverse and standard characteristics by which to differentiate groups become less perceptible (Loury, 2002; Freeman et al., 2011; Gaddis, 2017).
6.3 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 does not occur primarily due to performance in large group debates (third round) that test for socio-emotional skills. Moreover, nearly 85% of the jobs are non-client-facing (see Section 4.3), suggesting 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.

2. **Better outside options for advantaged castes through offline job search.** Better job offers procured “offline” (i.e., outside of the centralized placement process) may be used as leverage by advantaged castes for higher-paying offers. However, students who register for the placement process are prohibited by the college from searching “offline” and risk being debarred from the services of the placement office if discovered doing so. Therefore, registered students do not simultaneously search offline.

3. **Advantaged castes can bargain better over salaries and amenities.** Salaries and non-pecuniary amenities posted by jobs are non-negotiable during the course of the placement cycle. Compensation bundles are also are verified by the placement office at the conclusion of the placement process. Furthermore, exit data confirms that job getters start in the same jobs and receive the same compensation bundles, months after the placement process has concluded (see “Pre-Placement Phase” in Section 3 and Section 5.1).

4. **Employers are “playing along” at rounds prior to personal interviews due to the possibility of government audits or internal institutional pressure.** Government pressure has been weak in the absence of a formal regulatory agency to oversee hiring in the Indian private sector (Jodhka, 2008).

Overtly expressed attitudes by private-sector employers also suggest a lack of support for compensatory hiring policies (Jodhka and Newman, 2007; Jodhka, 2008). Perhaps unsurprisingly, 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 HR purposes (BusinessLine, 2018).

Diversity practices in multinational firms employing Indians are overwhelmingly influenced by the historical priorities of the West, where caste is not a protected category,
suggesting that internal institutional pressure to rectify caste disparities has either been sluggish or even non-existent (Chakravartty and Subramanian, 2021). Furthermore, the difficulty of observing caste prior to personal interviews also diminishes the possibility of firms responding to internal institutional pressure to advance disadvantaged caste candidates during prior screening rounds (see Section 6.1).

5. **Competition from the government sector.** Since government jobs have strong quota-based hiring policies, private sector employers may not make offers to disadvantaged castes for fear of losing out to the government sector (see Section 2). However, government jobs comprise only 4% of firms in my sample (see Section 4.3). Moreover, firms know the list of companies recruiting from campus (available on the job portal), suggesting that they are themselves aware of the meagre presence of public-sector firms in the job fair.

6. **Employers can easily identify disadvantaged castes and are casting a wide net to advance them at earlier screening rounds.** As mentioned in Section 6.1, caste status is difficult to discern before personal interviews. Therefore, employers are unlikely to be successful in explicitly screening on caste status prior to the personal interview rounds.

7. **Caste differences in preferences over job characteristics.** About 50% of the students who participate in the placement process get multiple job offers. A model of the placement process confirms that caste differences in preferences over job characteristics do not drive caste disparities in job offers. These job characteristics include stock options, signing bonuses, job sectors, and whether the job is located in a metropolitan city (see Section 9.1).

7 **A Model of the Job Placement Process**

In the second half of my paper, I propose and evaluate the effectiveness of policies to diversify hiring in elite entry-level jobs. For this purpose, I calculate employer willingness to pay for key characteristics, such as pre-college test scores and caste. These estimates are obtained from a model of the hiring process. The model incorporates the economically relevant stages of job search in my setting: firm hiring and final job choices. As will be emphasized later, employer willingness to pay for caste is invariant to the underlying motivations for caste.

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12Note that while employers observe GPA at the application reading stage, GPA serves as a very noisy signal of caste, especially outside the tails of the GPA distribution (see Online Appendix Figure OA.1).
disparities (see “Role of the caste coefficient” in Section 7.2.2). Therefore, the model does not distinguish between the sources of caste disparities.

7.1 Key Unmodeled Features

I begin by discussing some key features of the job placement process my model takes as exogenous.

**National Wage Setting.** The model takes wage setting as exogenous. This assumption is plausible because firms set job-specific wages *nationally* and do not pay meaningfully different salaries across their Indian locations to rookies hired from other universities. Using Glassdoor, I find that there is only a 2% average difference in salaries offered by firms for the same job (job designation within a firm) across their Indian locations (see Online Appendix Table OA.12). National wage setting is closely tied to features of the job placement process, typically shared across elite Indian colleges (see Section 3). Since firms cannot change advertised wages or non-pecuniary amenities during the course of the placement processes of elite Indian colleges, they typically provide similar information on the employer registration form equivalents required by the placement offices of other similar universities, as they recruit rookies from those universities during a single on-campus placement cycle, usually from mid-September to early January (see “Pre-Placement Phase” in Section 3, Online Appendix Section A).

**Interview Day Allotment.** The model also takes interview day allotment as exogenous. Recall that each firm is allotted an interview day to conduct on-campus interviews (see “Placement Phase” in Section 3). Past interview day allocations and job characteristics are almost perfectly predictive of current interview day allocations (see Online Appendix Table OA.13). 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 day by 8%. Since job salaries are nationally set, it is plausible to assume interview day allocations as exogenous (see “Pre-Placement Phase” in Section 3).

**Student Application Behavior.** I do not model student application behavior because students effectively apply to all eligible jobs (see Section 5.1). Omitting application behavior of elite Indian college students from the model is not necessarily a limitation. Job placement processes of elite colleges typically feature streamlined and centralized application systems,

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13 Note that salaries on Glassdoor are self-reported by employees.
14 The phenomenon of firms setting wages nationally has also been documented in the U.S. labor market for elite entry-level jobs (Hazell et al., 2021).
such as Job Openings for Economists, effectively making students apply for all eligible jobs recruiting from campus (see Mamgain, 2019). Nevertheless, I show how one could extend the model to incorporate application behavior that may be important in settings besides elite Indian colleges (see Online Appendix Section B).

7.2 Modeled Features

In this section, I elaborate upon the two key stages of the job placement process captured by the model: firm hiring and final job choices.

7.2.1 Stage 2: Job Choice by Students

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

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

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 that 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, a random effect $q_i$ that is unobserved by the econometrician, and a job offer acceptance shock, $\epsilon_{ij}$, realized after job offers are known but before final job choices are made. Mathematically,

$$U_{ij} = X'_{ij}\beta + \text{NP}_j'^{\Psi} + w_j\tau + q_i + q_i \times \sum_{m=1}^{M} \gamma_m \text{NP}_{jm} + \epsilon_{ij}, \quad (3)$$

where $X_{ij}$ includes student and job characteristics, especially interactions between caste and non-pecuniary amenities. The vector $\text{NP}_j = (\text{NP}_{j1}, \ldots, \text{NP}_{jM})$ is a vector of over 50 unique non-pecuniary amenities for job $j$, and $w_j$ is the (log) salary offered by job $j$. Note that I categorize some fringe benefits as “non-pecuniary” amenities because, for a substantial portion of the sample, I do not have information on direct cash-equivalents of such benefits.

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, and relocation allowances allows for random marginal effects of non-pecuniary amenities and
drives preferential selection over job offers. Each element in the vector of idiosyncratic student preference shocks over jobs, denoted by \( \epsilon_i = (\{\epsilon_{ij}\}_{j \in J}, \epsilon_{i0}) \) is drawn from an independent, identically distributed Type-1 extreme value distribution. I normalize the value of the outside option.\(^{15}\) This value is given by

\[
U_{i0} = \epsilon_{i0}.
\] (4)

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

\[
C_i^* = \arg \max_{j \in O(Z_i)} U_{ij} - U_{i0}.
\] (5)

### 7.2.2 Stage 1: Student Choice by Jobs

In this section, I introduce a model of labor demand with limited job-level heterogeneity. 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, as the placement 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 “Placement Phase” in Section 3).

Recall, a “job” means a job designation within a firm. 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 \( \pi^j_i \), 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 Online Appendix Section C.

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. In Proposition 1 at the end of this section, I show that each job \( j \) follows a job-specific cutoff hiring rule. Therefore, each job \( j \) hires a student \( i \) iff

\[
V_{ij} = S'_{ij}\alpha + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta + \mu_{ij} > k^*_j.
\]

\[
= S'_{ij}\alpha + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta + \mu_{ij} - k^*_j > 0.
\] (6)

where \( V_{ij} \) is the utility that job \( j \) gets from student \( i \), \( k^*_j \equiv k^*_j(w_j, X_j) \) is a job-specific cutoff

\(^{15}\)Disadvantaged castes are more negatively selected among non-job getters (see Section 5.1). However, caste differences in average welfare may be modest within this sample because such students, on average, may sort into lower paying jobs with better non-pecuniary amenities (e.g., public-sector jobs, which have caste-specific quotas, or other private-sector jobs).
that is estimated for each job $j$ with the vector $X_j$ denoting features of the job besides wage, and $S_{ij}$ includes student and job characteristics.

**Job-specific cutoff.** Notice that the inclusion of the job-specific cutoff, $k^*_j$, implies that parameters entering Equation 6 are identified from within-job variation. As mentioned in Section 4.3, each firm arrives on campus for a total of four years to conduct recruitment. During each of these years, a firm typically offers different salaries and non-pecuniary amenities for the same job designation. The cutoff, $k^*_j$, basically acts like a fixed effect that controls for job-level (firm-job-designation-level) heterogeneity. In practice, $k^*_j$ is modeled as a job-specific constant.

**Student and job characteristics.** Student characteristics entering $S_{ij}$ include controls for pre-college skills, within-college academic performance, previous labor market experience, and other employer-relevant skills, including indicators for whether the student qualified for various stages of job search. Importantly, while I model firm hiring as a one stage process, I still retain information about prior screening stages by adding indicators in $S_{ij}$ for students getting past the application reading, written test, or group debate stage. Note also that employers observe pre-college skills, including high school grades and college entrance exam scores.

