# Making the Elite: Discrimination at Top Firms

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**Abstract**

How quantitatively important is hiring discrimination in driving socioeconomic gaps in access to elite jobs, and where in the hiring process do disparities arise? To answer this question, I use recruitment data from over 1000 jobs at elite multinational corporations, primarily based in the United States or Europe, that hire from an elite Indian college. Each employer conducts four screening rounds. I show that nearly 90% of the caste disparities in hiring arise in the final screening round, which comprises personal interviews that often assess "fit." The caste penalty arises as soon as caste is revealed. Moreover, any extra diagnostic information learned by employers during personal interviews is not enough to justify caste differences in outcomes because disadvantaged castes have a nearly 20% higher promotion rate, even among the most selective jobs.

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# 1 Introduction

Gatekeepers in elite settings often discriminate on the basis of race, gender, ethnicity, or social class thereby influencing the distribution of opportunity in society (Stevens, 2009; Rivera, 2012, 2015; Friedman and Laurison, 2020; Arcidiacono et al., 2021; SFFA v. Harvard, 2023; Chetty et al., 2023; Stansbury and Rodriguez, 2024). This paper studies caste discrimination at elite US and European multinational corporations (MNCs) hiring in India. Despite affirmative action policies at elite Indian colleges aimed to improve the economic mobility of disadvantaged castes, they largely remain shut out of elite jobs (Madheswaran, 2008). The lagging representation of disadvantaged castes in such jobs could be partly driven by discrimination. Yet, little is known about how *quantitatively* important hiring discrimination is in driving caste disparities in access to the "elite," or *where* in the hiring process disparities arise.

My paper addresses these issues by studying a job fair at an elite Indian college and showing that the final screening round consisting of personal interviews that often assess "fit" creates barriers for disadvantaged castes in accessing elite jobs. Nearly 90% of the caste disparities in hiring arise due to personal interviews. Additionally, this screening round is also where employers likely learn about caste.

While personal interviews potentially test for many job-relevant skills, possibly including candidate fit, any extra diagnostic information learned during personal interviews is not enough to justify differences in outcomes between disadvantaged and advantaged caste interviewees. This is because disadvantaged castes who get jobs through such interviews have better performance on the job, as demonstrated by them having a nearly 20% higher promotion rate than advantaged castes, even among the most selective jobs. Therefore, personal interviews, a common component of recruitment at major multinationals, are a large contributor to unwarranted socioeconomic (caste) disparities in the labor market. To my knowledge, this paper is the first to quantify how much of the hiring disparities among elite jobs in a real world and high-stakes setting could be attributed to personal interviews.

It is important to understand how much the distribution of opportunity in elite jobs is influenced by caste discrimination, since nearly 70% of the Indian population of over 1.4 billion belongs to disadvantaged castes. The labor market that my paper studies is extremely important because elite entry-level jobs comprise the pipeline to business positions with power and influence (Rivera, 2015). I study the job fair of one prominent

Indian college and use recruitment data from elite MNCs, primarily based in the US or Europe. Firms visit about 40 other Indian colleges every year, each with over 1000 students, suggesting that about 50,000 students are impacted annually by the personnel practices of such firms. And because nearly all elite Indian colleges conduct similar job fairs with participation from nearly the same group of firms, my paper effectively offers a representative window into how college graduates transition into such jobs.

All jobs in my sample conduct four screening rounds and eliminate students at each of them. In the first round, employers read applications and determine whether to advance students further. The second round comprises written aptitude tests that are typically conducted online. After testing comes group debates, where students discuss non-technical topics and are evaluated on a broad range of socio-emotional skills, such as communication, collegiality, confidence, and consensus building. After these three increasingly subjective screening stages comes the final screening stage: the personal interview. These interviews screen on potentially many job-relevant skills, including candidate background or fit (Newman and Thorat, 2012; Rivera, 2012, 2015).

There are large caste disparities among the jobs received by graduates through the job fair. The caste gap in earnings is 23% without controls and reduces to 10% when controlling for pre-college skills, college academic performance, previous labor market experience, and other employer-relevant skills. Critically, because of how the job fairs are set up, there are no caste differences in pay for identical jobs. So the earnings gap is due to differences in job composition across castes. Because salaries offered in the job fair are also *non-negotiable*, the caste penalty in mean earnings at each job search stage can be calculated by comparing the salary differences in the jobs the caste groups are in contention for after each stage.[1] About 90% of the 10% conditional caste earnings penalty occurs between personal interviews and job offers. Similarly, about 95% of the caste penalty in the *success rate* at the job offer stage can be attributed to the personal interview round.

The paper's main point is not that personal interviews are useless. Rather, any *extra* diagnostic information learned through personal interviews, job-relevant or otherwise, is not enough to justify *differences in outcomes* between advantaged and disadvantaged caste interviewees because disadvantaged castes have a substantially higher promotion rate than advantaged castes. Note that average comparisons confound any differences at the margin with distributional differences away from the margin. Therefore, I estimate promotion

[1]It is common for placement offices in such colleges to enforce a rule preventing negotiation and verify that the offered salaries match those that were initially advertised by firms (Section 2.2).

rate differences across the distribution of "job selectivity," proxied by calculating the cumulative proportion of job applicants cut by a given job by the end of the final screening round. Even among the most selective jobs, disadvantaged castes are promoted at a much higher rate than advantaged castes, with the promotion rate difference being similar to that in the average job.

The caste penalty arises as soon as caste is revealed. While some surnames are indicative of caste, most of them do not convey caste signals—especially in urban-educated settings—due to migration and large geographical variation in names and naming conventions. The salience of last names in signaling caste is even weaker in elite colleges, as they are typically located in urban centers and draw students from all over India (Mamidi, 2011; Jodkha, 2017; Wiltshire, 2020). Consistent with these explanations, only about 15% of the students have distinctive caste names. In this small subsample where last names provide clearer caste signals, the caste penalty emerges much earlier: during the application reading round. However, the *overall* caste penalty during the application reading round is negligible because most of the sample (about 85%) has non-distinctive caste names. Instead, the caste penalty primarily emerges during personal interviews, where students are potentially screened on many job-relevant characteristics, including candidate background and cultural fit, that are strongly correlated with caste. Thus, the personal interview is likely the main mechanism through which caste is revealed, leading to caste-based discrimination.

Given the tight link between the emergence of caste penalty and caste revelation, my preferred interpretation is that hiring disparities stem from disparate treatment. Employers may penalize caste due to taste-based, statistical, customer, or coworker discrimination; unintentional biases due to homophily; or other factors. I do not distinguish between these sources of discrimination. While alternative explanations such as disparate impact are certainly plausible (e.g., through employers caring about characteristics like country club membership learned at the interview), the reduced-form caste coefficient embeds all such rationalizations.

The caste penalty following personal interviews also cannot be rationalized by many alternative explanations. These include jobs advancing weak performers before personal interviews to ensure caste balance at each screening round ("appearing fair") or inframarginal caste differences in performance at screening rounds before personal interviews. Other explanations are also unlikely to account for the caste penalty in hiring, including differences in socio-emotional skills, outside options, negotiation abilities, competition

from the government sector that has caste-based quotas, or lack of meaningful student attrition at each screening round.

This paper makes several contributions to the literatures at the intersection of labor and personnel economics. First, the paper's descriptive evidence advances the literature on identifying the sources of labor market disparities. Disparities based on socioeconomic cues are likely to become more salient in elite, urban-educated settings because standard characteristics by which to differentiate groups become less perceptible as these settings become more multi-ethnic and diverse (Loury, 2002; Freeman et al., 2011; Gaddis, 2017). Therefore, collecting data on various stages of job search, each having the potential to reveal different socioeconomic cues, is crucial to better identify the sources of disparities in the context of elite hiring. I provide an important example of the kinds of data future researchers may have to collect in such settings to pinpoint the barriers faced by disadvantaged groups in accessing the "elite." Even in much of the Western world, as racial boundaries blur, "caste" discrimination is likely to become a bigger part of the discourse globally (Bertrand and Mullainathan, 2004; Austen-Smith and Fryer, 2005; Kim and Loury, 2019; Rose, 2022; Sarsons, 2023). Indeed, as stated by Rose (2022), group differences could often "emerge *endogenously* as an outcome of stereotypes that, in equilibrium, engender real disparities across groups" and reinforce perceptions of racial, gender, class, or caste differences.

Second, the paper quantifies the salience of hiring discrimination in driving socioeconomic gaps in access to elite jobs. Many studies in sociology, psychology, organizational decision-making, and economics have shown that soft assessments of "fit" or other job-relevant skills conducted through unstructured interviews, evaluations, or other forms of subjective assessments are often where disparities emerge (see e.g., Highhouse, 2008; Rivera, 2012; Dana et al., 2013; Hoffman et al., 2018; Quillian et al., 2020; Kline et al., 2022). Therefore, the goal of this paper is not to posit personal interviews as a "new" mechanism for disparities. However, this paper goes beyond showing that interviews are where disparities arise, quantifying the real effects of such personnel practices in earnings and access to elite jobs in a high-stakes setting.

Third, the paper's evidence is helpful for identifying which policies are likely to be effective in remedying hiring disparities in India and elsewhere. Potential policies need to be consistent with India's legal environment, which allows for explicit caste-based affirmative action policies but only in public jobs and colleges. Therefore, unlike in the US, there is no federal ombudsman to regulate private-sector hiring. Moreover, while explicit

caste-based discrimination is illegal, the Indian legal system does not recognize "disparate impact," and there is no systematic legal provision (anywhere) to penalize employers for judging "candidate fit" based on myriad characteristics correlated with protected status (Rivera, 2015; Jodkha, 2017; Lang and Spitzer, 2020; Abdelrahman et al., 2024). Since the caste penalty primarily emerges after personal interviews in the multi-stage job search process, policies informing applicants about job opportunities, modifying student preferences, or improving performance at university are unlikely to meaningfully mitigate caste disparities. However, if educated about the potential productivity gains from hiring disadvantaged castes, elite multinationals hiring in India might even voluntarily adopt restrictions on the types of questions asked during personal interviews. Such policies also have relevance in the US where, despite arguably stronger enforcement against employment discrimination, qualitative surveys have shown that the types of questions asked during personal interviews tend to heavily favor the socioeconomically advantaged (Rivera, 2012, 2015). It is also not clear if hiring managers conducting informal evaluations have superior information or often know what they should be looking for in candidates (Hoffman et al., 2018). While truly "blind" hiring à la Goldin and Rouse (2000) may not be possible in the context of elite job recruitment, reducing reliance on informal screening tools such as personal interviews could be worth considering (Mocanu, 2024).

Fourth, this paper contributes to a growing but small literature showing that, contrary to popular belief, non-academic or "soft" characteristics used during candidate screening in high-stakes settings are often weakly correlated with performance. Chetty et al. (2023) show that non-academic characteristics (e.g., legacy preferences) used by elite US colleges to screen candidates are poor predictors of labor market performance. Benson et al. (2023) show that soft ratings on employee "potential" do not predict job performance. Likewise, in the Indian context, Bhavnani and Lee (2021) show that personal interview scores used to screen candidates for top bureaucratic jobs poorly predict performance.

Fifth, the paper contributes to the literature studying personnel practices at major organizations, especially multinationals (e.g., Bandiera et al., 2015, 2020; Bloom et al., 2010, 2012, 2017; Bloom and Van Reenen, 2011; Black and Lynch, 2001; Fisman et al., 2018; Friebel et al., 2017, 2022, 2024; Friebel and Raith, 2024; Kohlhepp, 2024; Minni, 2023; Oyer and Schaefer, 2011; Prat et al., 2020; Shaw and Lazear, 2007; Sadun, 2023). My findings show that commonly employed personnel practices at elite multinationals, such as interviews, often afford employers the opportunity to discriminate against disadvantaged groups.

# 2 Key Definitions and Institutional Setting

I elaborate on key terms used in the paper and the job fair of the elite college. I conclude by discussing why the job fair offers a representative window into how elite Indian college graduates transition into elite jobs.

## 2.1 Disadvantaged Castes, Elite Jobs, and Elite Colleges

I define "disadvantaged castes," "job," "elite jobs," and "elite colleges" below.

a. **Disadvantaged castes.** Consistent with government classification of caste categories, I define "disadvantaged castes" as those belonging to Scheduled Castes (SCs), Scheduled Tribes (STs), or Other Backward Castes (OBCs).[2]

b. **Job.** A "job" is defined as a job designation within a firm. For example, Google can hire a product manager and a software engineer. These are two different jobs. Section 3.3 expands further on why a "job" almost always means a firm and job designation pair and not the ultimate (Indian) office location.

c. **Elite jobs.** An "elite entry-level job" is defined as a formal entry-level job in a multinational corporation (MNC), a major national corporation, or a unicorn firm (startup with a valuation of over $1 billion) hiring in the Indian private sector. All jobs in my sample pay in the top 1% of entry-level job salaries in India (The State of Inequality in India Report, 2022). For the remainder of this paper, I use the terms "elite entry-level jobs" and "elite jobs" interchangeably.

d. **Elite colleges.** "Elite colleges" are those consistently ranked in the top 30 in their respective fields by *India Today*, which is the Indian equivalent of *US News & World Report*. Examples of fields include science, engineering, arts and humanities, social sciences, and business. Examples of elite Indian colleges include the Indian Institutes of Technologies (IITs), Indian Institutes of Managements (IIMs), National Institutes of Technologies (NITs), and highly selective colleges under the umbrella of the prestigious Delhi University, such as St. Stephens, Sri Ram College of Commerce, and Lady Sri Ram College.

[2]Scheduled Castes (SCs), also known as *Dalits*, are socially marginalized in India. Scheduled Tribes (STs), also known as *Adivasis*, also face discrimination because of their ethnicity. OBC was an additional caste category created by the Indian government in the early 1990s on the recommendations of the Mandal Commission that sought to 'identify the socially and educationally backward classes in India" that were not already represented in the previous two caste categories (Bayly, 2008).

## 2.2 The On-Campus Job Fair of the Elite College

The job fair of the elite college—the key institutional feature of the paper—takes place *entirely on the college's campus*. It can be divided into three broad phases: 1) pre-placement phase, 2) placement phase, and 3) post-placement phase or the "aftermarket."

a. **Pre-Placement phase.** The placement office invites firms prior to June. Between June to mid-August, firms visit the college campus and conduct pre-placement talks to advertise job profiles and gauge student interest. Firms make return offers from summer internships by late August. These offers are also called pre-placement offers (PPOs) and have late August deadlines. Students who accept their PPOs are *disallowed* ("de-registered") by the placement office from participating in the formal placement process for full-time jobs.

   Unlike in the US, return offers from junior year summer internships are *not an important feature* of full-time job search in elite Indian colleges. In my setting, less than 5% of the graduating cohort accepts return offers from summer internships and drops out of the regular, on-campus placement process for full-time jobs. Therefore, more than 95% of the graduating cohort participates in the job fair for full-time jobs and submits applications for top MNCs, with only about 2% of the students choosing public sector jobs (Section 3.3).

   Participating students "register" for the job placement process by late August. 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 or vacancies firms want to fill from the college that year. 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 during the course of the placement process. The placement office verifies advertised compensation bundles by requiring students to submit copies of their job offer letters and holds the power to prevent firms from returning to recruit on campus if the compensation package eventually offered to students deviates from what was advertised.