The term $w_j$ denotes the (log) salary offered by job $j$ and is included separately from $S_{ij}$, $q_i$ denotes econometrician-unobserved student-level attributes, and $\mu_{ij}$ is an idiosyncratic match term, which is unobservable to student $i$ but observable to job $j$. I will assume that each $\mu_{ij}$ follows a standard logistic distribution and is independent across all students and jobs. Notice that in Equation 6, job salaries are taken as exogenous based on the evidence documented in Section 7.1 that suggests firms set entry-level salaries nationally. I discuss the identification of wage effects in Section 8.

**Role of the caste coefficient.** The “caste penalty” is captured by $\eta$. Together, the coefficients on wages and caste in Equation 6 allow us to calculate employer willingness to pay for caste. This estimate is crucial to assess the effectiveness of policies to mitigate caste disparities.

As mentioned previously, background characteristics are almost perfectly predictive of caste in urban-educated India. Therefore, the reduced-form coefficient representing the caste penalty could capture discrimination due to employers valuing direct (caste) in addition to indirect characteristics (family background, neighborhood of residence, and upbringing) revealed during personal interviews. Such discrimination could stem from either taste-based or statistical motivations and the reduced-form caste coefficient embeds a mechanism for both. In other words, the magnitude of the caste penalty, and therefore, the employer willingness
to pay for caste is invariant to the underlying motivations for caste disparities.

**Incoming hires and firms’ utility maximization.** Let $C(j)$ denote the set of applicants who accept an offer from job $j$. I will assume that the utility of job $j$ from cohort $C(j)$ is given by

$$V_j(C(j)) = \sum_{i \in C(j)} V_{ij}. \quad (7)$$

An economic interpretation of Equation 7 is that jobs do not focus on complementarities or team building during hiring. The assumption is plausible, as the university comprises a small fraction of a job’s overall incoming cohort—i.e., a job does not coordinate student hires across universities. Moreover, jobs select students for interviews based on screening tests that are general in scope.

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 employer-unobserved idiosyncratic student preferences for job $j$ as well as those for other jobs (through $\epsilon_i$ 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

$$Z^*(j) = \arg \max_{Z(j) \in \{0,1\}^{A(j)}} \mathbb{E}\left[ V_j(C(j)) \right], \quad (8)$$

s.t. $\mathbb{E}(|C(j)|) \leq M_j \quad (9)$

$$= \sum_{i : V_{ij} > k^*_j, j \in A_i} \Pr(C^*_i = j) \leq M_j.$$

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 $j$, where $V_{ij}$ is the utility to job $j$ from student $i$, $k^*_j$ is the job-specific hiring cutoff, $A_i$ is the application vector of student $i$, and $C^*_i$ is the optimal job choice by student $i$ at the job choice stage. The right-hand side of Equation 9 is the ex-ante hiring cap of each job $j$, denoted by $M_j$.

Notice that job salaries also enter the ex-ante hiring constraint since they enter $V_{ij}$ through Equation 6, rationalizing the fact that a job (job designation within a firm) may make offers in proportion to their wages. For example, a job paying a higher wage in a given year may make fewer offers, all else being equal, and vice versa.
Interpreting the econometrician-unobserved random effect $q$. Note also that the random effect $q$ 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 over jobs. See Howell (2010) for a similar treatment of unobserved heterogeneity. An example of $q$ could be “student interest level,” which employers could learn during non-technical personal interviews.

Comment regarding the specification of random effect. 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. 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 to no variation in student application behavior, conditional on observables, such a correlation is infeasible to identify in my setting.

More precisely, the lack of variation in application behavior, conditional on observables, restricts the modeling choice on the student side to essentially one that just incorporates final job choice behavior. Recall that modeling application behavior of elite Indian college students is not necessarily economically interesting, as streamlined and centralized application systems effectively make students apply for all eligible jobs (see “Student Application Behavior” in Section 7.1). However, modeling only final job choices of students restricts how flexible one can be with random effects that enter students’ decisions over job offers and are correlated with the random effect entering firms’ hiring decisions. The basic constraint is that students can only accept one job offer.

Note also, however, that the main result on the student side—there are no average caste differences in preferences over non-pecuniary amenities—holds with or without the inclusion of a random effect in student utility (see Section 9.1). Additionally, employer willingness to pay estimates (crucial for counterfactuals) do not critically depend upon $q$ entering student utility.

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

**Proof.** The proof follows from Kapor (2022). I prove the proposition above by contradiction. Let $\text{Hire}\{j\} : \{1, \ldots, I\} \rightarrow [0, 1]$ be a hiring rule used by job $j$ that 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 $\text{Hire}(j)(i) < 1$ and $\text{Hire}(j)(i') > 0$. 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 $\text{Hire}(j)(i)$ by $\frac{\epsilon}{P_{ij}}$, reduce $\text{Hire}(j)(i')$ by $\frac{\epsilon}{P_{i'j}}$, and increase overall cohort quality.

The hiring cutoff result above relies on the assumption that the information observed by job $j$ 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 $k^*_j$ is not a structural parameter and will be allowed to change under counterfactuals.

### 7.3 Equilibrium

An equilibrium is a tuple

$$\{k^*_j, C^*_i\}_{i=1,...,I,j=1,...,J}$$

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 $O(Z_i)$ solves

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

   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

   $$Z^*(j) = \arg \max_{Z(j) \in \{0,1\}^{|A(j)|}} \mathbb{E}\left[ V_j(C(j)) \right],$$

   s.t. $\mathbb{E}(|C(j)|) \leq M_j$,

   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 $M_j$ is the ex-ante hiring cap for job $j$. 

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8 Identification and Estimation

This section describes the identification of key model parameters: student preferences over job characteristics, wage effects entering the employer’s utility function, the econometrician-unobserved random effect, $q$, and the “caste penalty.”

Recall that a “job” is a job designation within a firm. I assume that characteristics like caste, salaries, and non-pecuniary amenities entering the utility functions of students are exogenous. Similarly, exogenous characteristics entering the utility functions of jobs include salaries, sector, caste, major, and degree.

1. **Student preferences over job characteristics.** Identification of student preference parameters comes from variation in job characteristics of both accepted and rejected job offers, which also lead to variation in job choices between students.

2. **Wage effects.** Identification of parameters entering the employer’s utility function comes from within-job variation since the job-specific cutoff, $k_j^*$, basically acts like a fixed effect controlling for job-level heterogeneity. For example, identification of the wage effects in Equation 6 comes from within-job time variation in wages and offer rates, since each firm arrives on campus for a total of four years to conduct recruitment. During each of these years, a firm typically offers different salaries and non-pecuniary amenities for the same job designation.

   I assume that wages are causal primarily because evidence suggests that rookie salaries are set nationally so it is unlikely that local conditions or shocks influence them (see Section 7.1). Note also that this university comprises only a tiny fraction of a given firm’s total hiring pool.

3. **Econometrician-unobserved random effect.** Econometrician-unobserved $q$ is identified from correlation in offer probabilities across jobs within a student’s application portfolio. 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. Basically, identification comes from the fact that, conditional on observables, getting an offer from Facebook is correlated with getting an offer from Microsoft.

4. **Caste penalty.** I assume that the caste coefficient entering the utility functions of jobs is causal. 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, and other employer-relevant
skills, including indicators for whether the student got past the application reading, written test or group debate stage. I also assume that econometrician-unobserved $q$ in Equation 6 is not correlated with caste and that there is no other error term capturing unobserved ability of applicants.

I estimate the parameters by maximum simulated likelihood (Online Appendix Section D).

9 Parameter Estimates

In this section, I quantify student and employer willingness to pay for key characteristics. To do so, I scale the coefficients of interest by the coefficient on wage.

9.1 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 $q$ and dollar amounts are in PPP terms.

Main takeaways. About 50% of the students who participate in the placement process get multiple job offers. While non-pecuniary amenities are valuable to students on average, there are no caste differences in preferences over them. Non-pecuniary amenities include stock options, signing bonuses, relocation allowances, medical insurance, performance bonuses, whether the job is located in a metropolitan city, job sectors, and so on.\textsuperscript{16}

9.2 Job Preferences over Student Characteristics

Table 2 shows select parameter estimates entering the utility functions of jobs.

Main takeaways. Overall, firms discount the value of disadvantaged castes at the equivalent of 4.8\% of average annual salary ($2721), holding other student attributes constant. Employer willingness to pay for caste is large. All else being the same, an increase in college GPA of about one standard deviation equalizes hiring probabilities across castes. In addition, closing the caste gap in each pre-college test score quantile closes only about 10\% of the model-implied caste penalty.

\textsuperscript{16}Recall, I categorize some fringe benefits as “non-pecuniary” amenities because, for a substantial portion of the sample, I do not have information on direct cash-equivalents of such benefits.
9.3 Modeled Unobservables

Table 3 reports the standard deviation of econometrician-unobserved $q$ and random marginal effects for non-pecuniary amenities.

**Main takeaways.** Econometrician-unobserved $q$ plays only a modest role in student and firm utilities. Consider a job that does not offer any non-pecuniary amenities. To get the same utility from that job as a student with one standard deviation higher $q$, a student with mean $q$ needs to be compensated about 1.7% ($969) of average salary. Similarly, a firm needs to be subsidized 1.1% of average salary ($623) to offset a one standard deviation decrease in $q$.