   It is beyond the scope of the paper to study why certain placement rules exist. Such rules can be easily found on the websites of most elite Indian colleges (see e.g., Central Placement Cell, Delhi University).

b. **Placement phase.** Next comes the placement phase where students start applying for jobs in mid-September. Jobs make the "first cut" after skimming through applications, and invite students for additional screening. Jobs then conduct written and verbal (socio-emotional skills) tests to determine eligibility for on-campus interviews. These three pre-personal interview screening rounds—application reading, written aptitude tests, and group debates—are conducted between September to early December. Jobs conduct the fourth and final screening round, comprising personal interviews, between December and January. After conducting personal interviews, jobs extend offers to students. Finally, students make job choices, and the placement process concludes by January. About 70% of the entire student cohort secures full-time jobs by the end of the regular placement cycle in early January.

c. **Post-Placement phase or the "aftermarket."** Between late-January to the college's graduation ceremony in late-July, the placement office organizes an "aftermarket" for students who registered for the full-time placement process but did not secure jobs. These students comprise about 30% of the full student sample.[3] The recruiting process in this aftermarket relies heavily on referrals facilitated by the placement officer or other kinds of social networks. About 80% of the sample of students who participate in the aftermarket (about 25% of the full sample) eventually pursue other opportunities, such as entrepreneurship or advanced degrees (e.g., Master's and PhD), or take gap years to prepare for competitive exams for the civil services or elite MBA programs. The remaining 20% of students who participate in the aftermarket (about 5% of the full sample) find jobs in other firms.

   Firms that participate in the aftermarket are typically different (e.g., much less paying or very recent startups) from those that conduct recruitment only during the regular placement process for full-time jobs. The recruitment process in such firms is also much less standardized compared to the recruitment process at firms that hire only during the regular placement phase. Therefore, I focus *only* on job recruitment that is conducted during the regular placement cycle for which the elite college's placement office collects data, and students undergo a standardized hiring process comprising four screening rounds per job.

[3]Most such students tend to go on the market "softly" either because they already plan on pursuing other opportunities outside of finding employment in a select few firms or because they cast a narrow net while initially searching for jobs. Therefore, the trend among such students is that they either apply to very selective firms or startups in niche areas.

### 2.3 Representativeness of the College's On-Campus Job Fair

The college's job fair offers a representative window into how elite college graduates transition into elite jobs in India for four main reasons. First, almost all elite Indian colleges organize job fairs similar to the one studied in this paper. Second, almost the same group of firms recruits from on-campus job fairs across all elite Indian colleges. Third, elite entry-level jobs almost exclusively hire from elite colleges. Similarly, elite college graduates almost exclusively work in elite entry-level jobs. Fourth, all but a negligible proportion of elite college graduates search for jobs *solely* through the on-campus job placement fairs of their colleges (Online Appendix Section A.1).

## 3 Data

This section provides an overview of the data on students, jobs, and job search. I also discuss data on longer-term outcomes such as job promotions and tenure. I conclude by discussing some data limitations.

### 3.1 Time Span, College Degrees, and Admissions Criterion

The data belong to four placement cycles or years. The exact years are pre-pandemic and have been omitted to further preserve anonymity of students and jobs.

Table 1 shows the total number of students belonging to each caste within each college degree. The caste share within each college major is nearly equal. There are a total of 4164 students in the sample that are about evenly split between castes.

Caste in the data is reported by students, typically by presenting a formal "caste certificate" to the college, and is used for quota-based policies in admissions.

Male students comprise about 90% of the sample (not shown). This proportion is typical of those at elite technical colleges in India (Datta, 2017).

There are four college degrees in the sample (Table 1). 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.).

Students are admitted to the elite college *solely through national-level entrance exams* based on caste-major-specific cutoffs.

Table 1: **Total Students by Caste and Degree**

| | Total Students | | |
|---|---|---|---|
| | Advantaged Caste | Disadvantaged Caste | Degree Total |
| B.Tech. | 579 | 710 | 1289 |
| Dual Degree | 622 | 617 | 1239 |
| M.Tech. | 601 | 566 | 1167 |
| M.S. | 344 | 125 | 469 |
| Caste Total | 2146 | 2018 | 4164 |
| Fraction | 0.52 | 0.48 | 1.00 |

Notes: Table 1 shows the total number of students by caste within each college degree, the total number of students by caste, and the fraction of students by caste. B.Tech. stands for Bachelor of Technology, M.Tech. stands for Master of Technology, and M.S. stands for Master of Science. A Dual degree integrates undergraduate and post-graduate studies and is completed a year after the conventional four-year degree (B.Tech.).

## 3.2 Overview of Student Characteristics

Table 2 shows that there are large caste differences in college GPA but students from both castes within each GPA decile (Online Appendix Figure OA.1). Similar results hold for college entrance exam scores (not shown).

Interestingly, there is a weak correlation between caste and measures of previous labor market experience. For example, consider a key measure of previous labor market experience: sector of internship employment. There are modest caste differences in the sector of internship employment among both B.Tech. and Dual Degree students. Regardless of caste, about 25% of these students interned in the technology sector, 37% in consulting, and 38% in manufacturing. Similar results hold for students pursuing M.Tech. and M.S. degrees (not shown). The weak correlation between internship outcomes and pre-college skills is a common pattern at elite Indian colleges. Because return offers from junior year summer internships are not an important feature of full-time job search at elite Indian colleges (Section 2.2), students seem to care more about the job sector or the firm instead of salaries; apart from a select few firms, students are just happy to get any internship and vice-versa. This could partly explain modest caste differences in internship outcomes. More details on student characteristics, including the weak correlation between caste and previous labor market experience, can be found in Online Appendix Section A.2.

Table 2: **Summary Statistics (Students)**

| | Adv. Caste | Disadv. Caste | Diff (SD) |
|---|---|---|---|
| | | B.Tech. | |
| Avg. Entrance Exam Score | 0.41 | -0.33 | 0.74*** |
| Avg. 10th Grade Score | 0.24 | -0.19 | 0.43*** |
| Avg. 12th Grade Score | 0.24 | -0.20 | 0.44*** |
| Avg. Overall College GPA | 0.51 | -0.42 | 0.93*** |
| | | Dual Degree | |
| Avg. Entrance Exam Score | 0.35 | -0.35 | 0.70*** |
| Avg. 10th Grade Score | 0.20 | -0.20 | 0.40*** |
| Avg. 12th Grade Score | 0.14 | -0.14 | 0.28*** |
| Avg. Overall College GPA | 0.43 | -0.43 | 0.86*** |
| | | M.Tech. | |
| Avg. Entrance Exam Score | 0.27 | -0.30 | 0.57*** |
| Avg. 10th Grade Score | 0.23 | -0.15 | 0.38*** |
| Avg. 12th Grade Score | 0.17 | -0.10 | 0.27*** |
| Avg. Overall College GPA | 0.34 | -0.33 | 0.67*** |
| | | M.S. | |
| Avg. Entrance Exam Score | -0.02 | 0.02 | -0.04 |
| Avg. 10th Grade Score | 0.03 | -0.07 | 0.10 |
| Avg. 12th Grade Score | 0.02 | -0.06 | 0.08 |
| Avg. Overall College GPA | 0.04 | -0.14 | 0.18* |

Notes: Table 2 documents some select summary statistics for students on measures of pre-college skills and college academic performance. Pre-college skill measures include college entrance exam scores and scores in the 10th and 12th standard national-level exit exams. College academic performance is measured by college GPA. All scores are pooled and normalized to have zero mean and unit standard deviation within each degree and year. College entrance exam scores are originally ranks that have been renormalized so that higher numbers are better. The difference across castes is reported in standard deviation units. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Adv. Caste stands for advantaged caste and Disadv. Caste stands for disadvantaged caste.

## 3.3 Overview of Job Characteristics

Table 3 shows that there are about 1050 jobs in the sample, with only about 2% in the public sector. Non-client-facing jobs comprise almost 75% of all available jobs.

**Salary posting.** Jobs post uniform, job-specific (not match-specific) salaries that are non-negotiable during the course of job search (Section 2.2). Conditional on college degree, job salaries do *not* vary across major, caste, or gender (or any other candidate-specific factors).

In fact, firms appear to set salaries *nationally*, perhaps due to administrative convenience. The same firm will be touring multiple colleges for the same job profile and standardization of the compensation package for that job profile across all its Indian locations ("national wage setting") is likely a convenience measure.[4] More details on job characteristics can be found in Online Appendix Section A.3.

**Job location.** Over 98% of the jobs in my sample are in the Indian offices of firms. When hiring for Indian job positions, employers conduct screening rounds for all Indian offices at once. The specific Indian office that a candidate ultimately gets assigned to is decided later and usually depends on the location-specific needs of that employer. For example, Google will conduct a combined recruitment process for its software engineering role regardless of whether the candidate may ultimately get assigned to either the Mumbai or Bangalore office of Google. Therefore, a "job" will almost always mean a firm and job designation pair and not the ultimate (Indian) office location. Moreover, as mentioned above, the compensation package for a given employer and job designation pair is typically standardized across all its Indian locations. The standardization of compensation packages is also compatible with how recruitment is conducted for an employer's Indian locations.

For the firms in my sample that hire for their non-Indian locations (less than 2%), I consider them as a separate job. When hiring for non-Indian locations, an employer will specify an office location. Recruitment processes for firms hiring for non-Indian locations are typically conducted by recruitment teams different from the ones that hire for the same firm's Indian locations; however, such recruitment teams still mostly comprise Indian hiring professionals. Compensation packages of firms that hire for non-Indian locations also differ from those offered by them for their Indian locations. For example, Google hiring a software engineer for its Palo Alto office would offer a different compensation package than if it were hiring for the same position for its Mumbai office. Therefore, (Google, software engineer, Palo Alto) is a different job than (Google, software engineer, Mumbai). However, given the standardization of both the recruitment process and the compensation package across an employer's Indian locations, it is not meaningful to distinguish between (Google, software engineer, Mumbai) and (Google, software engineer, Bangalore).

**Who conducts recruitment?** Since more than 98% of the jobs are located in

[4]More details about national wage setting in this context are available upon request. National wage setting has also been found among elite entry-level jobs in the United States (Bloom et al., 2012; Hazell et al., 2021).

India, it is reasonable to assume that recruitment is typically conducted by Indian hiring professionals or managers.

**Return offers from internships.** Recall, these offers have late August deadlines and students who accept them are disallowed ("de-registered") by the placement office from participating in the formal placement process for full-time jobs (Section 2.2). Therefore, a typical student who applies to a full-time job during the regular placement season that begins in September would *not* have completed a summer internship in his junior year at the same job.

Table 3: **Summary Statistics (Jobs)**

| | Count | Fraction | Avg. Salary ($) | Std. Dev. ($) |
|---|---|---|---|---|
| Private | 1011 | 0.98 | 60341.38 | 32591.51 |
| Government | 19 | 0.02 | 56202.23 | 20240.01 |
| Headquartered Outside India | 620 | 0.60 | 64562.74 | 36038.04 |
| Headquartered in India | 410 | 0.40 | 53766.04 | 23946.16 |
| Client Facing | 246 | 0.24 | 57553.23 | 28288.23 |
| Non-Client Facing | 784 | 0.76 | 61115.92 | 33361.87 |
| All Jobs | 1030 | 1.00 | 60265.02 | 32391.89 |

Notes: Table 3 shows the proportion of jobs in the public versus private sector, the proportion of jobs headquartered outside versus in India, and the average salary breakdown (USD PPP) among client-facing jobs and non-client-facing jobs. Firms headquartered outside India are mostly based in the US or Europe.

## 3.4 Data on Job Selectivity and Screening Rounds

There is substantial variation across jobs in the cumulative proportion of students cut both at as well as by the end of each screening round. Table 4 shows the distribution of both the conditional and cumulative cuts across jobs. A "conditional cut" is the proportion of candidates cut by a given job *at* a particular screening round. A "cumulative cut" is the total proportion of candidates cut by a given job *by the end of* a particular screening round. For example, if a job cuts 50% of the candidates at each of the first two screening rounds, then the conditional cut made by the job at each round is 50%, whereas the cumulative cut made by the end of the second round is 75%. Students almost always have to be within the top 5% of a given job's initial applicant pool to get offers. Note that a decent proportion of jobs often do not make any offers, as the job search sometimes fails for many reasons.

Table 4: **Variation in Conditional and Cumulative Selectivity Across Jobs**

| Cut Type | Round | Q1 | Mean | Q2 | Q3 |
|---|---|---|---|---|---|
| Conditional Cut | App. Reading | 0.30 | 0.39 | 0.39 | 0.48 |
| Cumulative Cut | App. Reading | 0.30 | 0.39 | 0.39 | 0.48 |
| Conditional Cut | Written Test | 0.10 | 0.18 | 0.15 | 0.26 |
| Cumulative Cut | Written Test | 0.38 | 0.49 | 0.49 | 0.61 |
| Conditional Cut | Group Debate | 0.69 | 0.74 | 0.74 | 0.79 |
| Cumulative Cut | Group Debate | 0.83 | 0.87 | 0.87 | 0.91 |
| Conditional Cut | Personal Interview | 0.61 | 0.75 | 0.78 | 0.90 |
| Cumulative Cut | Personal Interview | 0.95 | 0.96 | 0.97 | 0.99 |

Notes: Table 4 shows the distribution of both the conditional and cumulative cuts across jobs.

## 3.5 Overview of Timeline and Details on Screening Rounds

The data comprise the list of job applications, written aptitude tests, group debates, interviews, job offers, and final job choices for each student. The job search typically begins in September when students submit applications (Section 2.2). Students apply for jobs through a centralized job application portal, similar to Job Openings for Economists. Applying to a job only involves "clicking" on the name of the job in the online job 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 job to apply. The streamlined job application process significantly reduces the marginal cost of an application.

*All jobs in my sample conduct four screening rounds and eliminate students at each of them.* In the first round, employers read applications and determine whether to advance students further. The second round comprises written aptitude tests that are typically conducted online. After testing comes group debates. During such debates, groups of thirty to thirty-five students are divided into teams of fifteen to twenty people and are made to discuss non-technical topics with one team assigned to each side of a debate. Group debates evaluate applicants on a broad range of socio-emotional skills, such as communication, collegiality, mannerisms, confidence, and consensus building. Written

tests and group debates are conducted from late September to late November. After these three increasingly subjective screening stages comes the final screening stage: the personal interview. Such interviews potentially screen on many job-relevant skills, including candidate fit, and are usually conducted between December and January.

**It is common for any given firm to conduct common screening rounds for all advertised job profiles.** For example, if Nvidia advertises 5 job profiles in a given year, it might choose to conduct a common written test ("technical") for all profiles at once. See Online Appendix Section A.4 for more details on each screening round.

## 3.6 Summary Statistics on Candidate Screening

Table 5 shows that the average (median) number of applications per job is 208.85 (140.17). Similarly, the average (median) number of written tests conducted, group debates conducted, interviews conducted, and job offers extended per job are 124.91 (87.00), 101.54 (70.00), 26.07 (18.00), and 6.49 (4.00), respectively.

*Application eligibility* depends upon a combination of factors such as major, degree, and GPA. For example, a software engineering position at Microsoft will typically restrict applications to students from the Computer Science major. On the other hand, an analyst position at Goldman Sachs will typically invite applications from all college majors. Such application eligibility criteria are typically why, despite the low marginal cost of an application (Section 3.5), a student cannot apply to all jobs recruiting from campus in a given year.

Table 5: **Summary Statistics (Candidate Screening)**

| Round | Mean | Median |
|---|---|---|
| Application Reading | 208.85 | 140.17 |
| Written Tests | 124.91 | 87.00 |
| Group Debates | 101.54 | 70.00 |
| Personal Interviews | 26.07 | 18.00 |
| Offers | 6.49 | 4.00 |

Notes: Table 5 shows the mean and median number of applications, written tests conducted, group debates conducted, interviews conducted, and offers extended per job. For a given screening round, these numbers can be calculated by averaging, per job, the number of students across years and then averaging across jobs.

### 3.7 Data on Job Tenure and Promotions

Linking the sample to data from a major employment-focused platform provides two measures of job performance: tenure and promotion rates. I can link over 98% of the sample of students who received jobs through the job fair with post-hiring measures of job performance. Job tenure is measured in months. "Promotion" is defined as a movement to a job designation higher in the firm hierarchy. To better capture "true" promotions, I compare job designations with job tenure. For example, an "Associate" position at a given consulting firm typically requires 2 years of experience. Thus, a student moving from an "Analyst" to an "Associate" position within that time period in that same firm would be considered as having been promoted.

### 3.8 Data Limitations

There are a few salient data limitations. First, I do not have access to student resumes. However, student resumes are written in a standardized format prescribed by the placement office so contain data available to me. I also do not have access to performance measures or scores at any screening round. I address limitations due to lack of access to such data in Sections 6 and 7.

## 4 Descriptive Evidence

I document large earnings disparities across castes, argue that the earnings gap is conservative, and show that caste disparities in hiring outcomes arise primarily after personal interviews. I also comment on heterogeneity in the results by job type. Finally, I show that disadvantaged castes have higher promotion rates, even among the most selective jobs.

### 4.1 Main Sample

About 70% of the entire student cohort secures full-time jobs by the end of the regular placement cycle in early January (Section 2.2). Recall that less than 5% of the entire student sample deregisters from the job placement process for full-time jobs by accepting summer internship offers. Therefore, more than 95% of the graduating cohort participates in the on-campus job fair of the elite college and submits applications for top MNCs (Section 2.2). Out of this sample of participants, about 2550 students or 65% get placed into jobs by participating in the job fair.

Students who register for the job fair but remain initially unplaced (about 30% of the full sample) often participate in the "aftermarket," where recruitment relies on referrals facilitated by the placement officer. See Section 2.2 for how the sample of students who participate in the aftermarket is split between those who pursue other opportunities (e.g., Master's and PhD) versus those who find other jobs. The section also expands on why firms that participate in the aftermarket are omitted from my main sample. Accordingly, I focus only on the sample of students who obtained full-time jobs through the college's job fair, and therefore underwent a standardized hiring process comprising four screening rounds per job.

As discussed in Section 4.2.1 below, nearly every student who secures employment through the job fair starts in the same position after graduation. Therefore, data provided by the placement office provide an accurate representation of a student's full-time employment status once she leaves college.

## 4.2 Large Earnings Gap Across Castes

There are large caste disparities among the jobs received by graduates through the job fair. The caste earnings gap is 23% without controls and reduces to 10% when controlling for pre-college skills, college academic performance, previous labor market experience, and other employer-relevant skills. There is modest heterogeneity in the caste earnings penalty across client-facing and non-client-facing jobs (Online Appendix Table OA.1). Relative to the mean earnings of graduates, this gap is about $6000 (PPP). Critically, because of how the job fairs are set up, there are no caste differences in pay for identical jobs. So the earnings gap is due to differences in job composition across castes.

**The earnings gap is conservative.** This is because students omitted from the earnings regression are much more negatively selected with respect to GPAs if they came from disadvantaged castes (Online Appendix Table OA.2), while earnings are increasing in GPA. Of course, looking *within* a job in the sample, the between caste differences in GPA reduce as screening proceeds, with disadvantaged castes who get any given job offer having a slightly higher GPA than advantaged castes (Online Appendix Table OA.3).

Students omitted from the earnings regression could belong to one of two categories. First, this group includes the less than 5% of students in the full sample who are "deregistered" from the regular placement process because they accepted summer internship offers after their junior year (Section 2.2). Second, this group includes those from the "registered"

category who do not receive any job offer during the regular placement process and therefore participate in the "aftermarket" (Section 2.2). In practice, no one who registers for the formal placement process rejects all of their job offers. Online Appendix Section A.5 provides more details on the selection induced by omitted students and why it results in the earnings gap being conservative.

### 4.2.1 Matching Salaries 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 regular placement process (around early January) and the rollout of the exit survey. Exit surveys are rolled out close to graduation (between May and June) and before the job start date (around late July). The data also include specifics of the negotiated terms and the reasons for negotiation. Note that students are restricted from bargaining over advertised compensation bundles only *during* the course of the regular placement process and not after its conclusion (Section 2.2). The placement office administers exit surveys to validate its employment data.[5]

Exit data is filled by nearly 98% of the graduating cohort, possibly since conveying information regarding their current roles and contact details is relevant for students to take advantage of the elite college's extensive alumni network. Reassuringly, exit data show that basically all 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 regular placement process.

## 4.3 Caste Earnings Penalty Is Due to Personal Interviews

Recall there are no caste differences in pay for an identical job. Because salaries offered in the job fair are also *non-negotiable*, the caste penalty in mean earnings at each job search stage can be calculated by comparing the salary differences in the jobs the caste groups are left in contention for after each stage. About 90% of the 10% conditional caste earnings penalty occurs between personal interviews and job offers.

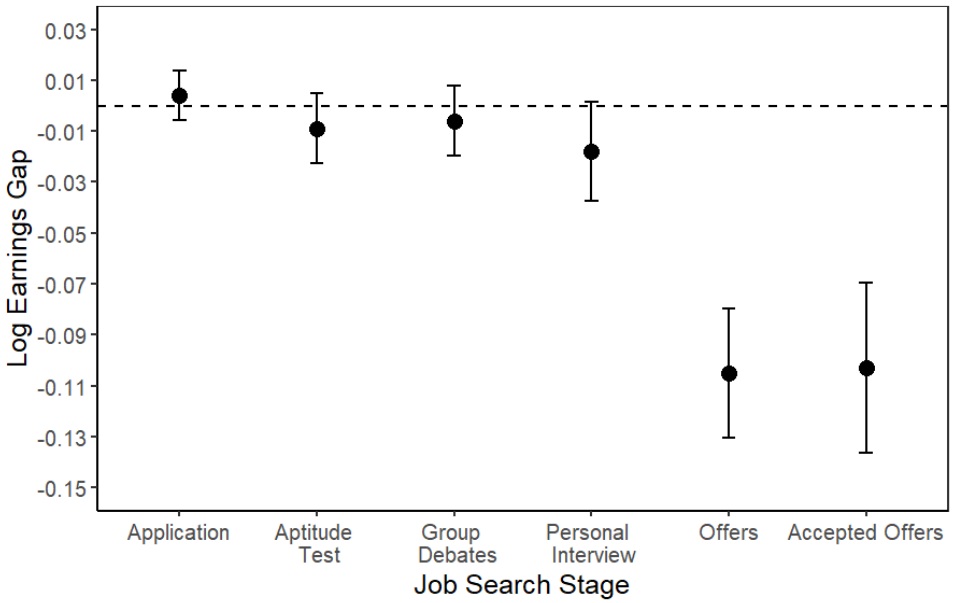
To show this, I run different specifications of the following linear regression:

$$\log(\text{Avg. Job Salary}_{it}^{\text{Search Stage}}) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \gamma_t + \epsilon_{it}, \quad (1)$$

[5]To further validate exit data, I also match the full-time job status of students with information obtained from a leading employment-focused platform (Section 4.5).

where $i \in \mathcal{I}$ indexes students, $\gamma_t$ denotes year fixed effects, and Search Stage $\in$ {Application, Aptitude Tests, Group Debates (GD), Personal Interviews, Offers, Accepted Offers}. The controls are characteristics such as college GPA, college entrance exam score, previous labor market experience, major, and degree. For each student $i$, "average job salary" at a given job search stage $s$ is calculated by averaging over the posted salaries of jobs $j$ that she remains in contention for at that stage. The coefficient of interest is $\beta$, which is shown in Figure 1 for each job search stage. Online Appendix Table OA.4 reports these regressions as well as bias-adjusted coefficients using Oster (2019).

Figure 1: **The Caste Earnings Penalty**




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 disadvantaged and advantaged castes. The vertical bars are 95% confidence intervals. These regressions include controls. There are no caste differences in pay for identical jobs and since offered salaries are non-negotiable during the job fair, the caste penalty in mean earnings at each stage can be calculated by comparing the salary differences in the jobs the caste groups are left in contention for after each stage.

## 4.4 Caste Penalty in the Success Rate Is Due to Interviews

Throughout the paper, "success rate" is defined as the probability that a given student $i$ makes it past screening round $s$ for job $j$ in year $t$. Table 6 shows that more than 95% of the caste penalty in the success rate at the job offer stage can be attributed to the personal interview round.

To show this result, I run standard linear probability regressions with job fixed effects. The results are reported in Table 6 along with bias-adjusted coefficients using Oster (2019).

An observation in each of the columns of Table 6 is a student who remains in contention at a given screening round in a given job in a given year. For example, all students in the first column of Table 6 are applicants. Similarly, all students in the second column of Table 6 are written test takers, and so on. Specifically, I estimate the following linear probability model:

$$\Pr(\text{Success}_{ijt}^{\text{Job Search Stage}}) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + k_j + \gamma_t + \epsilon_{ijt}, \quad (2)$$

where $i \in \mathcal{I}$ indexes students, $j \in \mathcal{J}$ indexes jobs, Search Stage $\in$ {Application, Aptitude Tests, Group Debates (GD), Personal Interviews, Offers, Accepted Offers}, $\gamma_t$ denotes year fixed effects, and $k_j$ denotes job fixed effects.[6] The controls are characteristics such as college GPA, college entrance exam score, previous labor market experience, major, and degree. Table 6 shows that the caste difference in the success rate is negligible at the application reading, written test, or group debate stage and emerges almost entirely at the personal interview round. Online Appendix Tables OA.5 and OA.6 show modest heterogeneity in the caste success rate penalty across client-facing and non-client-facing jobs.

Table 6: **Caste Differences in the Success Rate at Each Job Search Stage**

| | Success App (1) | Success Test (2) | Success Debate (3) | Success Interview (4) |
|---|---|---|---|---|
| Disadv. Caste (OLS) | -0.0025* | -0.0002 | -0.0005 | -0.2938*** |
| | (0.0014) | (0.0018) | (0.0027) | (0.0048) |
| Disadv. Caste (Oster) | 0.009 | 0.010*** | -0.002 | -0.296*** |
| | (0.0013) | (0.002) | (0.003) | (0.005) |
| Mean Success Rate | 0.5990 | 0.8110 | 0.2580 | 0.2610 |
| Observations | 305,541 | 183,150 | 148,489 | 38,378 |
| Adjusted $R^2$ | 0.61069 | 0.34360 | 0.01858 | 0.24450 |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Job FE | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ |

Notes: Table 6 shows the caste difference in the success rate at each stage of job search. Each observation is a student who remains in contention at a given screening round in a given job in a given year. Each column reports a separate linear probability regression and includes controls. These regressions also include job fixed effects. Note that some firms conduct the same screening round (written tests, group debates, interviews) for multiple job positions. However, since these job positions within the same firm represent different jobs, the regressions consider these jobs and the corresponding advance-or-out decisions made by them separately. Bias-adjusted coefficients are calculated using Oster (2019). *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

[6] See Section 3.3 for how a "job" is defined.

## 4.5 Caste Differences in Job Tenure and Promotion Rates

Linking over 98% of the sample of students who received jobs through the job fair to data from a major employment-focused platform provides two measures of job performance: tenure and promotion rates.[7] Job tenure is measured in months. Promotion is defined as the probability a student who received a job through the on-campus job fair is promoted (further defined in Section 3.7). To compare caste differences in job performance, I run different specifications of the following linear regression:

$$\text{Outcome}_{ijt} = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + k_j + \gamma_t + \epsilon_{ijt}, \tag{3}$$

where $i \in \mathcal{I}$ indexes students, $j \in \mathcal{J}$ indexes jobs, $\gamma_t$ denotes year fixed effects, and $k_j$ denotes job fixed effects. The controls are characteristics such as college GPA, college entrance exam score, previous labor market experience, major, and degree.

Disadvantaged castes have about 25% higher job tenure than advantaged castes (not shown). The average tenure duration in the first job is about 2 years. While there is precedence of using job tenure as a measure of job productivity (Hoffman et al., 2018), it could be that disadvantaged castes may have higher tenure because they have poorer outside options.

To improve upon this measure, I compare the caste difference in promotion rates among the jobs received by students through the college's job fair. Table 7 shows caste differences in job tenure and promotion rates, along with bias-adjusted coefficients using Oster (2019). Columns (1)-(2) show promotion rate differences between castes within a given job and year. Column (1) only includes job and year fixed effects. Column (2) adds controls such as GPA, major, degree, and job tenure. These promotion rate differences are about 20%.

However, average comparisons confound any differences at the margin with distributional differences away from the margin (also known as "inframarginality"). Therefore, I estimate promotion rate differences across the distribution of "job selectivity," proxied by calculating the cumulative proportion of job applicants cut by a given job by the end of the final screening round. For example, if a job makes job offers to only 5% of its initial applicant pool, the cumulative proportion of applicants cut by the job by the end of the final screening round is 95%. Using this measure, columns (3)-(8) of Table 7 categorize

[7] The size of the unlinked sample is 2,527 - 2,489 = 38 students, which is only about 1.5% of the sample that graduated with full-time jobs obtained through the college's job fair.

jobs according to their selectivity and quantify caste differences in promotion rates among jobs with varying levels of selectivity. *Even among the most selective jobs,* disadvantaged castes have a higher promotion rate than advantaged castes, with the caste difference in the promotion rate being similar to that in the average job.

Outcome tests typically come with two main caveats. First, there is inframarginality. Second, the researcher must correctly specify the payoff function (Becker, 1957; Ayres, 2002; Hull, 2021; Mogstad et al., 2023). Regarding inframarginality, that disadvantaged castes have a substantially higher promotion rate than advantaged castes—even among the most selective jobs—is consistent with caste discrimination under reasonable assumptions about the inframarginal distribution of latent talent. Regarding the payoff function, it is possible that promotions do not fully capture what firms are seeking to maximize, but it is hard to imagine that job performance is not captured by promotions. Promotions are also a particularly good measure of productivity in this setting because high-skilled, entry-level jobs at elite MNCs have rigid salary structures globally (Bloom et al., 2012; Hazell et al., 2021; Sarsons et al., 2022; Minni, 2024). Overall, while Table 7 shows one example of an outcome test, among possibly many, these results are consistent with caste discrimination in hiring.

Finally, absent barriers for disadvantaged castes at the workplace, caste differentials in promotion rates shown in Table 7 would likely be even higher.[8] Complementing this argument is the fact that those who leave their first jobs at some point are typically more negatively selected with respect to GPAs if they came from advantaged castes, while promotions are weakly positively correlated with GPA (Online Appendix Table OA.7).

[8]In reality, there is evidence of unfair treatment at work. A 2018 survey of South Asians in the US found that 67% of disadvantaged caste employees reported being treated unfairly at their American workplaces (California v. Cisco Systems, Inc., 2022).

Table 7: **Caste Differences in Promotion Rate**

| | *Dependent variable:* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Promoted | Promoted | Promoted at Top 75% | Promoted at Top 50% | Promoted at Top 40% | Promoted at Top 30% | Promoted at Top 20% | Promoted at Top 10% | Promoted at Client Facing | Promoted at Non-Client Facing |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Disadv. Caste (OLS) | 0.137*** | 0.096*** | 0.104*** | 0.112*** | 0.136*** | 0.147*** | 0.190** | 0.084 | 0.107** | 0.082** |
| | (0.025) | (0.026) | (0.029) | (0.038) | (0.043) | (0.054) | (0.073) | (0.109) | (0.044) | (0.032) |
| Disadv. Caste (Oster) | 0.142*** | 0.093*** | 0.108*** | 0.122*** | 0.141*** | 0.157** | 0.196** | 0.074 | 0.106*** | 0.075** |
| | (0.026) | (0.028) | (0.031) | (0.037) | (0.041) | (0.058) | (0.082) | (0.131) | (0.039) | (0.036) |
| GPA | | 0.064** | 0.055 | 0.053 | 0.068 | 0.036 | 0.022 | 0.027 | 0.077 | 0.056 |
| | | (0.031) | (0.035) | (0.051) | (0.062) | (0.075) | (0.119) | (0.026) | (0.057) | (0.037) |
| Tenure Duration | | 0.084*** | 0.082*** | 0.076*** | 0.074*** | 0.068*** | 0.054* | 0.115** | 0.065*** | 0.097*** |
| | | (0.012) | (0.014) | (0.019) | (0.021) | (0.025) | (0.030) | (0.049) | (0.021) | (0.015) |
| Mean Y | 0.684 | 0.684 | 0.667 | 0.668 | 0.676 | 0.711 | 0.711 | 0.730 | 0.687 | 0.682 |
| Observations | 2,489 | 2,489 | 2,012 | 1,246 | 997 | 748 | 502 | 252 | 835 | 1,654 |
| Adjusted $R^2$ | 0.183 | 0.205 | 0.203 | 0.216 | 0.211 | 0.182 | 0.192 | 0.127 | 0.194 | 0.214 |
| Job FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: Table 7 shows caste differences in job performance measures among students who graduated with full-time jobs through the college's on-campus job fair. All of these students had to succeed in the final personal interview round to obtain jobs. Column (1) reports caste differences in promotion rates only with job and year fixed effects. Column (2) reports the same regression as Column (1) but with all other controls such as GPA, major, degree, and job tenure. Columns (3)-(8) show caste differences in promotion rates with controls among jobs at different quantiles of "job selectivity," proxied by the cumulative proportion of applicants cut by a given job by the end of the final screening round. Columns (9)-(10) show caste differences in promotion rates with controls among client-facing and non-client-facing jobs, respectively. Bias-adjusted coefficients are calculated using Oster (2019). *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

### 4.6 What Happens During Personal Interviews?

The paper's main goal is not to provide conclusive evidence on what happens during personal interviews in terms of the exact content of conversation between hiring managers and candidates. It is reasonable to assume that interviews are where students are screened on many job-relevant characteristics, including candidate background, extracurriculars, and fit. Online Appendix Section A.6 discusses suggestive evidence on the content of personal interviews for elite jobs in India and the US.