9.4 Model Fit and Job Cutoffs

The model does a good job fitting many moments, including job offers, job choices, unemployment, and the earnings gap (see Online Appendix Table OA.14). As expected, the highest paying firms have the highest hiring cutoffs and vice versa (see Online Appendix Table OA.15).
Table 1: Select Parameter Estimates (Student Utility)

| Parameter                      | Estimate | Std. Error | Compensation ($) | Std. Error ($) | Compensation (%) | Std. Error (%) |
|--------------------------------|----------|------------|------------------|----------------|------------------|----------------|
| Salary (log), $\tau$          | 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          |
| Metro City                     | 0.045*** | 0.009      | +1038.842***    | 213.458        | +1.830***        | 0.357          |
| 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          |
| Disadv. Caste × Metro City     | 0.015    | 0.080      | +344.010         | 1834.969       | +0.606           | 3.261          |

Average Salary = $56,767.29 (PPP), $N = 4207$ (no. of students), $J = 644$ (no. of jobs). PPP stands for purchasing power parity.

Notes: Table 1 includes estimates for select student preference parameters over job characteristics. The compensation terms are calculated in units of dollars (PPP) for a person with mean econometrician-unobserved $q$. “Metro City” is a dummy for whether a job was located in a traditional metropolitan city, like Delhi, Mumbai, Kolkata, or Chennai. Full estimation tables are available upon request.

* significant at 10%, ** significant at 5%, *** significant at 1%.
Table 2: Select Parameter Estimates (Job Utility)

| Parameter                  | Estimate | Std. Error | Employer Subsidy ($) | Std. Error ($) | Employer Subsidy (%) | Std. Error (%) |
|----------------------------|----------|------------|----------------------|---------------|----------------------|---------------|
| Salary (log), $\phi$       | 1.893*** | 0.074      | —                    | —             | —                    | —             |
| Disadv. Caste, $\eta$      | -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      | +5722.520***         | 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). PPP stands for purchasing power parity.

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 are originally ranks, which have been renormalized 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 have been reparametrized to reflect differences relative to the manufacturing sector. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%. 
### Table 3: Modeled Unobservables

| Parameter                          | Estimate  | Std. Error |
|------------------------------------|-----------|------------|
| Standard deviation of $q$, $\sigma_q$ | 0.042***  | 0.004      |
| Parameter on $\sigma_q$, $\delta$  | 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 ($\gamma_m$) 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%.

10 Counterfactuals

Using employer willingness to pay for key characteristics, such as caste and pre-college test scores, I evaluate three counterfactual policies to improve both the absolute and relative caste hires at elite firms. These policies are:

**Hiring subsidies.** As mentioned in Section 9, model estimates show that eliminating the gap in each pre-college test score quantile closes only about 10% of the model-implied caste penalty, suggesting the need for policies that directly mitigate caste disparities. In the first counterfactual, I consider one such policy: a hiring subsidy that eliminates the caste penalty by making firms indifferent between observably identical applicants across castes. The subsidy is equivalent to the amount employers discount the value of disadvantaged castes—i.e., 4.8% of average annual salary. This amount is a one-time common payment to each elite entry-level job, per disadvantaged caste hired, and 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). Note that, in principle, the hiring subsidy reimburses the employer for a stream of costs incurred in the future and not just the cost of
hiring a disadvantaged caste over a single year.

Given the structure of rookie salaries in elite entry-level jobs in the Indian private sector, a subsidy is also a natural policy to promote hiring diversity. Since firms cannot not change advertised wages during the placement processes of elite Indian colleges, a subsidy can be conceptually thought of as firms “adjusting” wages for disadvantaged castes, which they might in a less restrained rookie market, with the difference being made up by the government (see “Pre-Placement Phase” in Section 3).

**Pre-college interventions.** Next, I consider a “pre-college intervention” that equalizes the distribution of pre-college skills (college entrance exam scores) across castes. The pre-college intervention policy encompasses different interventions—usually Randomized Controlled Trials (RCTs)—including hiring tutors, bonuses to teachers, and redesigning school curricula that are evaluated through their impact on educational outcomes, especially test scores (Asim et al., 2015).

**Hiring quotas.** Finally, I consider a hiring quota that requires firms to hire an equal proportion of applicants from advantaged and disadvantaged castes: a policy that mirrors reservation-based compensatory policies in government jobs (Madheswaran, 2008).

### 10.1 Counterfactual Results: Hiring Subsidies and Pre-College Intervention

The counterfactual analysis uses employer willingness to pay estimates to evaluate changes in the absolute and relative caste hires at elite firms in a partial equilibrium framework. Potentially relevant channels that are considered fixed in the analysis include wage changes in elite entry-level jobs, reallocation of workers to elite entry-level jobs, caste share of applicants to such jobs, and so on. In Section 10.3, I argue that omitting these channels does not necessarily limit the scope of my analysis for this population.

In this section and the next, I discuss results from the counterfactual analysis. I begin by discussing how the model can bound absolute displacement effects under hiring subsidies and the pre-college intervention policy. I then compare absolute effects and cost-effectiveness of these two policies.

**Bounding displacement effects.** Both of these counterfactual policies explicitly improve employers’ valuation of disadvantaged castes (see Equation 6).

1. **Labor demand is perfectly elastic.** When labor demand is perfectly elastic, jobs do not adjust cutoffs and hire everyone who qualifies. Disadvantaged caste hires are at least as large as in the baseline and there is no displacement of advantaged castes (see Online Appendix Figure OA.3).
2. **Labor demand is perfectly inelastic.** When labor demand is perfectly inelastic, jobs do not relax their employment targets, raise their cutoffs, and displace advantaged castes in favor of disadvantaged castes (see bottom panel of Online Appendix Figure OA.3).

Under both scenarios, more disadvantaged castes are hired relative to the baseline. However, disadvantaged caste hires are the highest (lowest) when labor demand is perfectly elastic (inelastic). Similarly, advantaged caste hires are the lowest (highest) when labor demand is perfectly inelastic (elastic).

The above viewpoint is a natural way to bound plausible responses under policies that explicitly improve employers’ valuation of disadvantaged castes. In such scenarios, firms would typically do a combination of increasing the hiring threshold a little and hiring a few more people.

**Comparing absolute effects.** Recall that the model-implied subsidy equivalent of the pre-college intervention policy is about 0.6% of average annual salary, which is only about 10% of the caste penalty or the employer willingness to pay for caste. In fact, employer willingness to pay for pre-college test scores is so small that even the upper bound of the earnings gap under hiring subsidies (in absolute value) is smaller than its lower bound under the pre-college intervention policy. Specifically, under the two alternative assumptions about labor demand, the earnings gap reduces from 11% in the baseline to between 6 to 8 percent under hiring subsidies and between 9 to 10 percent under the pre-college intervention policy (see Online Appendix Table OA.18). Analogous comparisons hold for the reduction in job displacements of disadvantaged castes under both policies (see Online Appendix Table OA.19).

**Comparing cost-effectiveness.** To evaluate cost-effectiveness, I use the employer willingness to pay estimates and compare the model-implied subsidy equivalent of the pre-college intervention policy to the direct costs of changing test scores. To calculate the latter, I use estimates from a meta-analysis of education-focused impact evaluations that documents the costs of changing test scores of primary and secondary school students in India (Asim et al., 2015). To extrapolate the direct cost of the pre-college intervention policy, I make three extremely conservative assumptions: 1) costs scale linearly with test score changes, 2) students can be perfectly targeted (i.e., the test score of a given student can be changed by any desired amount), and 3) there is no fade out (i.e., test score changes achieved through early interventions persist over the lifetime). Even under these extremely conservative assumptions, subsidies to hire applicants from disadvantaged castes are twice as cost-effective in diversifying elite hiring than the pre-college intervention policy.
10.2 Counterfactual Results: Hiring Quotas

In this section, I evaluate the university-level displacement effects of a government-mandated quota that equalizes the caste share of hires within each elite job.

**Implementation.** My model of the job placement process can readily accommodate hiring quotas. In contrast to responses to other hiring policies considered in this paper, jobs now explicitly decide on two hiring thresholds: one for the advantaged castes and vice versa.\(^{17}\)

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 7.1). Additionally, students are prevented from attending interviews on future interview days conditional on receiving job offers on the current interview day (see Section 4.3). 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.

**Results.** Unlike hiring subsidies or the pre-college intervention policy, a quota policy that equalizes the caste-share in elite jobs leads to a substantial decrease in overall recruitment from the university, as firms counteract the policy by making fewer job offers in total.\(^{18}\)

The following elucidates the economic reasoning driving the result above. Under the quota policy, a firm needs to balance hiring from advantaged and disadvantaged castes. While more disadvantaged castes are hired under quotas, the caste penalty is large enough to eventually make the average marginal utility of filling two slots lower than the average marginal cost. This happens well before firms can achieve baseline levels of hiring. Therefore, firms counteract the quota policy by making fewer job offers and decrease overall recruitment from the university. Note that employers in my model do not have a hard constraint on their hiring size.\(^{19}\) Thus, quotas may either increase or decrease the total number of students recruited from the university. Therefore, the results from the quota policy are not mechanical: they crucially depend upon the magnitude of the employer willingness to pay for caste.

More disadvantaged castes find jobs under quotas but the displacement effects on advantaged castes are severe. The proportion of unemployed disadvantaged castes falls from 36%\(^{17}\)I use the word “explicitly” because, under previous counterfactual policies, jobs implicitly solved for two hiring thresholds. The cutoffs for disadvantaged castes were shifted up by the “caste penalty” in Equation 6.\(^{18}\)In my model, job salaries are taken as given, so elite entry-level jobs do not respond on the intensive margin by exerting wage discrimination under quota policies (see Section 7.1).\(^{19}\)In my model, a job’s hiring cap is denoted by \(M_j\) and is not treated as a structural parameter (see Equation 9).
to 31%. However, 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 reduce college recruitment by 7% (see Online Appendix Table OA.19).