The main point of the paper is also not that personal interviews are useless. Rather, any *extra* diagnostic information learned through personal interviews, job-relevant or otherwise, is not enough to justify *differences in outcomes* between advantaged and disadvantaged caste interviewees because disadvantaged castes have a substantially higher promotion rate, even among the most selective jobs.

## 5 Caste Penalty and Caste Revelation

The results documented in Section 4 beg an obvious question: when does caste get revealed to employers? In this section, I argue that the caste penalty emerges as soon as caste is revealed.

### 5.1 What Does the Employer See At Each Screening Round?

I first clarify what the employer can reasonably see about the candidate at each screening round.

1. **Application Reading.** No part of the application process requires students to declare their caste status or incoming college entrance exam scores. At this round, the employer has access to CVs that are written in a standardized format prescribed by the placement office and typically comprise information about student names, college GPA, work experience, and extracurricular activities.

2. **Written Tests.** Written tests about technical skills related to the job are conducted online. Therefore, the only additional information employers obtain, relative to the previous application screening round, is the written test scores.

3. **Group Debates.** At this round, employers finally get to observe—but do not extensively interact with—students after an initial setup. They observe additional information like facial features, skin tones, accents, dialects, and demeanor. Section 5.3 argues why such aspects are weak signals of caste, especially in settings such as elite colleges.

4. **Personal interviews.** These interviews represent the only extensive one-on-one interaction between the employer and the candidate. Such conversations screen students on potentially many job-relevant characteristics, including candidate background, extracurriculars and fit, that are strongly correlated with caste (Section 4.6).

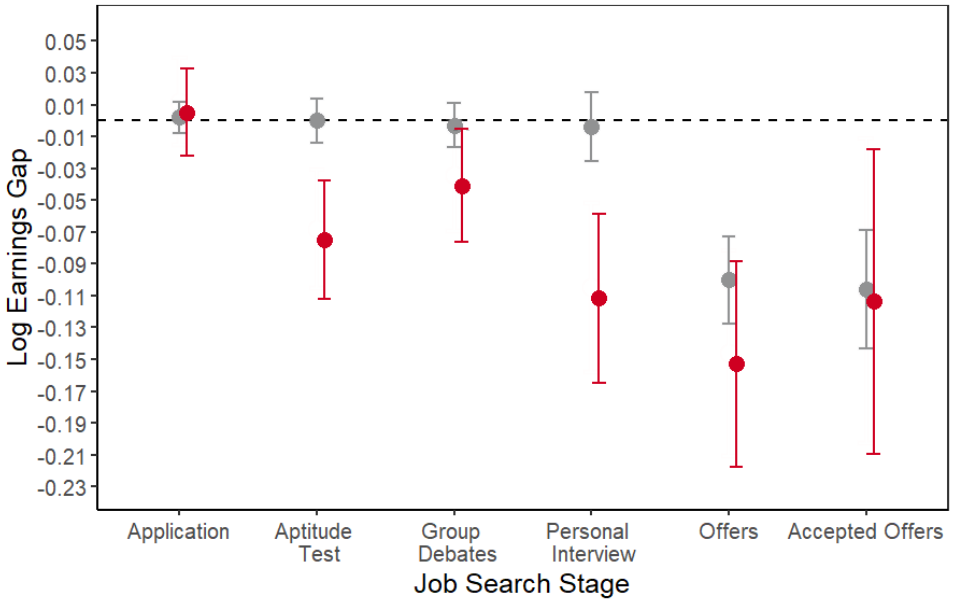
## 5.2 Quantitative Evidence

I provide quantitative evidence linking the caste penalty to caste revelation. While many surnames are indicative of caste, most of them do not convey caste signals—especially in urban-educated settings—due to migration and large geographical variation in names and naming conventions. The salience of last names in signaling caste is even weaker in elite colleges, as they are typically located in urban centers and draw students from all over India (Mamidi, 2011; Jodkha, 2017; Wiltshire, 2020). Consistent with these explanations, only about 15% of the students have distinctive caste names. In this subsample where last names provide clearer caste signals, I show that the penalty emerges much earlier: during the application reading round. However, the *overall* caste penalty during the application reading round is negligible because most of the sample (about 85%) has non-distinctive caste names. Instead, the caste penalty primarily emerges during personal interviews, where students are screened on potentially many job-relevant characteristics, including candidate background and cultural fit, that are strongly correlated with caste.

I show this result through Figures 2 and 3. Figure 2 shows a different version of Figure 1 by splitting the sample into two groups: students with clearly identifiable caste names and those without. I separately estimate Equation 1 for these two samples and report the coefficients with 95% confidence intervals in Figure 2. Online Appendix Tables OA.8 and OA.9 reports these regressions. For students with non-identifiable names, the results are in gray, and for students with identifiable caste names, the results are in red. The difference is marked. When students are not identifiable, the impact of caste only shows up in the personal interview round, but where their caste is strongly signaled by their names, there is no waiting period for the caste penalty to show up—it emerges during the application reading round.

Online Appendix Section A.7 explains how last names are classified as caste identifiable versus not.

Figure 2: **The Caste Earnings Penalty by Subsample**




Notes: Figure 2 shows the log earnings gap across castes at successive stages of job search in the identifiable (red) versus the non-identifiable (gray) sample. 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 disadvantaged and advantaged castes. The vertical bars are 95% confidence intervals. These regressions include controls. There are no caste differences in pay for identical jobs and since offered salaries are non-negotiable during the job fair, the caste penalty in mean earnings at each stage can be calculated by comparing the salary differences in the jobs the caste groups are left in contention for after each stage.

The evidence for caste discrimination becomes even more direct if we simply compare the caste difference in the success rates at the first cuts. To do so, I first extend the definition of "job selectivity" introduced in Section 4.5 to include the cumulative proportion of students cut by a given job by the end of *any* screening round. Next, for each job $j \in \mathcal{J}$, I estimate the following linear probability model:

$$\Pr(\text{Success}_{ijt}^{\text{Job Search Stage}}) = \alpha_j + \beta_j \times \text{Disadv. Caste}_i + \text{Controls}_i + \gamma_t + \epsilon_{ijt}, \qquad (4)$$

where $i \in \mathcal{I}$ indexes students and $\gamma_t$ denotes year fixed effects. The controls are characteristics such as college GPA, college entrance exam score, previous labor market experience, major, and degree.

Figure 3 shows the results of these regressions. The x-axis shows the cumulative cuts made

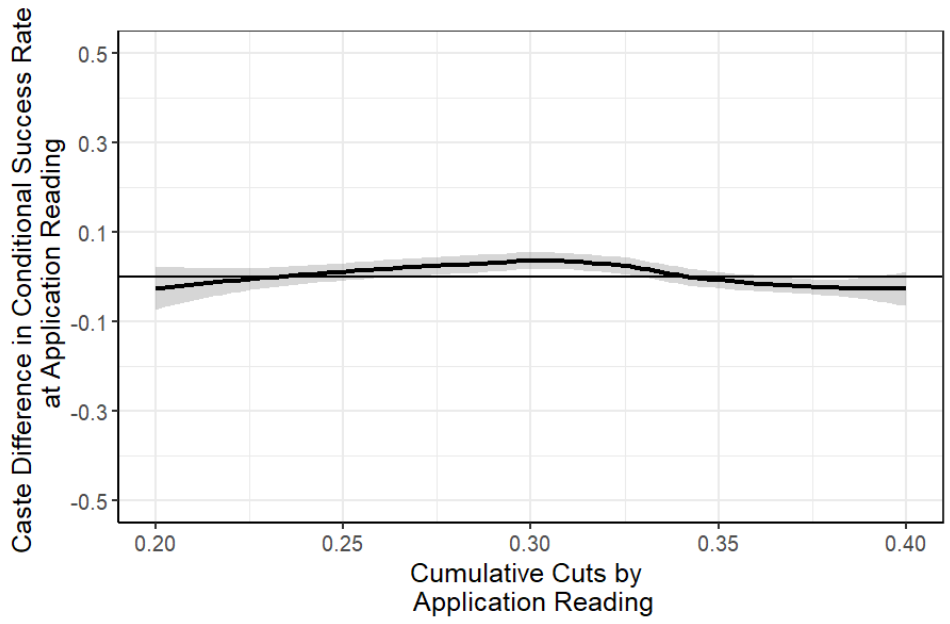
by jobs by the end of the application reading round.[9] The y-axis shows the conditional (i.e., with controls) caste gap in the success rate at the application reading round. A caste gap in the success rate below zero means that disadvantaged castes have a lower success rate or a higher cut rate than advantaged castes.

The top panel shows that, in the full sample of students, there are negligible caste differences in the success rate at the application reading round across jobs with varying levels of selectivity. The average caste penalty in the success rate at the application reading round in the full sample (top panel, thick black line) is similar to the one reported in Column (1) of Table 6.

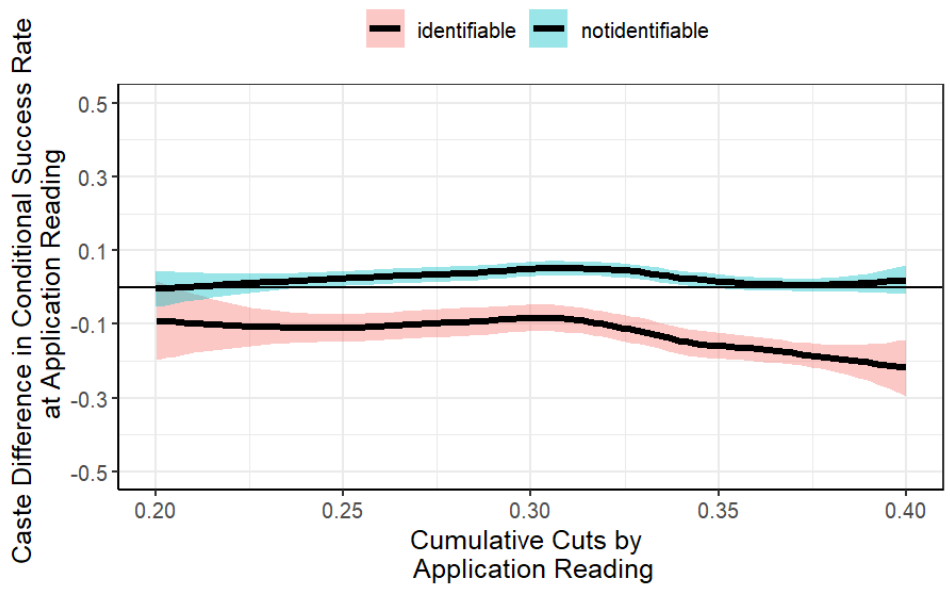
However, the bottom panel shows that clearly identifiable disadvantaged castes have a substantially lower success rate than comparable advantaged castes at the application reading round, essentially across the *entire distribution* of job selectivity. The caste penalty in the success rate at the application reading round in the sample with identifiable caste names is about 15 percentage points or about 30% relative to the mean success rate for this sample at the application reading round. In contrast, no notable caste penalty in the success rate at the application reading round exists in the sample of students with non-identifiable caste names.

[9]Note that since the application reading round is the first screening round, the "conditional cuts" at this round are identical to the "cumulative cuts." For more details, see Section 3.4.

Figure 3: **Caste Penalty in the Conditional Success Rate At the Application Reading Round in the Identifiable and the Non-Identifiable Sample**




(a) Caste Penalty in Conditional Success Rates versus Cumulative Cuts by Application Reading in the Full Sample




(b) Caste Penalty in Conditional Success Rates versus Cumulative Cuts by Application Reading in the Identifiable and Non-Identifiable Sample

Notes: Figure 3 shows the caste difference in the conditional (i.e., with controls) success rate against the cumulative cuts made by jobs by the end of the application reading round. Smoothed conditional means (thick black lines) are calculated using the "loess" function in R. The shaded areas in gray, blue, and red denote 95% confidence intervals. The thin solid horizontal line denotes a y-intercept of 0. Panel (a) is constructed from the full sample. Panel (b) is constructed separately for the sample with identifiable (red) and nonidentifable (blue) caste names. The x-axis shows the cumulative proportion of students cut by jobs by the end of the application reading round. The y-values are calculated by estimating, *for each job*, a standard linear probability model with controls and then plotting the coefficient on disadvantaged caste from these individual regressions on the y-axis. Each regression includes controls for student characteristics such as degree, major, college GPA, entrance exam score, and cohort year.

## 5.3 Qualitative Evidence

The quantitative evidence presented in Section 5.2 linking the caste penalty to caste revelation is also consistent with the growing role of socioeconomic cues or other "soft" factors in aiding caste identification in elite, urban-educated settings. While admittedly weaker than direct data-based evidence, it is still important to qualitatively discuss the nuances of caste identification and how it typically operates in modern India. Further, the qualitative evidence should align with the quantitative evidence presented in Section 5.2 showing that the caste penalty emerges as soon as caste is revealed.

As already discussed, for the vast majority of the sample, the salience of last names in signaling caste is weak in urban-educated settings and especially in elite colleges because they draw students from various geographic regions, often characterized by large variation in naming conventions (Sections 1 and 5.2). Similarly, it is also unlikely that caste is known during written aptitude tests or "technicals," as these tests are typically conducted online. Other than scores obtained during written tests, employers do not observe any additional information about candidates relative to the previous application screening round.[10]

Caste identification is also unlikely to be reliable during group debates. Recall that during such debates groups of thirty to thirty-five students are divided into teams of fifteen to twenty people and are made to discuss non-technical topics with one team assigned to each side of a debate. 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 observe additional information like facial features, skin tones, accents, dialects, and demeanor. However, 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 little to no remnants of caste dialects that are prevalent in most Indian languages (Kothari, 2013; Ransubhe, 2018). Rather, perception of accent variation among young, English-speaking university graduates in India is linked to broad regional factors, such as a North Indian versus South Indian accent, instead of caste status (Wiltshire, 2020). Relatedly, multiple studies show substantial "convergence" in English accents and dialects in broad, urban-educated Indian regions due to migration, urbanization, and improved levels of education (Wiltshire, 2020). Unless the hosts at group debates are experts are phenotyping caste (which they plausibly are not), group debates are not a setting where caste identifiable is

[10]In fact, even assuming that employers actually know the degree-by-year distribution of key student characteristics at the first two screening rounds (e.g., college GPA), such characteristics are typically a noisy signal of caste, especially outside of the tails of the distribution (Online Appendix Figure OA.1).

likely to be reliable. To summarize the discussion so far, cues such as last names, accents, dialects, and skin color are likely to be weak signals of caste status, especially in settings such as elite colleges because they draw students from myriad geographical regions.