Together, these findings suggest that a well-designed temporary subsidy for hiring disadvantaged castes will be a cost-effective method to diversify elite hiring in the Indian private sector.

10.3 Modeling Choices and Their Implications

In Sections 10.1 and 10.2, I used employer willingness to pay estimates to evaluate the performance of counterfactual policies in improving both the absolute and relative caste hires at elite firms. In doing so, I considered as fixed other aspects, including wage changes in elite entry-level jobs, reallocation to elite entry-level jobs, caste share of applicants to such jobs, and so on. As I discuss in this section, omitting these channels does not necessarily limit the scope of my analysis for this population. I also comment on some other modeling decisions.

1. **Focusing on one elite college and elite entry-level jobs in the private sector.** Elite entry-level jobs are important to focus on as they can shape not just an individual’s economic trajectory but also broader societal inequalities (Rivera, 2015). Additionally, the job placement process of this elite college—the institutional setting of the paper—offers a representative window into how elite college graduates transition into elite entry-level jobs in the Indian private sector (see points 2, 3, 4, and 5 in Section 3). Note also that firms offer about the same job-specific wage to students from other universities across all locations in India (see Section 7.1).

2. **No reallocation to elite entry-level jobs in the private sector from other jobs following compensatory policies and vice versa.** Separate samples from the Periodic Labour Force Survey, which is collected by the National Sample Survey Office (NSSO), and the India Human Development Survey show that the probability of transitioning into elite entry-level jobs in the private sector from “other” jobs (elite entry-level public-sector jobs, other entry-level private-sector jobs, unemployment, and so on) is less than 2.5% and vice versa (see Section 4.3). Note that the pay in even elite entry-level jobs in the public sector is about 50% of that in elite entry-level jobs in the private sector.\(^{21}\)

\(^{20}\)This result could also explain the prevalence of hiring backlogs in elite public-sector jobs in India despite a similar government-mandated hiring quota policy (Press Trust of India, 2019).

\(^{21}\)See the report of the Seventh Central Pay Commission, 2016.
These transition probabilities suggest that elite entry-level workers in the private sector tend to stay there and transitioning into such jobs is challenging, especially since 95% of their hires are from elite colleges (see Section 3). The high concentration along the diagonals of job transition matrices is also common pattern in formal labor markets in India (see Sarkar et al., 2017; Bhattacharya, 2021). Thus, not capturing the reallocation of talent either from or to elite entry-level jobs in the private sector following compensatory policies is not a major limitation.

Moreover, under the plausible assumption that advantaged castes benefit more from “job changing” within elite entry-level jobs, (e.g., by procuring other job offers once the current job starts and using them as leverage), my paper likely underestimates caste disparities in initial placements.

3. **No wage changes in counterfactuals.** Note that I take wages as exogenous because firms set them nationally (see Section 7.1). I also argue that omitting wage changes from the counterfactual analysis is not a major limitation. First, recall my data collection shows that almost all firms recruiting from this elite college also visit other elite Indian colleges and are foreign-based MNCs that hire overwhelmingly for their Indian offices (see Section 3). However, about 97% of the offices and 96% of the entry-level labor force of these foreign-based MNCs are outside of India (see Section 3). Therefore, elite Indian college graduates comprise a small fraction of the global entry-level labor demand of foreign-based MNCs.

I also show that there is only a 3% average difference between real job-specific salaries offered at establishments located in the “MNC headquarter region or similar” (typically locations in North America and Europe), which hire more than 90% of the firm’s entry-level labor force, versus those at their Indian offices (see Online Appendix Table OA.16). This finding corroborates recent research on the wage anchoring behavior of elite MNCs. Such firms may care about minimizing job-specific pay inequality across countries to facilitate the international movement of employees (Alonso et al., 2021; Sarsons et al., 2022). Relatedly, Bloom et al. (2012) argue that elite MNCs

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22 Relatively, the NSSO defines unemployment as a situation in which all those who owing to lack of work are not working, but seek work through employment exchanges, intermediaries, friends or relatives (National Sample Survey Organisation, 2001). Therefore, being unemployed in the data collected by the NSSO is closer to being actually out of work (e.g., it does not include self-employment). On the other hand, students who are “unemployed” through job the placement process I study could include those who are self-employed or taking gap years (see Section 5.1).

23 Participants in the placement processes of elite Indian colleges are barred from offline job search (Section 6.3).

24 Information on the entry-level labor share of firms was taken using a combination of data made available through Craft.com, LinkedIn or personal websites, brochures, and HR departments of firms.
typically follow firm-wide wage setting procedures *internationally*, but decentralize hiring decisions or make them *locally*. These behaviors are consistent with my model allowing elite foreign-based MNCs to locally (i.e., in India) adjust on the extensive margin by changing both absolute and relative caste hires due to compensatory policies, while keeping wages fixed due to strong wage anchoring behavior.

4. **Fixed share and composition of castes admitted to elite colleges following counterfactual policies.** Most elite colleges in India are public institutions and explicitly set aside 50% of seats *within each major* for disadvantaged castes. Political establishments across India are also highly reluctant to modify the caste share of reserved seats in such colleges. Moreover, adding new seats in elite colleges is a long-drawn process due to bureaucratic red tape (Newman and Thorat, 2012). Given that the number of elite colleges is likely fixed in the short-run, it is reasonable to assume that the share and composition of castes admitted to such colleges remains fixed following counterfactual policies.

5. **Fixed share and composition of castes applying to elite jobs following counterfactual policies.** These are not major limitations for the following reasons. First, almost 96% of elite Indian college graduates work in elite entry-level jobs in the private sector. Moreover, graduates from elite Indian colleges account for more than 95% of the hires in such jobs (see Section 3). Second, job placement processes of elite colleges typically feature streamlined and centralized application systems, effectively making students apply for all eligible jobs recruiting from campus (see Section 5.1; Mamgain, 2019). Third, within-major caste shares and the total number of seats in elite colleges are likely stable in the short-run (see point 4 above). Finally, the probability of transitioning into elite entry-level jobs in the private sector from other jobs is negligible and vice versa (see point 2 above). Given these facts, it is reasonable to assume that the caste share of students applying to elite entry-level jobs following compensatory policies is fixed in the short- to medium-run.

Assuming that the composition of castes applying to elite jobs remains fixed following counterfactual policies is also not a major limitation. If advantaged castes prefer to go elsewhere (e.g., abroad) as a consequence of losing their “unfair” advantage in elite entry-level jobs, my paper likely underestimates the effects on absolute and relative disadvantaged caste hires due to counterfactual policies. Similarly, assuming a fixed composition of disadvantaged caste applicants to elite jobs is likely to underestimate the effects on absolute and relative disadvantaged caste hires due to counterfactual policies.
6. **Caste penalty fixed in the counterfactual analysis.** My counterfactual policies consider employer weights on various sources of caste disparities as policy invariant. These include weights on both direct (caste) as well as indirect sources facilitating caste identification (family background, father’s job, cosmopolitan attitudes, upbringing, neighborhood of residence, personal hobbies, and desire for traveling) that are likely revealed during non-technical personal interviews. These weights are captured, as a whole, by the reduced-form caste coefficient in the employer’s utility function that is used to calculate employer willingness to pay for caste (see Section 7.2.2). The main goal of the policy exercise is to use this estimate to motivate and evaluate potential solutions to caste disparities. Capturing the full equilibrium effects of counterfactual policies on the weights employers put on various direct or indirect characteristics that lead to caste disparities is outside the scope of this paper.

7. **Information-based policies.** My counterfactuals do not consider information-based policies to correct employers’ potentially biased beliefs about the correlation between background characteristics and productivity. Such policies are likely to be ineffective, especially given evidence that correlates of socioeconomic status are highly predictive of career success (Eschleman et al., 2014; Clark, 2015; Correa et al., 2019).

8. **Not modeling GPA.** I do not model GPA since GPA and entrance exam scores are slightly negatively correlated in the data, conditional on caste and other observables (see Online Appendix Table OA.17). Therefore, my model overestimates the impact of one of my counterfactual policies that increases college entrance exam scores of disadvantaged castes.\(^ {25} \) One possible explanation for this correlational pattern could be random variation in college entrance exam scores, conditional on ability. Students at the top of the distribution are more likely to have positive error in their entrance exam scores. Since the pool of students at the elite college is truncated at relatively high entrance exam scores, the correlation between GPA and entrance exam scores is plausibly dominated by the top of the distribution.

Omitting GPA effects from the counterfactual analysis is not necessarily a broader limitation. This is because of two reasons. First, Frisancho Robles and Krishna (2015) also find slightly negative correlation between college GPA and entrance exam scores among disadvantaged caste students belonging to a different elite Indian college. As in my data, these effects are stronger within the most selective majors. Second, among elite Indian college students, even college performance and high school grades are

\(^ {25} \)Recall that 10th and 12th standard grades are not statistically different across castes (see Section 4.1).
weakly correlated, largely because such students are already highly selected on the latter (Frisancho Robles and Krishna, 2015).

9. **Not modeling internship choices.** I omit modeling internship choices from my model as they are negatively correlated with pre-college skills (see Section 4.2). The weak (and sometimes negative) correlation between internship outcomes and pre-college skills among elite Indian college students is a common pattern plausibly because, unlike in the U.S., internships are viewed by students as exploratory. This view is supported by the fact that only modest proportions of students accept return offers from summer internships thereby not skipping the placement processes of elite colleges (Singh, 2018; Section 5.1).

10. **No bargaining by workers over wages and non-pecuniary amenities.** Placement processes of elite colleges prohibit bargaining over compensation bundles during the course of the placement cycle (see “Pre-Placement Phase” in Section 3). As mentioned previously, exit surveys confirm that job getters in my setting start in the same jobs and receive the same compensation bundles, months after the placement process has concluded (see Section 5.1). Therefore, my data offers an accurate description of the compensation bundles offered to students at the start of their new jobs. Moreover, under the plausible assumption that bargaining over salaries, non-pecuniary amenities, and promotions later in workers’ careers favor advantaged castes more, my paper likely underestimates caste disparities in initial placements.

In Online Appendix Section E, I discuss other modeling choices and argue that they do not necessarily limit the scope of my analysis for this population. These include: 1) not modeling firm entry, 2) keeping student preference measures fixed in the counterfactuals, 3) not considering bans on subjective interviews, 4) not incorporating firms potentially changing their recruitment practices following counterfactual policies, 5) not modeling either multiple job screening stages or job applications, 6) not considering either wages, performance, and hiring by firms of workers from other universities or job changing, 7) having the same random effect, \( q \), enter both student and firm utility, 8) not omitting the random effect from student utility, 9) not modeling the equity-efficiency tradeoff, and 10) not modeling the financing of subsidies.

### 11 Conclusion

This paper studies how socioeconomically biased screening practices impact access to elite firms and what policies might effectively reduce bias. Using administrative data on job search
from an elite Indian college, I document large caste disparities in earnings. I show that these disparities arise primarily in the final round of screening, comprising non-technical personal interviews that inquire about characteristics correlated with socioeconomic status. Through a novel model of the job placement process, I show that employer willingness to pay for an advantaged caste is as large as that for a full standard deviation increase in college GPA. A hiring subsidy that eliminates the caste penalty would be more cost-effective in diversifying elite hiring than other policies, such as those that equalize the caste distribution of pre-college test scores or enforce hiring quotas.

Discrimination based on socioeconomic cues in elite, urban-educated settings is likely to become more salient as the world becomes increasingly multi-ethnic and diverse and standard characteristics by which to differentiate groups become less perceptible (Loury, 2002; Freeman et al., 2011; Gaddis, 2017). I provide an important example of the kinds of data future researchers may have to collect in such settings to better detect disparities from outwardly neutral screening practices. By connecting how perceptions of socioeconomic cues determine barriers to elite attainment, this paper also helps advance how to conceptualize, quantify, and address racial, class, or caste disparities in such opportunities, most of which are situated in a rapidly diversifying urban landscape.

While this paper attempts to do many things, no paper is exhaustive. Future research could collect similar data to detect less visible forms of discrimination in other parts of the world. Other works could also examine the evolution of the caste penalty beyond the first job. Experimental follow-ups studying different firm-level policies such as standardized interview questions, decision review, and interviewer representation are also promising areas for future exploration.

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ONLINE APPENDIX

A  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, and select majors who qualify to apply.

A) Job Details:
   - Job Designation* :
   - Offer Types* : Domestic □ International □
   - Startup* : Yes □ No □
   - Job Description* : Job_Details.pdf [details of non-pecuniary amenities here]
   - Probable number of slots per job*:

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       |                  |                   |                     |

B  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.

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

$$ A_{i/k} = \begin{cases} 
  \{m|m \in A_i, m \neq k\} & \text{if } k \in A_i \\
  \{m|m \in A_i\} \cup \{k\} & \text{if } k \notin A_i
\end{cases} \quad (\text{OA.1})$$
Then, it must be true that
\[ MV_{i/k} > 0 \quad \forall k \in A_i \tag{OA.2} \]
\[ MV_{i/p} < 0 \quad \forall p \notin A_i \tag{OA.3} \]

\( MV_{i/k} = V(A_i) - V(A_{i/k}) \) denotes the marginal value from modifying the application vector according to Equation OA.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, \( A_i = \{ \text{Goldman Sachs, Microsoft, Google} \} \). 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 \( O(2^J) \), where \( J \) is the number of jobs. However, when searching over jobs, the complexity of the problem is only \( O(J) \), where \( J \) is the number of jobs. The cost of job applications can then be modeled in a manner similar to Howell (2010). Finally, a logit kernel smoother is used to obtain closed form solutions (Train, 2003).

C 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 that takes the value 1 if student \( i \) applies to a job allotted interview day \( k \). Similarly, let \( Z_i^k \) be a vector of indicators that 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 \( \pi_i^j \), 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

\[\text{Recall, a “job” means a job designation within a firm.}\]
\[ f_k(Z_i^k|A_i^k) = \prod_{j=1}^{J} \left( A_{ij}^k \left[ \pi_j^i Z_{ij}^k + (1 - \pi_j^i)(1 - Z_{ij}^k) \right] + (1 - A_{ij}^k)(1 - Z_{ij}^k) \right). \] (OA.4)

From Section 7.1, 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

\[
f(Z_i|A_i) = \begin{cases} \prod_{l=0,1,...,K} f_l((0,0,\ldots,0)|A_i) & \text{if } Z_{ij} = 0 \forall j \\ \sum_{k=1}^{K} \left( \prod_{l=0,1,...,k-1} f_l((0,0,\ldots,0)|A_i) \right) \tilde{f}_k(Z_i|A_i) & \text{else}, \end{cases}
\] (OA.5)

where \( \tilde{f}_l(Z_i|A_i) = \sum_{\{m:Z_i \times D_m^l = Z_i^k\}} \Pr(D_m^l)f_l(Z_i^k|A_i^l) \) 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 \( \tilde{f}_0((0,0,\ldots,0)|A_i) = 1 \).

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

**D Estimation Details and Standard Errors**

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

**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, \( \epsilon_i \), follows independent Type-1 extreme value distributions, the probability of student \( i \) choosing job \( j \) at the job choice stage is

\[
\Pr(C_i = j|X_{ij}, w_j, NP_j, q_i) = \frac{\exp(u_{ij})}{\sum_{k \in O(Z_i)} \exp(u_{ik})},
\] (OA.6)

where \( O(Z_i) \) denotes the 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 \( u_{ij} = X_{ij}' \beta + NP_j' \Psi + w_j \tau + q_i + q_i \times \sum_{m=1}^{M} \gamma_m NP_{jm} \).
Student Choice by Jobs. Conditional on \(q_i \sim N(0, \sigma_q^2)\) and given the assumption that the idiosyncratic match specific term \(\mu_{ij}\) between student \(i\) and job \(j\) follows a standard logistic distribution, the probability of student \(i\) getting accepted from job \(j\) is

\[
\pi_i^j(S_{ij}, w_j, q_i, k_j^*; \alpha, \eta, \phi, \delta, \theta) = \frac{\exp(S_{ij}' \alpha + \text{Disadv. Caste}_i \times \eta - w_j \phi + q_i \delta - k_j^*)}{1 + \exp(S_{ij}' \alpha + \text{Disadv. Caste}_i \times \eta - w_j \phi + q_i \delta - k_j^*)},
\]

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 indicators for whether the student qualified got past the application reading, written aptitude test, or group debate stage. Job characteristics include indicators for the job sector and the entire set of over 50 non-pecuniary amenities, as applicable. These job characteristics are usually interacted with student characteristics entering \(S_{ij}\). The term \(w_j\) denotes the (log) salary offered by job \(j\), \(q_i\) is econometrician-unobserved student-level attributes, and \(k_j^* = k_j^*(w_j, X_j)\) is a job-specific cutoff that is estimated for each job \(j\) with the vector \(X_j\) denoting features of the job besides wage. 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 C.

Likelihood. Let \(\theta\) 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

\[
\mathcal{L}_i(Z_i^*, C_i^*|A_i, X_i, \theta) = \int_q f(Z_i^*|A_i, X_i, q, \theta) \times \Pr(C_i^* = j|Z_i^*, X_i, q, \theta) dF(q|\theta),
\]

where \(A_i\) is the application vector for student \(i\) and \(X_i\) is the vector of all other exogenous characteristics entering the likelihood function of student \(i\).

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

\[
\hat{\mathcal{L}}_i(\theta) = \frac{1}{R} \sum_{r=1}^R \mathcal{L}_i(\theta),
\]

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

\[
\hat{\theta}_{MSL} = \arg \max_{\theta} \frac{1}{N} \sum_{i=1}^N \log \mathcal{L}_i(\theta) = \arg \max_{\theta} \left( \frac{1}{N} \sum_{i=1}^N \log \left[ \frac{1}{R} \sum_{r=1}^R \mathcal{L}_i^r(\theta) \right] \right),
\]

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, \(\hat{H}\), can be computed by the average outer product of the gradient of simulated likelihood evaluated at \(\hat{\theta}_{MSL}\) i.e.
\[
\hat{H} = \frac{1}{N} \sum_{i=1}^{N} \nabla_{\theta} \log \hat{L}_i(\hat{\theta}_{MSL}) \nabla_{\theta} \log \hat{L}_i(\hat{\theta}_{MSL})' .
\] (OA.11)

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

E Modeling Choices and Their Implications (Continued)

In this section, I discuss some other modeling choices and argue that they do not necessarily limit the scope of my analysis for this population. These include:

1. Firm entry. The cost of doing business in India is substantial. World Bank’s “Ease of Doing Business” rankings lists India low, alongside Mexico, Colombia, and Jamaica. Moreover, starting a new business in India takes about 5 times the duration as it does in the U.S. (World Bank, 2020). Given these factors, it is unlikely that elite firm entry would meaningfully respond to compensatory policies, such as hiring subsidies, in the short- to medium-term.