In contrast to information revealed at previous screening rounds, conversations during personal interviews likely provide additional information that could reveal caste. Personal interviews are where conversations about shared experiences, extracurriculars, hobbies, preference for living in a cosmopolitan city, desire for traveling, and other aspects of "candidate fit" are considered par for the course (Section 4.6). Such aspects are also likely strongly correlated with caste in elite, urban-educated India (Jodhka and Newman, 2007; Deshpande, 2011; Mamidi, 2011; Jodkha, 2017; Jodhka and Naudet, 2019; Bhavnani and Lee, 2021; California v. Cisco Systems, Inc., 2022). These caste-correlated characteristics are generally hard to fake because caste networks are deeply entrenched (Beteille, 1969; Jodkha, 2017). Recent experimental studies among college educated students in urban India have also shown that background characteristics, often learned through free-form conversations of the kind that often occur in personal interviews, convey almost perfect signals of caste status relative to surface-level attributes (e.g., last names, facial features, and dialects) that are highly evenly shared across castes, and therefore, obfuscate caste identification (Mamidi, 2011; Jodkha, 2017; Bhavnani and Lee, 2021).

### 5.4 Preferred Interpretation of the Caste Penalty

Given the tight link between the emergence of caste penalty and caste revelation, my preferred interpretation is that hiring disparities stem from disparate treatment. Employers may penalize caste due to taste-based, statistical, customer, or coworker discrimination; unintentional biases due to homophily; or other factors. I do not distinguish between these sources of discrimination. While alternative explanations such as disparate impact are certainly plausible (e.g., through employers caring about characteristics like country club membership learned at the interview), the reduced-form caste coefficient embeds all such rationalizations.

## 6 Ruling Out Other Explanations

I show that the caste penalty in hiring outcomes cannot be rationalized by jobs bumping up weaker performers before personal interviews to "appear fair" (ensure caste balance at each screening round) or due to large inframarginal caste differences in performance at

screening rounds before personal interviews.

## 6.1 Are Jobs Bumping Weak Performers Before Interviews?

It is unlikely. I provide both quantitative and qualitative arguments below.

### 6.1.1 Quantitative Evidence: Disadvantaged castes do not have a higher success rate than advantaged castes before personal interviews

I can quantitatively rule out a scenario where employers are lowering standards before interviews and bumping up weaker performers at earlier screening rounds to "appear fair" (ensure caste balance at each screening round), only to later use personal interviews to "catch up" to previous performance and not extend job offers to such students.

To do so—and since I do not observe direct performance measures at any screening round but only if students qualified past a given round (Section 3.8)—I use large variation across jobs in the cumulative proportion of students cut *by the end of* each screening round (defined as "cumulative cuts" in Section 3.4). Using this variation, I test if disadvantaged castes have a higher success rate compared to advantaged castes before the final screening round, especially among highly selective jobs. If not, then it is unlikely that jobs are advancing weaker performers before interviews.

The intuition for this result is straightforward. Consider a job that cuts a high cumulative proportion of applicants before personal interviews. Such a job would probably have to lower standards considerably to achieve caste balance at each screening round, especially since disadvantaged castes have weaker academic credentials (e.g., GPA), on average, than advantaged castes. If there are enough such jobs in the sample, then conditional on characteristics such as GPA, one should expect disadvantaged castes to have a *higher* success rate compared to advantaged castes at screening rounds before personal interviews, particularly among the most selective jobs. Essentially, variation in job selectivity is used to truncate the distribution of latent candidate talent and examine if disadvantaged castes have a higher success rate compared to advantaged castes when one goes further and further to the right of this distribution as candidate screening advances.

I formalize the results of this test by estimating, for each job $j \in \mathcal{J}$, the following linear probability model:

$$\Pr(\text{Success}_{ijt}^{\text{Job Search Stage}}) = \alpha_j + \beta_j \times \text{Disadv. Caste}_i + \text{Controls}_i + \gamma_t + \epsilon_{ijt}, \quad (5)$$

where $i \in \mathcal{I}$ indexes students and $\gamma_t$ denotes year fixed effects. The controls are characteristics such as college GPA, college entrance exam score, previous labor market experience, major, and degree. Figure 4 shows the results from these regressions. Each blue triangle denotes a job. The x-axis shows the cumulative cuts made by jobs by the end of each screening round. Note that as we move from the top panel to the bottom panel of Figure 4, the lower and upper bounds of the x-axis increase because jobs cumulatively cut larger and larger proportions of their initial candidate pool as screening advances. The y-axis shows the conditional (i.e., with controls) caste gap in the success rate. A caste gap in the success rate above zero means that disadvantaged castes have a higher success rate or a lower cut rate compared to advantaged castes ("caste advantage").

I find no evidence of a notable caste advantage in the success rate at any of the three screening rounds prior to personal interviews, essentially across the *entire distribution* of job selectivity. This result suggests that jobs are not lowering standards to bump up weaker performers before personal interviews to appear fair. A similar argument also rules out caste differences in the propensity to be at the margins of the unobserved "cutoff thresholds" employed by jobs to advance candidates at screening rounds prior to personal interviews.

The results in Figure 4 are consistent with there being no differential scrutiny by caste for the majority of the student sample before personal interviews. Recall, however, that a caste penalty in the success rate *did emerge* immediately during the application reading round, but only amongst those with obvious caste names (Figure 2). If employers were trying to appear fair or virtue signal, one would think that students they would most want to give a bump to are those with obvious caste names.

#### 6.1.2 Qualitative Evidence: Weak institutional pressure on employers to "appear fair" at screening rounds before personal interviews

The above quantitative evidence is also consistent with qualitative evidence suggesting little pressure on recruiters at elite MNCs to bump up disadvantaged castes at screening rounds prior to personal interviews to "appear fair." This lack of impetus is not only due to the absence of a federal ombudsman to regulate private-sector hiring in India but also due to weak internal institutional pressure at elite MNCs to promote caste diversity.

India lacks a formal regulatory agency, such as the Equal Employment Opportunity Commission (EEOC) in the United States. Informal government-led discussions have also found the private sector lacking support, even for the voluntary adoption of basic codes of conduct for advancing policies to promote caste diversity in hiring (Jodhka, 2008). Additionally, in the absence of an EEOC-like ombudsman, government pressure has been weak. Overtly expressed attitudes by private-sector employers also suggest a lack of support for policies to promote caste diversity in hiring, even absent formal government pressure. Survey responses of HR managers at elite private-sector firms have found unanimous opposition toward consciously promoting caste diversity in hiring, with some respondents even suggesting that being caste-conscious is synonymous with being anti-merit (Jodhka and Newman, 2007; Newman and Thorat, 2012). Perhaps unsurprisingly, as recently as 2018, only 3 of the top 100 firms listed on India's premier stock exchange collected caste data for internal HR purposes (BusinessLine, 2018). Moreover, diversity practices in foreign-based multinationals employing Indians are overwhelmingly influenced by historical considerations of the West, where caste is not a protected category, suggesting that internal institutional pressure to rectify caste disparities have either been sluggish or, worse, non-existent.[11] And if institutional pressure on employers to "appear fair" is particularly pressing, it seems reasonable for these constraints to also be present at the job offer stage where, paradoxically, almost all hiring disparities arise in my setting. Final hires are more visible to the broader public than shortlists from screening rounds.

**Are interviews being used to express a "delayed preference" for caste?** Relatedly, because of the weak institutional pressure to bump up disadvantaged castes at earlier rounds, it is unlikely that personal interviews are being used to express a "delayed preference" for caste. First, even if caste disparities are expressed "later" or not at all (in the sense that employers only value other caste-correlated characteristics), this would not necessarily change the *magnitude* of the caste disparities in initial hiring (Section 5.4). Second, it remains unclear why employers do not penalize caste earlier if they already know it before personal interviews for a vast majority of the sample. As shown in Section 5.2, a caste penalty in the success rate emerges immediately at the application reading round, but only in a small sample of students with identifiable caste names. One might argue that, due to their subjective nature, personal interviews give employers enough leeway, thereby allowing them to delay their preference for caste. However, this does not fully

[11] In February 2023, Seattle became the first US city to ban caste-based discrimination (Rajvanshi, 2023). However, despite increasing awareness of caste discrimination in the West, there has been little tangible progress to tackle it (Chakravartty and Subramanian, 2021).

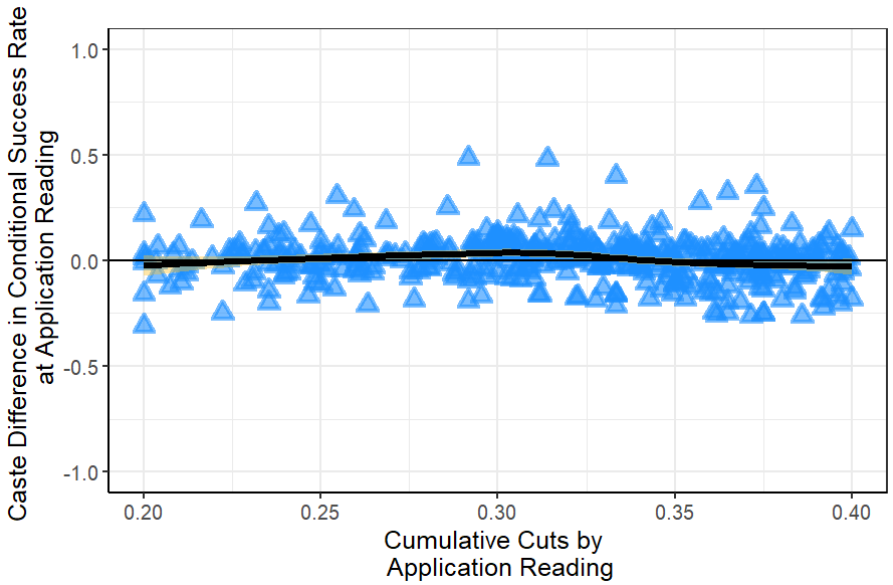
settle why employers cannot use group debates in a similar manner to engage in such dilatory methods. At group debates, employers presumably have as much free rein to assess social skills as they do when assessing potentially job-relevant characteristics, such as candidate background and fit, during personal interviews. At least after the written test round, employers could have their hands tied because tests have objective scores attached to them. However, no such constraint is present during group debates that are conducted before personal interviews and are very subjective in their assessment of the "right" soft skills. Additionally, identifying caste at group debates is difficult (Section 5.3).

## 6.2 Are There Large Inframarginal Caste Differences in Performance Before Interviews?

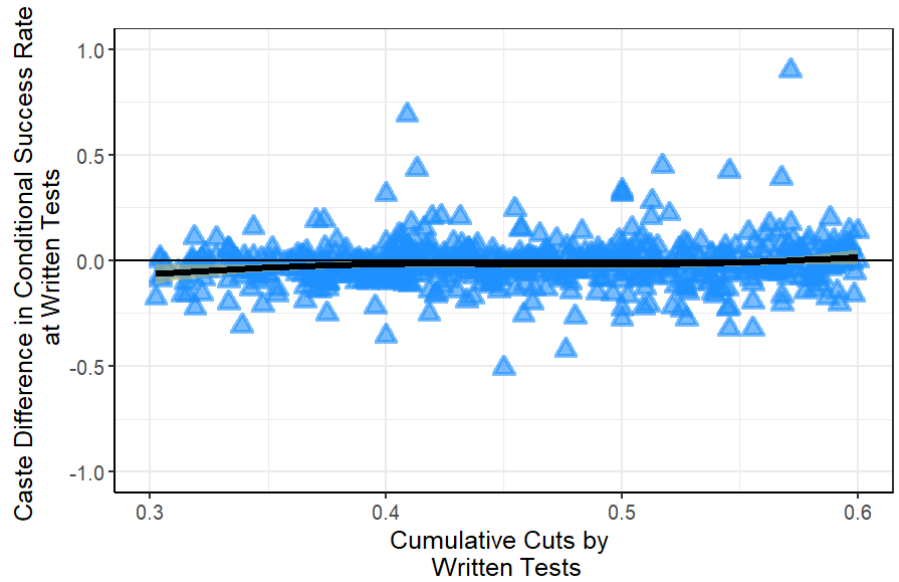
Unlikely. To show that employers are not relying on large inframarginal caste differences in performance before personal interviews to remove the worst *cumulative* performers, I again use large variation across jobs in the cumulative proportion of students cut by the end of each screening round. If there are large caste differences in performance before personal interviews, then disadvantaged castes should eventually have a *lower* success rate than advantaged castes at the screening rounds before personal interviews, especially among the most selective jobs. However, I find that there is a negligible "caste disadvantage" (i.e., disadvantaged castes having a lower success rate compared to advantaged castes) before personal interviews, essentially across the *entire distribution* of job selectivity. Only after personal interviews do disadvantaged castes have a notably lower success rate than advantaged castes, again across the *entire distribution* of job selectivity (Figure 4). These results are inconsistent with employers relying on cumulative performance differences at screening rounds prior to personal interviews to advance disadvantaged castes at lower rates than advantaged castes following personal interviews.

Finally, *similar patterns* of caste differences in the success rate at each screening round arise *with or without other controls* (Figures 4 and 5). The only notable difference is at the application reading round, reflecting that disadvantaged castes have a stronger left tail on many employer-relevant characteristics such as GPA, and most students from the bottom-most end of the ability distribution get cut immediately when applications are read (college GPA is a common filter used by employers at the first screening round).