2. Student preference measures kept fixed in counterfactuals. It is possible that compensatory policies for disadvantaged castes may change the willingness of advantaged caste students to accept elite jobs. While modeling these dynamics would be interesting, my model does not capture such “full equilibrium” effects.

3. Banning subjective interviews. My analysis does not consider such counterfactuals. Legally challenging practices such as personal interviews is likely untenable, as employers typically have free rein to value non-group characteristics, like candidate background (Lang and Spitzer, 2020). Moreover, the loss in screening precision due to the removal of subjective screening practices may outweigh equity gains (Mocanu, 2022).

4. Firms not changing their recruitment practices. Following counterfactual policies, firms might reevaluate potential trade-offs regarding the number of schools to visit, which screening steps to keep in place, how many candidates to interview, and how many resources to invest in hiring candidates. Modeling such dynamics is beyond the scope of my paper. Moreover, it is also unclear if such changes are likely to materialize in the short-run, given that job placement processes of elite Indian colleges are standardized, dictated by universities, and closely modeled after those organized by elite Indian colleges established in the early 1950s (see Section 3).

5. Not modeling multiple firm screening stages and job applications. The choice of modeling firm screening as a one-stage process is guided by the decomposition of the earnings drop-off. This choice does not necessarily restrict my model’s generalizability. The extension of my model of firm screening can be done in a manner similar to the
basic model of labor demand laid out in Section 7.2.2, with the written test, group debate, and interview stage each having its own cutoff. Modeling application behavior of elite Indian college students is not necessarily economically interesting, as streamlined and centralized application systems effectively make students apply for all eligible jobs (see Section 7.1).

6. **Not considering wages, performance, hiring by firms of workers from other universities, and job changing.** The job placement process studied in this paper offers a representative window into how elite college graduates transition into elite entry-level jobs, firms offer about the same job-specific wage to students from other universities across all locations in India, and focusing on just initial placements in elite jobs is important (see point 1 above and Section 7.1). Moreover, under the plausible assumption that advantaged castes benefit more from “job changing” (e.g., by procuring other job offers once the current job starts and using them as leverage), my paper likely underestimates caste disparities in initial placements.\(^{27}\)

7. **Same random effect, \(q\), entering both student and firm utility.** See the discussion under “The above specification of the random effect is not necessarily a limitation” in Section 7.2.2.

8. **Omitting \(q\) from student utility does not affect the main conclusions in the paper.** The main result on the student side—that there are no average caste differences in preferences over non-pecuniary amenities—holds with or without the inclusion of a random effect in student utility (see Section 9.1). In addition, the magnitudes of the coefficients on employer utility (crucial for counterfactuals) do not critically depend upon \(q\) entering student utility.

9. **Equity-efficiency tradeoff.** My counterfactual analysis does not directly take this tradeoff into account. My estimates show that the model-implied subsidy equivalent to elite firms of the pre-college intervention policy is about 0.6% of average annual salary, which is only about 10% of the caste penalty. Therefore, the efficiency gains from pre-college interventions (omitted from my cost-effectiveness analysis) are likely small. Moreover, leaning toward equity through interventions in later stages, like hiring subsidies, might not necessarily sacrifice efficiency. Recent work has shown 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 (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 (Fisher v. University of Texas, 2016).

10. **Financing of subsidies.** The model does not consider financing of policies such as hiring subsidies, which is one of the counterfactual policies (see Section 10). However, hiring subsidies may raise tax receipts by increasing employment and also reduce expenditure on unemployment assistance. Recent studies of hiring subsidies in Germany

\(^{27}\)Participants in the placement processes of elite Indian colleges are barred from offline job search (Section 6.3).
and France have even found them to be self-financing (Brown et al., 2011; Cahuc et al., 2014).

F Tables and Figures
**Table OA.1:** Foreign-Based versus India-Based Firms in the Data

| Designation          | Count | Proportion |
|----------------------|-------|------------|
| Foreign-Based Firms  | 622   | 96.58      |
| India-Based Firms    | 22    | 3.42       |
| Total Firms          | 644   | 1          |

Notes: Online Appendix Table OA.1 shows the proportion of foreign-based MNCs versus India-based firms in the data that spans from 2012-2015.

**Table OA.2:** Share of Offices and Entry-Level Employees Outside India for Foreign-Based MNCs

| (1) Firm Name                | (2) Headquarters         | (3) Offices Outside India (%) | (4) Entry-Level Employees Outside India (%) |
|-----------------------------|---------------------------|-------------------------------|---------------------------------------------|
| Citicorp                    | New York, USA             | 99.62                         | 98.62                                       |
| eBay Inc.                   | San Jose, USA             | 97.67                         | 98.22                                       |
| Rolls Royce                 | London, UK                | 97.61                         | 96.36                                       |
| LinkedIn                    | Sunnyvale, USA            | 94.66                         | 96.73                                       |
| Google                      | Mountain View, USA        | 94.28                         | 97.50                                       |
| Intel                       | Santa Clara, USA          | 97.11                         | 96.48                                       |
| Amazon                      | Seattle, USA              | 97.45                         | 96.13                                       |
| Boston Consulting Group     | Boston, USA               | 96.27                         | 96.23                                       |
| Cisco                       | San Jose, USA             | 96.59                         | 84.91                                       |
| Schlumberger                | Houston, USA              | 98.60                         | 98.91                                       |
| NetApp                      | Sunnyvale, USA            | 96.77                         | 83.33                                       |
| Citrix                      | Fort Lauderdale, USA      | 94.11                         | 95.85                                       |
| Ronald Berger               | Munich, Germany           | 96.15                         | 96.83                                       |
| Applied Materials           | Santa Clara, USA          | 96.91                         | 96.30                                       |
| Epic                        | Verona, USA               | 96.29                         | 98.23                                       |
| General Electric            | Boston, USA               | 97.92                         | 94.73                                       |
| Analog Devices Pvt. Ltd.    | Norwood, USA              | 96.67                         | 98.75                                       |
| ARM Embedded Technologies   | Cambridge, UK             | 92.59                         | 97.20                                       |
| Microsoft                   | Redmond, USA              | 98.17                         | 95.58                                       |
| VISA                        | San Francisco, USA        | 97.72                         | 96.35                                       |
| Texas Instruments           | Dallas, USA               | 96.71                         | 96.56                                       |
| Samsung                     | Suwon-si, South Korea     | 98.69                         | 96.34                                       |
| J.P. Morgan & Chase         | New York, USA             | 95.59                         | 97.42                                       |
| Capital One                 | McLean, USA               | 95.12                         | 98.08                                       |
| ASEA Brown Boveri (ABB)     | Zurich, Switzerland       | 95.60                         | 97.14                                       |
| Caterpillar                 | Deerfield, USA            | 97.95                         | 94.02                                       |

Notes: Online Appendix Table OA.2 reports the proportions of offices of foreign-based MNCs that are outside of India for a select sample of firms. In addition, the table also reports the shares of firm-specific entry-level employees that are hired from India. Column (1) includes the firm name, column (2) denotes the location of the firm headquarters, column (3) reports the proportions of offices of foreign-based MNCs that are outside of India, and column (4) shows the shares of firm-specific entry-level employees that are hired from India. The average of the proportions reported in column (3) is 96.65%. The average of the proportions reported in column (4) is 96.88%. The numbers reported in columns (3) and (4) are also similar in magnitude across all jobs in the sample, although only a select number of jobs are shown in Online Appendix Table OA.2. Some of the above data is available at Craft.com, which is a supplier intelligence platform, whereas other data required a combination of information made available through LinkedIn or personal websites, brochures, and HR departments of firms.
Table OA.3: Distribution of Students by Caste for 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: Online Appendix Table OA.3 includes the total number of students belonging to each caste for 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.

Table OA.4: Differences in Pre-College Skills across Castes

| 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   |
| B.Tech. Degree        | 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  |
|        | 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.Tech. Degree        | 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: Online Appendix Table OA.4 documents differences in pre-college skills across castes. Pre-college skills include scores on 10th and 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 are originally ranks, which have been renormalized so that higher numbers are better. The difference across castes is reported in standard deviation units. Adv. Caste stands for advantaged caste and Disadv. Caste stands for disadvantaged caste. \( *p < 0.1; \) \( **p < 0.05; \) \( ***p < 0.01. \)
### Table OA.5: Differences in Average Overall GPA (Not Adjusted for Major) across Castes

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

Notes: Online Appendix Table OA.5 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. Adv. Caste stands for advantaged caste and Disadv. Caste stands for disadvantaged caste. *p < 0.1; **p < 0.05; ***p < 0.01.

### Table OA.6: Differences in Previous Labor Market Experience across Castes

| Degree          | Adv. Caste | Disadv. Caste | Difference |
|-----------------|------------|---------------|------------|
| B.Tech. and Dual Degrees |
| 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 at a Startup | 0.34 (0.05) | 0.30 (0.05) | 0.04 |
| Total Internship Pay ($) | 3042.24 (249.40) | 2877.28 (220.89) | 164.96 |
| M.Tech. and M.S. Degrees |
| Avg. Part-Time/Full-Time Employment Duration (Weeks) | 68.48 (4.52) | 68.93 (6.96) | −0.45 |
| Fraction Worked in the IT Sector | 0.36 (0.04) | 0.18 (0.07) | 0.18*** |
| Fraction Worked in the Consulting Sector | 0.19 (0.04) | 0.15 (0.06) | 0.04 |
| Fraction Worked in the Manufacturing Sector | 0.45 (0.05) | 0.67 (0.08) | −0.12*** |
| Total Part-Time/Full-Time Employment Pay ($) | 22523.80 (1458.03) | 19645.89 (1390.32) | 2877.91 |

Notes: Online Appendix Table OA.6 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 parentheses. All dollar amounts are in purchasing power parity units. T-tests are conducted for differences in overall means. *p < 0.1; **p < 0.05; ***p < 0.01.

OA.11
Table OA.7: Firm Transition Matrix

| From/To          | Elite Private-Sector | Other  |
|------------------|----------------------|--------|
| Elite Private-Sector | 97.88                | 2.12   |
| Other            | 1.21                 | 98.79  |

Notes: Online Appendix Table OA.7 shows the probability of transitioning from elite private-sector jobs to “other” jobs. “Other” jobs include elite public-sector jobs, other private-sector jobs, unemployment, and so on. The dataset is constructed from separate samples of the India Human Development Survey (IHDS) and the Periodic Labor Force Survey (PLFS), which is collected by the National Sample Survey Office (NSSO). Note that the NSSO defines unemployment as a situation in which all those who owing to lack of work are not working, but seek work through employment exchanges, intermediaries, friends or relatives (National Sample Survey Organisation, 2001). Therefore, being unemployed in the data collected by the NSSO is closer to being actually out of work (e.g., it does not include self-employment). On the other hand, students who are “unemployed” through job the placement process I study could include those who are self-employed or taking gap years. The sample construction from the PLFS follows Bhattacharya (2021). The same construction from the IHDS follows (Sarkar et al., 2017).

Table OA.8: Total Number of Firms and Average Salary by Sector

| Sector         | (1) | (2)       |
|----------------|-----|-----------|
|                | Total (Fraction) | Avg. Salary ($) |
| Technology     | 335 (0.52)   | 67302.64  |
| Consulting     | 129 (0.20)   | 63544.02  |
| Manufacturing  | 180 (0.28)   | 43525.25  |

Notes: Online Appendix Table OA.8 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 parentheses. Column (2) shows the average salary of all jobs in a given sector. All dollar amounts are in purchasing power parity (PPP) terms.
### Table OA.9: 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 at the firm?            |                                                         |
| 8.         | Bonus for spending 2 years at the firm?           |                                                         |
| 9.         | Bonus for spending 3 years at the firm?           |                                                         |
| 10.        | Bonus for spending 4 years at 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?                                 | Arranging moving company                                |
| 20.        | Relocation assistance?                            |                                                         |
| 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: Online Appendix Table OA.9 shows the complete list of unique non-pecuniary amenities offered by each job (job designation within a firm) along with an added description of the perks, unless self-explanatory.
| 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 up to 6 months                               |
| 54.        | Subsidized educational leave?                            |                                                      |
| 55.        | Subsidized high-school education for kids?               |                                                      |
| 56.        | Subsidized housing?                                     |                                                      |
| 57.        | Gratuity?                                                | Lump sum payment after 4 years and 8 months of service|
| 58.        | Leave encashments?                                       | Unused paid leave reimbursed as part of salary        |
| 59.        | Option to return after sabbatical?                       |                                                      |

Notes: Online Appendix Table OA.9 shows the complete list of unique non-pecuniary amenities offered by each job (job designation within a firm) along with an added description of the perks, unless self-explanatory.
### Table OA.10: Earnings Gap

Baseline Log Earnings (USD PPP)

| Baseline Specification | (1) | (2) | (3) | (4) |
|------------------------|-----|-----|-----|-----|
| 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 |

**Manufacturing Sector**

| Coefficient            | Linear | Quadratic | Cubic | Splines |
|------------------------|--------|-----------|-------|---------|
|                       |       |     |      |       |
| **Disadv. Caste**      |       |     |      |       |
| −0.084*** (0.022)      |       |     |      |       |
| −0.070** (0.027)       |       |     |      |       |
| −0.091*** (0.032)      |       |     |      |       |
| −0.091*** (0.032)      |       |     |      |       |
| **N**                  | 789    | 789    | 789   | 789    |
| **R^2**                | 0.344  | 0.547  | 0.604 | 0.619  |
| Adjusted **R^2**       | 0.323  | 0.402  | 0.408 | 0.431  |

**Technology Sector**

| 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  |

**Consulting Sector**

| Coefficient            | Linear | Quadratic | Cubic | Splines |
|------------------------|--------|-----------|-------|---------|
|                       |       |     |      |       |
| **Disadv. Caste**      |       |     |      |       |
| −0.119*** (0.032)      |       |     |      |       |
| −0.104*** (0.041)      |       |     |      |       |
| −0.087** (0.048)       |       |     |      |       |
| −0.109** (0.054)       |       |     |      |       |
| **N**                  | 703    | 703    | 703   | 703    |
| **R^2**                | 0.494  | 0.636  | 0.688 | 0.689  |
| Adjusted **R^2**       | 0.473  | 0.502  | 0.528 | 0.528  |

**Client-Facing Jobs**

| Coefficient            | Linear | Quadratic | Cubic | Splines |
|------------------------|--------|-----------|-------|---------|
|                       |       |     |      |       |
| **Disadv. Caste**      |       |     |      |       |
| −0.117*** (0.029)      |       |     |      |       |
| −0.129*** (0.037)      |       |     |      |       |
| −0.115*** (0.044)      |       |     |      |       |
| −0.119*** (0.045)      |       |     |      |       |
| **N**                  | 822    | 822    | 822   | 822    |
| **R^2**                | 0.437  | 0.568  | 0.614 | 0.616  |
| Adjusted **R^2**       | 0.418  | 0.434  | 0.454 | 0.456  |

**Non-Client-Facing Jobs**

| 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 | 0.610  |
| Adjusted **R^2**       | 0.492  | 0.522   | 0.528 | 0.529  |

Notes: Online Appendix Table OA.10 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. The 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 4). 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. PPP stands for purchasing power parity. *p < 0.1; **p < 0.05; ***p < 0.01.
**Table OA.11:** GPA and Entrance Exam Comparisons of All Students vs. Those Without Jobs

| GPA Comparisons | B.Tech. Degree | Students without Jobs |
|-----------------|----------------|-----------------------|
|                 |                |                       |
|                 | (1) Overall    | (2) Overall           |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 8.08          | 7.00                  |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 7.97          | 6.58**                |
|                 |                |                       |
|                 | Overall       | Students without Jobs |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 8.05          | 7.15                  |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 8.02          | 6.86**                |
|                 |                |                       |
|                 | Overall       | Students without Jobs |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 8.33          | 7.62                  |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 8.00***       | 7.35***               |
|                 |                |                       |
|                 | Overall       | Students Without Jobs |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 8.49          | 8.42                  |
|                 | Adv. Caste    | Disadv. Caste         |
|                 | 8.46          | 8.23*                 |

| Entrance Exam Score Comparisons | B.Tech. Degree | Students without Jobs |
|---------------------------------|----------------|-----------------------|
|                                 |                |                       |
|                                 | Overall        | Students without Jobs |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -1617.89       | -3707.45              |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -1879.32*      | -4315.18**            |
|                                 |                |                       |
|                                 | Overall        | Students without Jobs |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -2096.60       | -4067.13              |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -2602.79***    | -5743.80***           |
|                                 |                |                       |
|                                 | Overall        | Students without Jobs |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -653.94        | -2445.64              |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -1052.61***    | -3310.677**           |
|                                 |                |                       |
|                                 | Overall        | Students without Jobs |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -558.94        | -1416.09              |
|                                 | Adv. Caste     | Disadv. Caste         |
|                                 | -642.18        | -1411.26              |

Notes: Online Appendix Table OA.11 compares the average GPA and entrance exam scores of all 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. Adv. Caste stands for advantaged caste and Disadv. Caste stands for disadvantaged caste. *p < 0.1; **p < 0.05; ***p < 0.01.
| (1) Firm Name                   | (2) Job Designation | (3) Job Location | (4) Headquartered in         | (5) ∆(%) |
|--------------------------------|---------------------|------------------|-----------------------------|----------|
| Citicorp                       | Analyst             | India            | New York, USA              | 0.07     |
| eBay Inc.                      | Software Engineer   | India            | San Jose, USA              | 1.29     |
| Indian Register of Shipping    | Assistant Surveyor  | India            | Powai, India               | 1.45     |
| Rolls Royce                    | Engineering Graduate| India            | London, UK                 | 1.46     |
| LinkedIn                       | Software Engineer   | India            | Sunnyvale, USA             | 1.86     |
| Google                         | Software Engineer   | India            | Mountain View, USA         | 2.76     |
| Intel                          | Component Design Engineer | India         | Santa Clara, USA           | 2.44     |
| Amazon                         | Area Manager        | India            | Seattle, USA               | 0.47     |
| Boston Consulting Group        | Associate           | India            | Boston, USA                | 1.42     |
| Cisco                          | Software Engineer   | India            | San Jose, USA              | 1.80     |
| Schlumberger                   | Software Engineer   | India            | Houston, USA               | 3.08     |
| NetApp                         | Member Technical Staff | India          | Sunnyvale, USA             | 1.48     |
| Citrix                         | Software Engineer   | India            | Fort Lauderdale, USA       | 2.66     |
| Ronald Berger                  | Business Analyst    | India            | Munich, Germany            | 2.80     |
| Applied Materials              | Application Engineer| India            | Santa Clara, USA           | 0.85     |
| Epic                           | Software Developer  | India            | Verona, USA                | 1.64     |
| General Electric               | Edison Engineer     | India            | Boston, USA                | 2.33     |
| Analog Devices Pvt. Ltd.       | Software Engineer   | India            | Norwood, USA               | 1.88     |
| ARM Embedded Technologies      | Graduate Engineer   | India            | Cambridge, UK              | 4.01     |
| Microsoft                      | Software Engineer   | India            | Redmond, USA               | 2.31     |
| VISA                           | Software Engineer   | India            | San Francisco, USA         | 1.74     |
| Texas Instruments              | Analog Engineer     | India            | Dallas, USA                | 4.85     |
| Samsung                        | Software Engineer   | India            | Suwon-si, South Korea      | 4.92     |
| J.P. Morgan & Chase            | Associate           | India            | New York, USA              | 1.38     |
| Capital One                    | Associate           | India            | McLean, USA                | 4.35     |
| ASEA Brown Boveri (ABB)        | Software Engineer   | India            | Zurich, Switzerland        | 1.38     |
| Caterpillar                    | Associate Engineer  | India            | Deerfield, USA             | 2.88     |