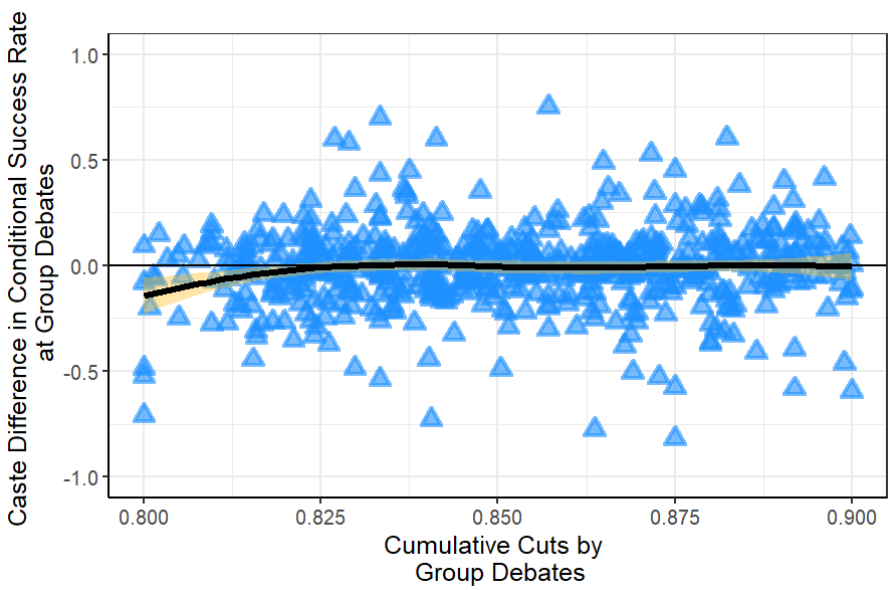
Figure 4: **Caste Penalty in the Conditional Success Rate At Each Screening Round**



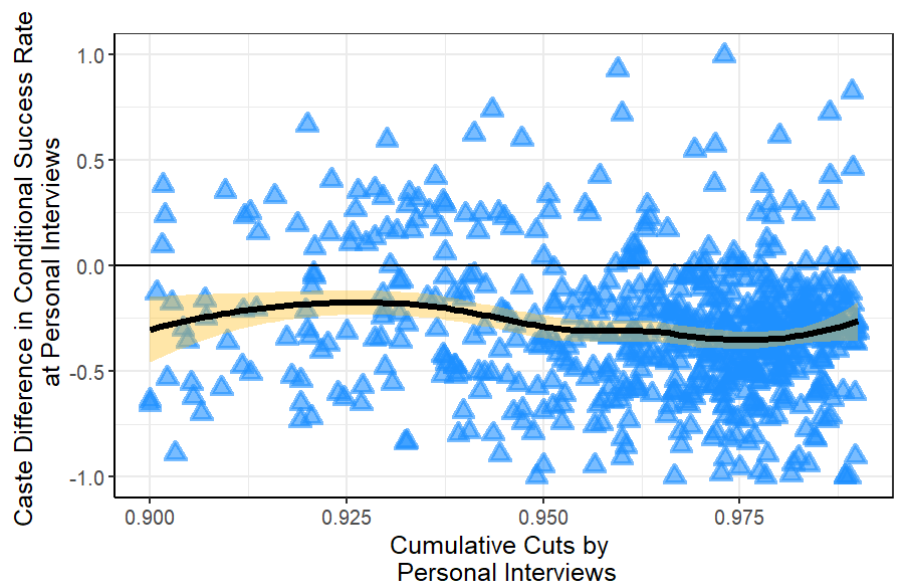

(a) Caste Penalty in Conditional Success Rates versus Cumulative Cuts by Application Reading




(b) Caste Penalty in Conditional Success Rates versus Cumulative Cuts by Written Tests



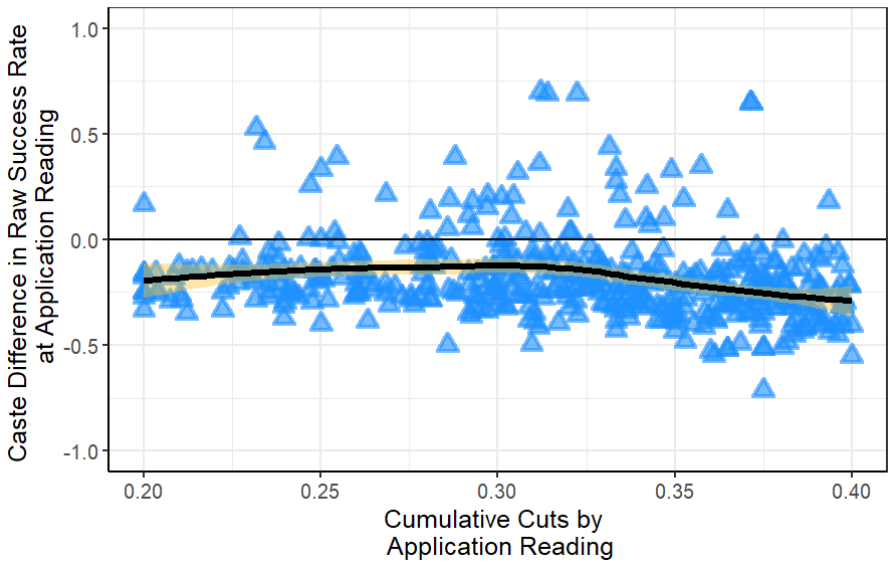

(c) Caste Penalty in Conditional Success Rates versus Cumulative Cuts by Group Debates



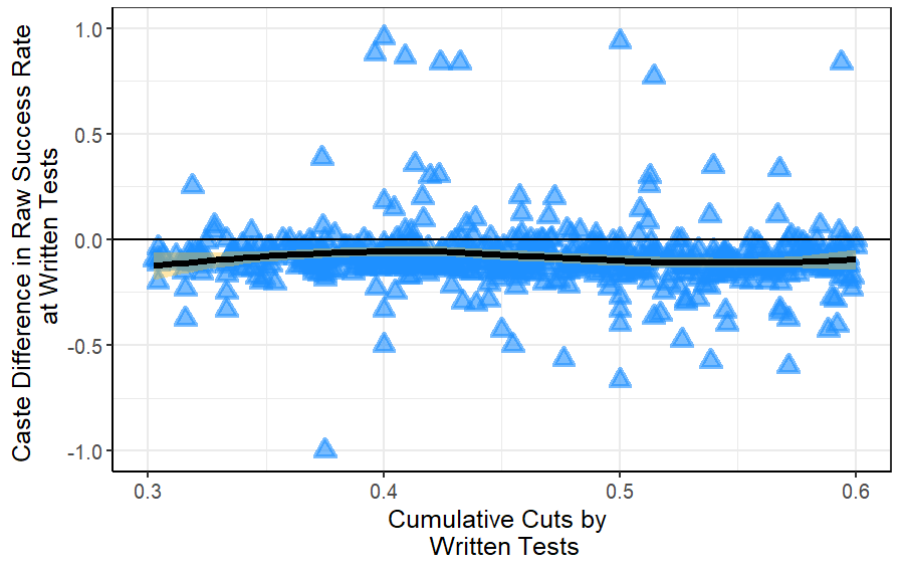

(d) Caste Penalty in Conditional Success Rates versus Cumulative Cuts by Personal Interviews

Notes: Figure 4 shows the caste difference in the conditional (i.e., with controls) success rate against the cumulative cuts made by jobs by the end of each screening round. Each blue triangle denotes a job. Smoothed conditional means (thick black lines) are calculated using the "loess" function in R. The shaded areas in yellow denote 95% confidence intervals. The thin solid horizontal line denotes a y-intercept of 0. The x-axis shows the cumulative proportion of students cut by jobs by the end of each screening round. The y-values are calculated by estimating, *for each job*, a standard linear probability model with controls and then plotting the coefficient on disadvantaged caste from these regressions on the y-axis. Each regression includes controls for student characteristics such as degree, major, college GPA, entrance exam score, and cohort year.

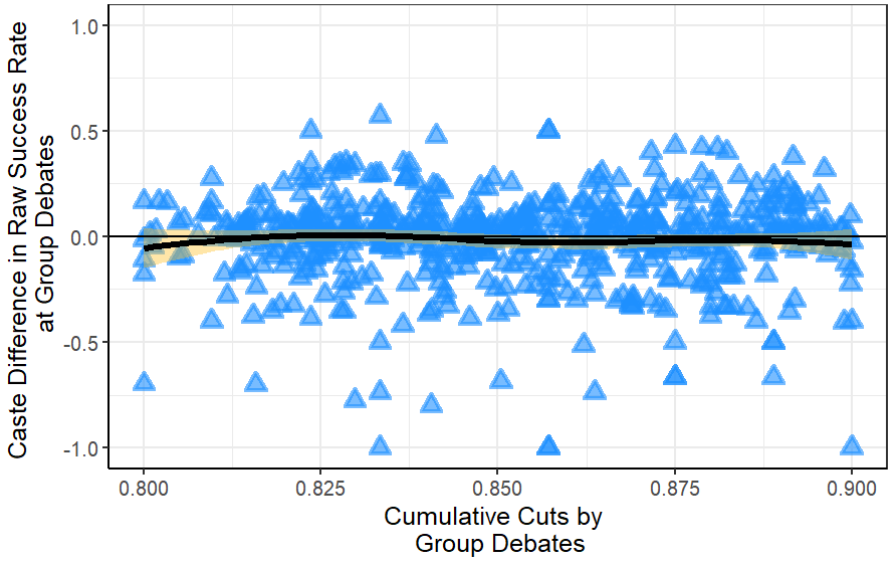
Figure 5: **Caste Penalty in the Uncontrolled Success Rate At Each Screening Round**



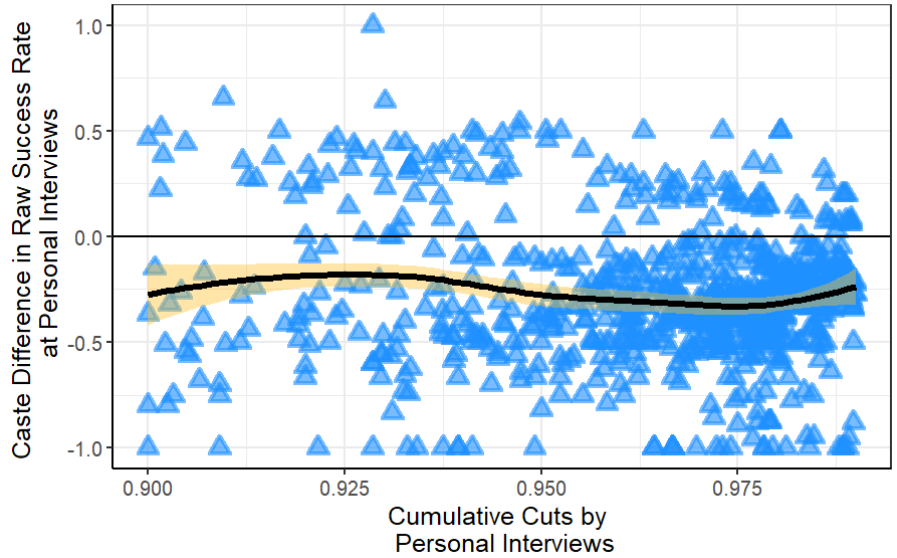

(a) Caste Penalty in Raw Success Rates versus Cumulative Cuts by Application Reading




(b) Caste Penalty in Raw Success Rates versus Cumulative Cuts by Written Tests




(c) Caste Penalty in Raw Success Rates versus Cumulative Cuts by Group Debates




(d) Caste Penalty in Raw Success Rates versus Cumulative Cuts by Personal Interviews

Notes: Figure 5 shows the caste difference in the "raw" (i.e., without any controls) success rate against the cumulative cuts made by jobs by the end of each screening round. Each blue triangle denotes a job. Smoothed conditional means (thick black lines) are calculated using the "loess" function in R. The shaded areas in yellow denote 95% confidence intervals. The thin solid horizontal line denotes a y-intercept of 0. The x-axis shows the cumulative proportion of students cut by jobs by the end of each screening round. The y-axis shows the uncontrolled caste penalty in the success rate at each screening round.

# 7 More Alternative Explanations

In this section, I discuss more alternative explanations that could explain caste disparities in hiring outcomes arising primarily after personal interviews.

1. **Lack of meaningful student attrition at each job search stage.** Each job conducts four screening rounds and eliminates students at each of them (see also Figures 4, 5, and Table 4).

2. **Both firms and students must go through all screening rounds and cannot make or accept offers earlier.** Every job in my sample conducts all four screening rounds before making job offers (see Section 3.5). Moreover, having applied to a job, students are prohibited by the placement office to skip any of three rounds of screening conducted by that job prior to personal interviews. Students are also not allowed by the placement office to skip the sequence of scheduled on-campus job interviews that are typically spread over multiple days. Neither are students allowed to accept offers "early" in the process (e.g., by negotiating offers midway before they are officially announced for others after personal interviews).

   See Online Appendix Section A.8 for a more detailed discussion of various rules both firms and students must follow to participate in the on-campus job fairs of elite Indian colleges.

3. **Better outside options for advantaged castes procured "offline."** The placement office of the college requires that students must decide on summer internship return offers *before* registering for the full-time job placement process. As already discussed, less than 5% of the graduating cohort deregisters from the regular placement process by accepting summer internships (Section 2.2).

   Moreover, registered students are prohibited by the college's placement office from searching "offline" (i.e., outside of the centralized placement process) and, if discovered doing so, risk being debarred from the services of the placement office in assisting them during their full-time job search. Thus, registered students do not simultaneously search offline (Online Appendix Section A.8).

4. **Differences in socio-emotional skills.** This explanation is not consistent with panels (c) of Figures 4 and 5 that show negligible caste differences in the success rate at the group debate round among jobs with varying levels of selectivity. We would have seen a notable caste gap in the success rate below zero in panels (c) of Figures 4 and 5, if caste differences in socio-emotional skills were substantial.

5. **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 on-campus placement process (see "Pre-Placement phase" in Section 2.2). Compensation bundles are also verified by the placement office at the conclusion of the placement process. Furthermore, "exit data" confirms that job getters in my setting start in the same jobs and receive the same compensation bundles, months after the placement process has concluded (Section 4.2.1).

6. **Competition from the government sector.** While government jobs have caste-based quotas, they comprise less than 2% of all jobs in my sample (Section 3.3). Moreover, private-sector firms are themselves aware of the meager presence of public-sector firms at the job fair of the elite college. This is because the list of firms recruiting from campus is available to everyone on the online job portal designed by the college for the job placement process.

7. **Caste differences in preferences over job characteristics.** As suggested by Figure 1, differential caste preferences over job characteristics likely explain only an economically small portion of the overall caste penalty in initial hiring.

# 8 External Validity

One potential limitation of this study is that it focuses on hiring from only one elite Indian college and only among elite-entry level jobs at multinationals hiring for their India operations. However, this does not necessarily restrict the scope of this study for a few reasons. First, jobs at multinationals comprise the pipeline to business positions with power and influence (Rivera, 2012; Subramanian, 2019). Second, firms in my sample are typically headquartered in the US or Europe. Thus, the impact of their hiring practices are not only limited to India. Third, it is important to understand how much caste discrimination could impact access to elite jobs, as nearly 70% of the Indian population of over 1.4 billion belongs to disadvantaged castes. Fourth, the job placement process of this elite college offers a representative window into how elite Indian college graduates transition into elite entry-level jobs (Section 2.3). Finally, several other studies in fields ranging from sociology, psychology, organizational decision-making, and medicine have replicated one of the paper's core findings that unstructured interviews, evaluations, or other forms of subjective assessments are often where disparities emerge.

# 9 Conclusion

This paper shows that caste discrimination is a quantitatively salient barrier for disadvantaged castes in accessing jobs at elite multinationals hiring in India. Moreover, commonly employed personnel practices, such as interviews, often afford employers at such firms the opportunity to discriminate in favor of the socioeconomically advantaged.

Disparities based on socioeconomic cues are likely to become more salient in elite, urban-educated settings because standard characteristics by which to differentiate groups become less perceptible as these settings become more multi-ethnic and diverse (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 identify the sources of socioeconomic gaps in accessing the "elite." By connecting how perceptions of socioeconomic cues determine barriers to economic mobility, this paper 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. As with any study that uses hiring data from one elite college, there should be further research to establish more external validity. Experimental follow-ups studying different firm-level policies such as standardizing interview questions, decision review, and improving interviewer diversity are promising areas for future exploration. Examining the evolution of the caste penalty beyond the first job could also be promising.

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# A ONLINE APPENDIX

## A.1 Representativeness of the Job Fair of the Elite College

This section argues that the on-campus job fair of the elite college provides a representative view of how elite college graduates in India transition into elite jobs. This is because of the following four reasons:

1. **Elite colleges have similar on-campus job fairs.** Elite Indian colleges have similar on-campus job fairs due to an extended process of historical imitation. Post independence, the earliest elite Indian colleges were built in the 1950s and were closely modeled on elite US universities, particularly MIT and Stanford. The earliest elite Indian colleges served as role models for elite Indian colleges built later, which imitated key aspects such as academic calendars, faculty-to-student ratios, and job fairs. Thus, almost all elite Indian colleges today have similar mechanisms for selectively placing graduates into elite jobs (Central Placement Cell, Delhi University). Examples of elite Indian colleges sharing common job fairs include 23 IITs, 20 IIMs, and several colleges under the umbrella of the prestigious Delhi University.

2. **Elite college graduates primarily work in elite entry-level jobs.** These jobs are primarily situated in the private sector and in major multinational corporations. See Subramanian (2019) and Jodhka and Naudet (2019) for a comprehensive overview.

3. **Elite entry-level jobs almost exclusively hire from elite colleges.** Firms in my sample visit about 40 other Indian colleges every year, each with over 1000 students.[OA.1] See Subramanian (2019) and Jodhka and Naudet (2019) for a comprehensive overview.

4. **Small proportions of students skip the job fairs of elite colleges.** Students must register for the formal on-campus job fairs of elite colleges, but otherwise must "deregister" or formally drop out. Only a small proportion (less than 5%) of college graduates in my setting skip the formal placement process for full-time jobs (Section 2.2). Given the similarity of the placement process across elite Indian colleges, this proportion is likely to be similar in other institutions as well. See Mamgain (2019) and Subramanian (2019) for more details.