Notes: Online Appendix Table OA.12 includes comparisons between job-specific salaries offered on Glassdoor versus my sample. The table reports these comparisons for select firms in the sample. Column (1) includes the firm name, column (2) includes job designation, column (3) includes the job location, column (4) reports the location of the firm headquarters, and column (5) reports the absolute percentage difference between the salaries from Glassdoor (in PPP) versus those in my sample (in PPP), where the denominator is the average salary across all jobs in the sample ($56,767.29 PPP). The average of ∆(%) reported in column (5) is 2.21%. This average difference is also similar in magnitude across all jobs in the sample, although only a select number of jobs are shown in Online Appendix Table OA.12. The PPP conversion factor is taken from the OECD website. Job-specific salaries in India are taken from the Glassdoor website and then compared to those offered in my sample.
Table OA.13: Predicting Interview Days with Job Characteristics and “Firm Identity”

|                      | Job Characteristics Only       |                      |                      |
|----------------------|-------------------------------|----------------------|----------------------|
|                      | (1)                           | (2)                  | (3)                  |
| 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                |

|                      | Job Characteristics and “Firm Identity” |
|----------------------|-----------------------------------------|
|                      | (1)                           | (2)                  | (3)                  |
| 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: Online Appendix Table OA.13 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. The 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 OA.14: Model Fit: Job Offer, Job Choice, Unemployment, and Earnings

|                | Model Fit          |
|----------------|--------------------|
|                | (1)                |
|                | (2)                |
| **Job Offer**  |                    |
| Data           | Model              |
| Consulting     | 0.25               |
| Technology     | 0.48               |
| Manufacturing  | 0.27               |
|                | 0.23               |
|                | 0.51               |
|                | 0.26               |
| **Job Choice** |                    |
| Data           | Model              |
| Consulting     | 0.24               |
| Technology     | 0.49               |
| Manufacturing  | 0.27               |
|                | 0.22               |
|                | 0.51               |
|                | 0.27               |
| **Unemployed** |                    |
| Data           | Model              |
|                | 0.30               |
|                | 0.31               |
| **Earnings Gap** |                |
| Data           | Model              |
|                | -11.3%             |
|                | -10.6%             |

Notes: Online Appendix Table OA.14 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. Model-simulated moments are computed by simulating the model 300 times for each observation in the sample and then averaging over the number of observations and the number of simulation draws.
Table OA.15: Select Job Cutoffs by Pay Category, Job Sector, and Job Title

| 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      |

Notes: Online Appendix Table OA.15 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. Average Salary = $56,767.29 (PPP), N = 4207 (no. of students), J = 644 (no. of jobs). PPP stands for purchasing power parity.
* significant at 10%, ** significant at 5%, *** significant at 1%.
| Firm Name                  | Job Designation         | Job Location     | Headquartered in | ∆(%)  |
|---------------------------|-------------------------|------------------|------------------|-------|
| Citicorp                  | Analyst                 | India            | New York, USA    | 2.12  |
| eBay Inc.                 | Software Engineer       | India            | San Jose, USA    | 0.45  |
| Rolls Royce               | Engineering Graduate    | India            | London, UK       | 2.67  |
| LinkedIn                  | Software Engineer       | India            | Sunnyvale, USA   | 3.52  |
| Google                    | Software Engineer       | India            | Mountain View, USA | 2.34 |
| Intel                     | Component Design Engineer | India           | Santa Clara, USA | 1.74  |
| Amazon                    | Area Manager            | India            | Seattle, USA     | 2.82  |
| Boston Consulting Group   | Associate               | India            | Boston, USA      | 0.66  |
| Cisco                     | Software Engineer       | India            | San Jose, USA    | 2.91  |
| Schlumberger              | Software Engineer       | India            | Houston, USA     | 3.22  |
| NetApp                    | Member Technical Staff  | India            | Sunnyvale, USA   | 1.32  |
| Citrix                    | Software Engineer       | India            | Fort Lauderdale, USA | 3.67 |
| Ronald Berger             | Business Analyst        | India            | Munich, Germany  | 2.49  |
| Applied Materials         | Application Engineer    | India            | Santa Clara, USA | 3.56  |
| Epic                      | Software Developer      | India            | Verona, USA      | 3.47  |
| General Electric          | Edison Engineer         | India            | Boston, USA      | 3.04  |
| Analog Devices Pvt. Ltd.  | Software Engineer       | India            | Norwood, USA     | 1.76  |
| ARM Embedded Technologies | Graduate Engineer       | India            | Cambridge, UK    | 3.94  |
| Microsoft                 | Software Engineer       | India            | Redmond, USA     | 2.91  |
| VISA                      | Software Engineer       | India            | San Francisco, USA | 2.84 |
| Texas Instruments         | Analog Engineer         | India            | Dallas, USA      | 3.11  |
| Samsung                   | Software Engineer       | India            | Suwom-si, South Korea | 2.75 |
| J.P. Morgan & Chase       | Associate               | India            | New York, USA    | 2.74  |
| Capital One               | Associate               | India            | McLean, USA      | 3.67  |
| ASEA Brown Boveri (ABB)   | Software Engineer       | India            | Zurich, Switzerland | 3.61 |
| Caterpillar               | Associate Engineer      | India            | Deerfield, USA   | 3.42  |

Notes: Online Appendix Table OA.16 includes select comparisons between real job-specific salaries offered by MNCs at Indian locations versus locations in the “MNC headquarter region or similar” (typically North America and Europe). Column (1) includes the firm name, column (2) includes job designation, column (3) includes the job location, column (4) denotes the location of the firm headquarters, and column (5) reports the absolute percentage difference between real job-specific salaries at Indian locations versus locations in the “MNC headquarter region or similar,” where the denominator is the average salary across all jobs in my sample ($56,767.29 PPP). The average of ∆(%) reported in column (5) is 2.72%. This average difference is also similar in magnitude across all jobs in the sample, although only a select number of jobs are shown in Online Appendix Table OA.16. Firm salaries for Indian locations are taken from my sample. Firm salaries at locations in the “MNC headquarter region” are taken from a combination of Glassdoor and Levels.fyi.
Table OA.17: Negative Correlation between College GPA and Entrance Exam Score

| Dependent Variable: log GPA |
|-----------------------------|
| **B.Tech. Degree Students** |
| 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            |

| **Dual Degree Students**     |
| 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            |

| **M.Tech. Degree Students**  |
| 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            |

| **M.S. Degree Students**     |
| 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: Online Appendix Table OA.17 includes estimates from a regression of grade point averages of B.Tech., Dual, M.Tech., and M.S. degree holders on student characteristics. The dependent variable is log GPA. Controls include college major, entrance exam score (standardized), grades on 10th and 12th grade national level examinations (standardized), and caste. College major includes indicators for each major. College entrance exam scores (ranks) have been renormalized 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.
### Table OA.18: Earnings Gap under Subsidies versus Pre-College Intervention

|                      | Earnings Gap (%) |                      |
|----------------------|------------------|----------------------|
|                      | Perfectly Elastic Labor Demand |                      |
| Hiring Subsidy       | -5.5%            | Pre-College Intervention | -8.9%          |
| Perfectly Inelastic Labor Demand |                      |                      |
| Hiring Subsidy       | -7.6%            | Pre-College Intervention | -9.5%          |

Notes: Appendix Table OA.18 shows the earnings gap under hiring subsidies and the pre-college intervention policy.

### Table OA.19: Displacement Effects (Unemployment)

|                      | % Unemployed | Δ Unemployed (%) |
|----------------------|--------------|------------------|
|                      | 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%     |
| Hiring Quotas        |             |              |         |            |               |         |
| Baseline             | 25%        | 36%         | 31%     | —          | —             | —       |
| Hiring Quotas        | 35%        | 31%         | 33%     | +37%       | -16%          | +7%     |

Notes: Online Appendix Table OA.19 shows unemployment by caste under the baseline, hiring subsidies, PCI and quotas. “PCI” stands for the pre-college intervention (PCI) policy.
Figure OA.1: This figure shows full support for students belonging to either disadvantaged or advantaged castes within each entrance exam score or GPA decile.
Figure OA.2: This figure shows the coefficient $\beta$ corresponding to the regression in Equation 1 across job sectors and job types. $\beta$ represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient $\beta$ from a separate regression.

The vertical bars are 95% confidence intervals. These regressions include controls.
Figure OA.3: This figure shows how the model bounds both the displacement and placement of advantaged and disadvantaged castes, respectively, under hiring subsidies and the pre-college intervention policy. The distribution of advantaged caste “scores” are shown in red. These scores are to the right of the distribution of disadvantaged caste scores, shown in 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. The top panel represents a scenario where labor demand is perfectly elastic. In this scenario, there is no displacement of advantaged castes and the number of disadvantaged caste hires is at least as large as in the baseline. The bottom panel represents a scenario where labor demand is perfectly inelastic. In this scenario, the number of disadvantaged caste hires is at least as large as in the baseline but not as large as when labor demand is perfectly elastic. On the other hand, the displacement of advantaged castes is larger than when demand is perfectly elastic (where it is zero).