   The discussion above implies that the job placement process studied in this paper offers a representative window into how elite college graduates transition into elite entry-level jobs in the Indian private sector.

[OA.1] These details were calculated by scraping the identities of firms from the placement websites of many Indian colleges. More details available upon request.

## A.2 More Details on Student Characteristics

This section discusses caste differences in key student characteristics.

1. **College GPA.** The data includes the college GPA of students. There are substantial caste differences in college GPA within each degree (Table 2). Importantly, there are students from both castes (i.e., common support) within each GPA decile (Online Appendix Figure OA.1).

2. **Pre-college skills.** The data includes entrance exam (EE) scores of students. EE scores are the only criterion for college admission (Section 3.1). EE scores in the data are *originally exam ranks* that have been renormalized so that larger numbers are better. Caste differences in EE scores are large (Table 2). As with college GPA, there are students from both castes within each EE score decile (not shown).

3. **Previous labor market experience.** The data also include 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 and desired skills. Application eligibility depends upon a combination of factors such as major, degree, and GPA.

   **Weak correlation between internship outcomes and pre-college skills.** There are modest caste differences in previous labor market experience. For example, consider a key measure of previous labor market experience: sector of internship employment. There are modest caste differences in the sector of internship employment among both B.Tech. and Dual Degree students. Regardless of caste, about 25% of these students interned in the technology sector, 37% in consulting, and 38% in manufacturing. Similar results hold for students pursuing M.Tech. and M.S. degrees (not shown).

   The weak correlation between internship outcomes and pre-college skills is a common pattern in elite Indian colleges. Unlike in the US, return offers from junior year summer internships are *not an important feature* of full-time job search in elite Indian colleges. Indeed, less than 5% of students accept return offers from summer internships and skip the regular placement fair of this elite college (Section 2.2). Similar proportions of students skip the job fairs of other elite Indian colleges (Online Appendix Section A.1).

   Informal conversations with employers and students suggest that internships are less of a worker-firm matching problem. Students seem to care more about the job sector or the firm instead of salaries; apart from a select few firms, students are just happy to get any internship and vice-versa. This could partly explain modest caste differences in internship outcomes.

4. **Other employer-relevant skills.** These measures include college major, college

degree, and coursework. Admissions quotas coupled with fairly rigid college curricula lead to almost no caste differences on many measures of these employer-relevant skills. For example, the caste share within each college major is roughly 50% because of quota-based admissions policies within each major. Similarly, the caste share within each college degree is about 50% (Section 3.1).

## A.3 More Details on Job Characteristics

This section provides more details on job characteristics.

1. **Location of jobs.** The majority of elite jobs are within multinational corporations headquartered in the US or Europe. Many of these firms are regularly featured in the Fortune 500. Although the majority of the jobs are based in firms headquartered outside India, over 98% of the jobs in my sample are in the Indian offices of those firms (Table 3).

2. **Number of jobs in the sample.** There are about 1050 jobs in the sample. Only about 2% of the jobs in the sample are in the Indian public sector (Table 3). The rest are in the private sector.

3. **Number of years each job recruits from campus.** As mentioned in Section 3.1, the data belong to four placement cycles or years. While there are four full cohorts of students in the sample, each job may not recruit from the college campus during each of the four placement years. Some jobs recruit during only one placement cycle while others recruit from campus during each of the four placement cycles. Most jobs in the sample recruit from this college's campus for at least two out of the four placement cycles.

4. **Almost all hiring professionals are Indians.** Since more than 98% of the jobs are located in India, it is reasonable to assume that recruitment is typically conducted by Indian hiring professionals or managers.

5. **Omitting public-sector jobs.** I omit public-sector jobs from my analysis for two reasons. First, such jobs comprise less than 2% of all jobs in the sample (Table 3). Second, public-sector jobs in India are quite different from their private-sector counterparts, especially in areas like salary structure and job stability.[OA.2]

6. **Distribution of jobs and salaries by job type.** Table 3 shows the distribution of jobs and the average salary across all jobs by job type. About 76% of jobs are non-client-facing and the remaining 24% are client-facing.

7. **Client-facing and non-client-facing jobs.** As shown in Table 3, non-client-facing jobs comprise almost 75% of all available jobs. 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

[OA.2] See the report of the Seventh Central Pay Commission, 2016.

considered non-client-facing, whereas a consulting or managerial role would be considered client-facing.

Almost all jobs in the technology sector are non-client-facing whereas almost all jobs in the consulting sector are client-facing. The manufacturing sector has a roughly even mix of client-facing ("Management Trainee" and "Manager") and non-client-facing ("Graduate Engineer" and "Structural Engineer") jobs.

8. **Job descriptions and non-pecuniary amenities.** Jobs declare job details in the *employer registration forms* made available to them by the college's placement office (see "Pre-Placement Phase" in Section 2.2). 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 or 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.

## A.4 More Details on Timeline and Screening Rounds

This section provides more details on the job search timeline and data from each of the four screening rounds conducted by each job.

**Four Screening Rounds Per Job.** Each job in my sample conducts four screening rounds and eliminates students at each of them. The four job screening rounds are as follows:

1. **Application reading.** In the first screening round, employers read applications and determine whether to advance students further. This "first cut" is typically made using a combination of college GPA, major, degree, and other characteristics on student CVs (e.g., summer internships and exceptional performance in international competitions). Informal conversations with employers suggest that college GPA is one of the main filters used during the application reading round. The first screening round is usually conducted in September after applications are submitted.

   Following the application reading round, the second and third screening rounds are conducted between September to late November.

2. **Written aptitude tests.** The second screening round is a written aptitude test. These tests, also called "technicals," are mostly conducted online. Technicals differ by job roles and usually include coding tests for manufacturing or technology jobs and case-study-based tests ("general aptitude tests") for consulting jobs. Written tests are almost always conducted online.

   It is typical for a firm advertising many job profiles to conduct common written tests for all advertised profiles within that firm. For example, if Nvidia advertises 5 job profiles in a given year, it might choose to conduct a common written test ("technical") for all profiles at once.

3. **Group debates.** The third screening round is a "group debate." It is a *non-technical* round. Group debates are conducted for all jobs in my sample, whether client-facing or non-client-facing.

    a. **Group debates are conducted in multiple batches per job, with each batch evaluated by different members of the full recruiting team.** Each batch comprises a total of 30-35 students. This batch is further divided into two teams of 15-20 students each. Group debates last a few hours and assess a wide array of socio-emotional skills, including: communication, mannerisms, consensus building, collegiality, confidence, and teamwork. Group debate topics are general in scope (e.g., "Is social media a boon or a bane?").

    During group debates, recruiters make students discuss a general or non-technical topic with one team speaking for each side. Meanwhile, recruiters behave like passive observers, with 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 debate.

    b. **Many firms conduct common group debates for multiple job positions.** Like written tests, it is typical for a firm advertising many job profiles to conduct common group debates for all advertised profiles within that firm. For example, if Google advertises 5 job profiles in a given year, it might choose to conduct a common group debate for all profiles at once. This practice reflects the fact that employers care about basic soft skills and the ability to work in teams across job profiles in different core roles within a firm (e.g., software engineer or program manager at Google).

4. **Personal interview.** The fourth and final screening round is personal interview. Section A.6 below provides suggestive evidence on the content of personal interviews conducted by recruiters at elite MNCs hiring both in India and the United States. Personal interviews are usually conducted between December and January.

    a. **Personal interviews are conducted in multiple batches per job, with each batch evaluated by different members of the full recruiting team.** Like group debates, personal interviews are typically conducted in multiple batches per job, with each batch evaluated by different members of the full recruiting team.

    b. **Many firms conduct common interviews for multiple job positions.** Like written tests and group debates, firms typically conduct common personal interviews for multiple job positions. For example, Uber might be hiring a program manager, data scientist, a frontend engineer, and a backend engineer in a given year. Interviews for all these job positions within Uber are typically bundled into one, again reflecting the fact that many common skills or aspects

related to candidate background or "fit" are relevant in the employer's eye across all job positions within a firm.

c. **Almost all interviewers are likely Indians.** Recall, I do not directly have information on interviewer nationality. However, since more than 98% of the jobs are located in India, it is reasonable to assume that recruitment is typically conducted by Indian hiring professionals or managers (Section 3.3).

## A.5 Selection and Implications for the Earnings Gap

This section discusses differential selection by caste among those omitted from the earnings regressions reported in Section 4.2.

1. **Less than 5% of the student sample "deregisters" from the job placement process of this elite college.** "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 in their junior year, and therefore are disallowed by the placement office to participate in the job placement process for full-time jobs (see "Pre-Placement phase" in Section 2.2).

   Less than 5% of students deregister from the on-campus placement process of the elite college. This number can be directly seen by comparing the total number of students in the sample with the total number of students who ultimately participate in the job fair (i.e., "register") and apply for full-time jobs. Out of a total of 4164 students in the sample (Table 1), 4005 students apply for jobs recruiting from the job fair of the elite college (Online Appendix Table OA.4). The remaining 159 students are "deregistered" either because they accepted their summer internship offers or because they wanted to pursue other opportunities. Almost all deregistrations before the beginning of the regular placement process are due to the acceptance of junior year summer internships. Similar proportions of students skip the job fairs of other elite Indian colleges (Online Appendix Section A.1). In summary, more than 95% of about 4200 graduating students participate in the job fair of the elite college and submit applications for top MNCs.

2. **The earnings gap is conservative.** In addition to belonging to the "deregistered" category, students omitted from the earnings regressions reported in Section 4.2 could also belong to the "registered" category. In principle, omitted students from the registered category could 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. In practice, no one who registers for the formal placement process rejects all of their job offers, so this additional omitted category typically comprises only those who fail to receive any job offer during the regular placement phase of the on-campus job fair.

   I compare the GPAs of students omitted from the earnings regressions with the GPAs of those who got jobs through the college's job fair. I find that, relative to

the sample of students who got jobs, disadvantaged castes omitted from the earnings regressions are much *more negatively selected* on college GPA than advantaged castes (Online Appendix Table OA.2). This result is intuitive because students who typically do not get jobs (i.e., the majority of students omitted from the earnings regressions) are negatively selected on college GPA and most of the extremely negatively selected students on college GPA belong to disadvantaged castes. Since average earnings are increasing in GPA (not shown), the reported earnings gap is conservative.

## A.6 Suggestive Evidence on the Content of Personal Interviews at Elite MNCs Hiring in India and the United States

This section presents suggestive evidence on the content of personal interviews at elite MNCs hiring in India and the United States. There are three key takeaways from this section. First, personal interviews are discretionary. Second, such interviews are avenues for soft assessments of many job-relevant characteristics, including shared experiences, hobbies, preference for living in a cosmopolitan city, desire for traveling, and other aspects of candidate background or fit are considered par for the course. Third, such interviews are commonly used in the recruitment practices of elite MNCs hiring both in India and the US.

This section should **not** be interpreted as providing dispositive evidence on the content of personal interviews in my setting. I do not have access to interview transcripts. Nevertheless, it is important to emphasize that extensive survey evidence in high-stakes settings, both in India and the US, has shown that personal interviews are often discretionary and serve as common avenues for soft assessments of many job-relevant characteristics, including candidate background and fit, that are strongly correlated with socioeconomic status and therefore with race, gender, or caste.

### A.6.1 Personal interviews at elite MNCs hiring in India

In the Indian context, the evidence on the content of personal interview questions at elite jobs comes mainly from Jodhka and Newman (2007) and Deshpande and Newman (2007). In a detailed survey of HR managers at elite MNCs in the Indian private sector, Jodhka and Newman (2007) documented opinions regarding the role of personal interviews in the hiring process. These firms employ a total of nearly 2 million workers. The authors found unanimous agreement on the importance of asking questions pertaining to candidate background characteristics in personal interviews, including sometimes even family background. One HR manager expressed the signaling value of background characteristics by mentioning that conversations about upbringing is useful in forming impressions about trustworthiness to potential clients, cultural 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 [his ability to work] 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 personal interview questions often included queries into their extracurriculars, 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.

### A.6.2 Personal interviews at elite MNCs hiring in the United States

In the US context, there is a lot more evidence on the content on personal interviews at elite jobs. Personal interviews that screen on conversations related to shared experiences, candidate fit, and hobbies are not unique to India. Such practices are also common in the screening practices of elite US colleges and corporate America (Stevens, 2009; Dana et al., 2013; Rivera, 2012, 2015). For example, Rivera (2012) shows that managers in the US offices of 120 elite MNCs prioritized candidate fit in interviews largely because they believed, unlike job skills, "fit" could *not* be easily taught. One evaluator categorically desired biographic similarities:

> I usually start an interview by saying, "Tell me about yourself." When I get asked that, I talk about where I'm from, where I was raised, and then my background ... I want to hear your life story. Hopefully there's something more interesting about your life than deciding to go to school ... When they tell me about their background, it's easier to find things in common ... Maybe ... they're from Seattle and I've been to Seattle. We can talk about that and develop a connection.

Furthermore, nearly 80% of the professionals surveyed in Rivera (2012) endorsed the use of an interview evaluation heuristic called the "airplane test." As one manager explains:

> One of my main criteria is what I call the "stranded in the airport test." Would I want to be stuck in an airport in Minneapolis in a snowstorm with them? And if I'm on a business trip for two days and I have to have dinner with

them, is it the kind of person I enjoy hanging with? And you also have to have some basic criteria, skills and smarts or whatever, but you know, but if they meet that test, it's most important for me.

Interestingly, about 70% of hiring professionals in law firms and investment banks interviewed in Rivera (2012) considered "cultural fit" to be the *most important* hiring criterion (see Figure 2 in Rivera, 2012).

## A.7 Classifying Caste Identifiable Names

The method for associating students with clearly identifiable caste names closely follows Bertrand et al. (2009). While it is straightforward to find clearly identifiable advantaged caste names, I got the identifiable disadvantaged caste (SC/ST/OBC) last names from two main sources. The first was Election Records available on the website of the Election Commission of India, from where I acquired a list of the most common SC, ST, and OBC last names by state, exploiting the fact that constitutionally-mandated positive discrimination policies in India earmark some seats in the national Parliament as reserved exclusively for members of the SCs, STs and OBCs. By scanning the list of candidates from reserved seats in multiple general elections, I was able to draw up a list of the most common SC, ST and OBC last names. Second, I also consulted the official lists of SCs, STs and OBCs for several Indian states.

## A.8 Key Rules of the College's On-Campus Job Fair

Almost all other elite Indian colleges organize on-campus job fairs similar to the one studied in this paper (Section 2.3). Elite Indian colleges typically also set similar rules that both firms and students must follow to participate in the on-campus job fairs of such colleges. It is beyond the scope of the paper to understand why certain placement rules exist. Such rules can be easily found on the websites of most elite Indian colleges (see Central Placement Cell, Delhi University). Therefore, this section simply describes some key rules of the on-campus job fair set by this elite college's placement office for students and firms that participate in the regular placement phase for full-time jobs:

a. **Interview day allotment.** Each firm is allotted one "interview day" by the college's placement office to conduct the final screening round comprising personal interviews. There are typically between 7-10 interview days, spread over 2-3 weeks. Unlike job recruitment at US colleges, there are *no further onsite interviews*. A particular rule of the job fair 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 offer on a particular interview day, she can participate in interviews on future interview days.

   Salaries are typically one of the most important determinants of interview day allotment. However, firms do not appear to strategically respond to such interview day

allotment by altering their compensation package to be seen as more "desirable," so that they could get an earlier interview slot. Indeed, job salaries appear to be set *nationally*, perhaps due to administrative convenience. The same firm will be touring multiple colleges for the same job profile and standardization of the compensation package for that job profile across all its Indian locations ("national wage setting") is likely a convenience measure (Section 3.3). National wage setting has also been found among elite entry-level jobs in the US (Hazell et al., 2021).

b. **All job offers are announced at the end of the interview day.** All job offers are announced within a short interval of time at the end of the interview day to prevent jobs that are allotted the same interview day from coordinating on offers.

## A.9 Tables and Figures

Table OA.1: **Caste Differences in Mean Salary Among Graduates**

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | log (Salary) | | | |
| | Without Controls | With Controls | Client Facing | Non-Client Facing |
| | (1) | (2) | (3) | (4) |
| Disadv. Caste | $-0.231^{***}$ | $-0.103^{***}$ | $-0.107^{***}$ | $-0.089^{***}$ |
| | (0.020) | (0.017) | (0.027) | (0.022) |
| Disadv. Caste (Oster) | | $-0.076^{***}$ | $-0.095^{***}$ | $-0.072^{***}$ |
| | | (0.019) | (0.026) | (0.022) |
| Constant | $11.235^{***}$ | $10.863^{***}$ | $10.883^{***}$ | $10.848^{***}$ |
| | (0.012) | (0.040) | (0.057) | (0.052) |
| Observations | 2,527 | 2,527 | 849 | 1,678 |
| Adjusted $R^2$ | 0.049 | 0.412 | 0.549 | 0.382 |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ |
| Job FE | | | | |

Notes: Online Appendix Table OA.1 includes estimates from an earnings regression run on the sample of all students who graduated with jobs obtained through the college's job fair for full-time jobs. The dependent variable is log earnings. The regressions include detailed controls including measures of pre-college skills, college academic performance, previous labor market experience, and other employer-relevant skills such as major and degree. Column (1) reports estimates from a linear earnings regression without controls. Column (2) reports estimates from a linear earnings regression with controls. Columns (3) and (4) report estimates from a linear earnings regression with controls run separately for client-facing and non-client-facing jobs, respectively. Note that the earnings regressions do not include job fixed effects because there are no caste differences in pay for identical jobs. Bias-adjusted coefficients are calculated using Oster (2019). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table OA.2: **Caste Differences in GPA Between Those Omitted From the Earnings Regression Versus Those Who Are Not**

| | *Dependent variable:* | |
|---|---|---|
| | log (GPA) | |
| | (1) | (2) |
| Disadv. Caste | −0.033*** | −0.032*** |
| | (0.004) | (0.004) |
| Omitted | −0.167*** | −0.158*** |
| | (0.005) | (0.005) |
| Omitted * Disadv. Caste | −0.071*** | −0.070*** |
| | (0.007) | (0.007) |
| Constant | 2.147*** | 2.127*** |
| | (0.004) | (0.008) |
| Observations | 4,164 | 4,164 |
| Adjusted $R^2$ | 0.546 | 0.559 |
| Year FE | ✓ | ✓ |
| Major | | ✓ |
| Degree | | ✓ |
| Job FE | | |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | |

Notes: Online Appendix Table OA.2 shows the caste differences in GPA between those omitted from the earnings regression versus those who are not. The "omitted" category includes those who deregistered from the placement process and those who registered but did not receive any job offers. The latter group often participate in the aftermarket and pursue higher education or entrepreneurship. Column (1) only includes year fixed effects. Column (2) adds major and degree as controls. Note that the regressions do not have job fixed effects because these can typically only be included for jobs in my main sample. Therefore, these job fixed effects cannot be separately identified from the coefficient on "omitted."

Table OA.3: **Caste Differences in GPA At Each Job Search Stage**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log (GPA) | | | | | |
| | App | Test | Debate | Interview | Offer | Choice |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Disadv. Caste | −0.111*** | −0.049*** | −0.039*** | −0.019*** | 0.010*** | 0.009*** |
| | (0.005) | (0.003) | (0.002) | (0.001) | (0.002) | (0.002) |
| Disadv. Caste (Oster) | −0.104*** | −0.035*** | −0.034*** | −0.014*** | 0.015*** | 0.014*** |
| | (0.006) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | 2.057*** | 2.131*** | 2.163*** | 2.212*** | 2.214*** | 2.199*** |
| | (0.028) | (0.024) | (0.023) | (0.006) | (0.006) | (0.028) |
| Mean GPA | 7.776 | 7.967 | 8.17 | 8.26 | 8.419 | 8.419 |
| Observations | 4,005 | 3,618 | 3,266 | 3,031 | 2,527 | 2,527 |
| Adjusted $R^2$ | 0.264 | 0.726 | 0.745 | 0.801 | 0.822 | 0.822 |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Job FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Major | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Degree | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 |

Notes: Online Appendix Table OA.3 compares the *between* caste and *within* job GPA differences at each job search stage. These are *controlled* differences with the linear regressions including standard controls such as major, degree, year as well as job fixed effects. Bias-adjusted coefficients are calculated using Oster (2019). *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table OA.4: **Caste Differences in Mean Salary at Each Job Search Stage in the Full Sample**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log (Salary) | | | | | |
| | App | Test | Debate | Interview | Offer | Choice |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Disadv. Caste | 0.004 | −0.009 | −0.006 | −0.018* | −0.105*** | −0.103*** |
| | (0.005) | (0.007) | (0.007) | (0.010) | (0.013) | (0.017) |
| Disadv. Caste (Oster) | 0.005 | 0.010 | 0.011 | 0.012 | −0.079*** | −0.076*** |
| | (0.005) | (0.008) | (0.008) | (0.011) | (0.014) | (0.019) |
| Constant | 11.032*** | 10.904*** | 10.848*** | 10.758*** | 10.672*** | 10.863*** |
| | (0.011) | (0.015) | (0.015) | (0.023) | (0.030) | (0.040) |
| Observations | 4,005 | 3,618 | 3,266 | 3,031 | 2,527 | 2,527 |
| Adjusted $R^2$ | 0.578 | 0.491 | 0.547 | 0.549 | 0.488 | 0.412 |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Job FE | | | | | | |

Notes: Online Appendix Table OA.4 includes estimates from an earnings regression run on the sample of all students who remain in contention for some job at a given job search stage. For example, column (1) includes the sample of all students who apply for jobs recruiting from the college's job fair. Similarly, column (2) includes the sample of all students who remain in contention for some job at the written test round, and so on. The dependent variable is log earnings. I include detailed controls including measures of pre-college skills, college academic performance, previous labor market experience, and other employer-relevant skills such as major and degree. Each column is a separate regression and includes these controls. Note that the earnings regressions do not include job fixed effects because there are no caste differences in pay for identical jobs. Bias-adjusted coefficients are calculated using Oster (2019). *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table OA.5: **Caste Differences in the Success Rate at Each Job Search Stage Among Client-Facing Jobs**

| | Success App (1) | Success Test (2) | Success Debate (3) | Success Interview (4) |
|---|---|---|---|---|
| Disadv. Caste (OLS) | -0.0066*** | -0.0007 | -0.0136*** | -0.3062*** |
| | (0.0022) | (0.0030) | (0.0046) | (0.0081) |
| Disadv. Caste (Oster) | 0.002 | 0.006 | -0.015*** | -0.314*** |
| | (0.002) | (0.004) | (0.005) | (0.009) |
| Mean Success Rate | 0.5770 | 0.7860 | 0.2590 | 0.2600 |
| Observations | 117,770 | 67,927 | 53,422 | 13,842 |
| Adjusted $R^2$ | 0.61588 | 0.37467 | 0.01189 | 0.24298 |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Job FE | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ |

Notes: Online Appendix Table OA.5 shows the caste difference in the success rate at each stage of job search among client-facing jobs. Each observation is a student who remains in contention at a given screening round in a given job in a given year. Each column reports a separate linear probability regression and includes controls. These regressions also include job fixed effects. Note that some firms conduct the same screening round (written tests, group debates, interviews) for multiple job positions. However, since these job positions within the same firm represent different jobs, the regressions consider these jobs and the corresponding advance-or-out decisions made by them separately. Bias-adjusted coefficients are calculated using Oster (2019). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table OA.6: **Caste Differences in the Success Rate at Each Job Search Stage Among Non-Client-Facing Jobs**

| | Success App (1) | Success Test (2) | Success Debate (3) | Success Interview (4) |
|---|---|---|---|---|
| Disadv. Caste (OLS) | 0.0024 | 0.0011 | 0.0070** | -0.2867*** |
| | (0.0018) | (0.0022) | (0.0034) | (0.0060) |
| Disadv. Caste (Oster) | 0.008*** | 0.014*** | 0.007** | -0.286*** |
| | (0.002) | (0.002) | (0.003) | (0.007) |
| Mean Success Rate | 0.6140 | 0.8250 | 0.2580 | 0.2620 |
| Observations | 187,771 | 115,223 | 95,067 | 24,536 |
| Adjusted $R^2$ | 0.60783 | 0.32634 | 0.02270 | 0.24723 |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Job FE | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ |

Notes: Online Appendix Table OA.6 shows the caste difference in the success rate at each stage of job search among non-client-facing jobs. Each observation is a student who remains in contention at a given screening round in a given job in a given year. Each column reports a separate linear probability regression and includes controls. These regressions also include job fixed effects. Note that some firms conduct the same screening round (written tests, group debates, interviews) for multiple job positions. However, since these job positions within the same firm represent different jobs, the regressions consider these jobs and the corresponding advance-or-out decisions made by them separately. Bias-adjusted coefficients are calculated using Oster (2019). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table OA.7: **Caste Differences in GPA Between Those Who Left the First Job Versus Those Who Did Not**

| | *Dependent variable:* | | |
|---|---|---|---|
| | log (GPA) | | |
| | (1) | (2) | (3) |
| Disadv. Caste | $-0.065^{***}$ | $-0.065^{***}$ | $0.010^{***}$ |
| | (0.004) | (0.004) | (0.002) |
| Left Job | $-0.072^{***}$ | $-0.072^{***}$ | $-0.004^{**}$ |
| | (0.003) | (0.003) | (0.002) |
| Left Job * Disadv. Caste | $0.047^{***}$ | $0.047^{***}$ | $-0.004$ |
| | (0.005) | (0.005) | (0.003) |
| Constant | $2.188^{***}$ | $2.182^{***}$ | $2.198^{***}$ |
| | (0.003) | (0.005) | (0.028) |
| Year FE | ✓ | ✓ | ✓ |
| Major | | ✓ | ✓ |
| Degree | | ✓ | ✓ |
| Job FE | | | ✓ |
| Observations | 2,489 | 2,489 | 2,489 |
| Adjusted $R^2$ | 0.260 | 0.265 | 0.822 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Notes: Online Appendix Table OA.7 shows the caste differences in GPA between those who left the first job versus those who did not. Column (1) only includes year fixed effects. Column (2) adds major and degree as additional controls. Column (3) additionally controls for job fixed effects.

Table OA.8: **Caste Differences in Mean Salary at Each Job Search Stage in the Identifiable Sample**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log (Salary) | | | | | |
| | App | Test | Debate | Interview | Offer | Choice |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Disadv. Caste (OLS) | 0.012 | −0.068*** | −0.034* | −0.105*** | −0.146*** | −0.107** |
| | (0.014) | (0.019) | (0.018) | (0.027) | (0.033) | (0.049) |
| Disadv. Caste (Oster) | 0.013 | −0.049*** | -0.016 | −0.078** | −0.119*** | −0.082 |
| | (0.016) | (0.021) | (0.022) | (0.032) | (0.042) | (0.055) |
| Constant | 10.991*** | 10.869*** | 10.807*** | 10.734*** | 10.601*** | 10.834*** |
| | (0.030) | (0.042) | (0.041) | (0.064) | (0.078) | (0.114) |
| Observations | 619 | 552 | 500 | 449 | 378 | 378 |
| Adjusted $R^2$ | 0.546 | 0.470 | 0.537 | 0.535 | 0.509 | 0.362 |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Job FE | | | | | | |

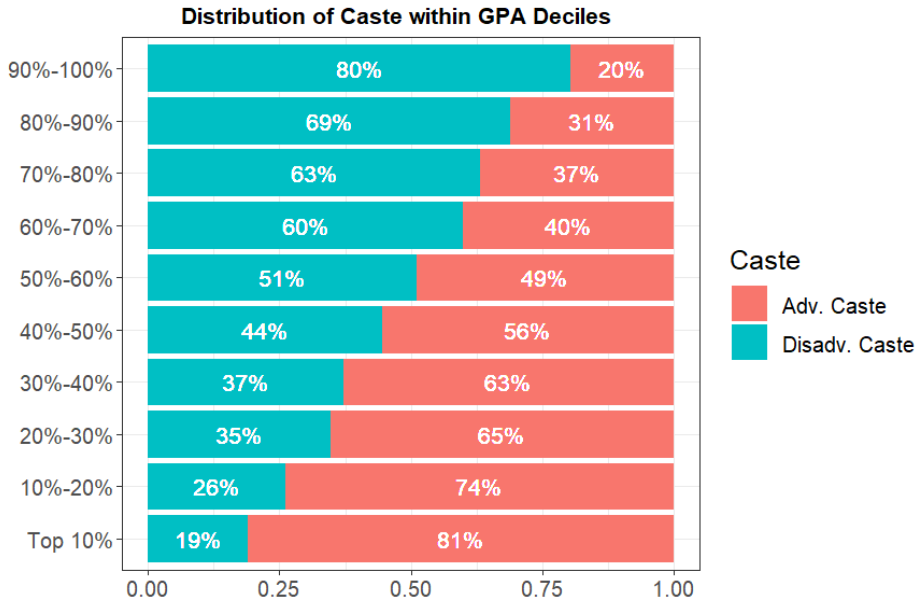
Notes: Online Appendix Table OA.8 includes estimates from an earnings regression run on the sample of students with identifiable caste names who remain in contention for some job at a given job search stage. For example, column (1) includes the sample of all students with identifiable caste names who apply for jobs recruiting from the college's job fair. Similarly, column (2) includes the sample of all students with identifiable caste names who remain in contention for some job at the written test round, and so on. The dependent variable is log earnings. Each column is a separate regression and includes controls. Note that the earnings regressions do not include job fixed effects because there are no caste differences in pay for identical jobs. Bias-adjusted coefficients are calculated using Oster (2019). *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table OA.9: **Caste Differences in Mean Salary at Each Job Search Stage in the Non-Identifiable Sample**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | log (Salary) | | | | | |
| | App | Test | Debate | Interview | Offer | Choice |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Disadv. Caste (OLS) | 0.002 | 0.0004 | −0.003 | −0.004 | −0.100*** | −0.106*** |
| | (0.005) | (0.007) | (0.007) | (0.011) | (0.014) | (0.019) |
| Disadv. Caste (Oster) | 0.004 | 0.019*** | 0.013 | 0.024** | −0.075*** | −0.076*** |
| | (0.006) | (0.007) | (0.008) | (0.011) | (0.015) | (0.018) |
| Constant | 11.041*** | 10.913*** | 10.857*** | 10.766*** | 10.685*** | 10.869*** |
| | (0.012) | (0.017) | (0.016) | (0.024) | (0.033) | (0.043) |
| Observations | 3,386 | 3,066 | 2,766 | 2,582 | 2,149 | 2,149 |
| Adjusted $R^2$ | 0.584 | 0.500 | 0.552 | 0.556 | 0.486 | 0.421 |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Job FE | | | | | | |

Notes: Online Appendix Table OA.9 includes estimates from an earnings regression run on the sample of students with non-identifiable caste names who remain in contention for some job at a given job search stage. For example, column (1) includes the sample of all students with non-identifiable caste names who apply for jobs recruiting from the college's job fair. Similarly, column (2) includes the sample of all students with non-identifiable caste names who remain in contention for some job at the written test round, and so on. The dependent variable is log earnings. Each column is a separate regression and includes controls. Note that the earnings regressions do not include job fixed effects because there are no caste differences in pay for identical jobs. Bias-adjusted coefficients are calculated using Oster (2019). *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Figure OA.1: **Common Support Within Each College GPA Decile**




Notes: Online Appendix Figure OA.1 shows that there are students from both disadvantaged and advantaged castes within each college GPA decile. College GPA is normalized within each college degree and year.