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

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In India's urban labor markets, disadvantaged castes earn 15% less than comparable advantaged castes, with the largest disparities concentrated in the private sector. Such disparities remain pronounced despite widespread and effective affirmative action policies in college admissions. Still, there are no compensatory hiring practices for disadvantaged castes in the private sector. To address this gap, my paper studies the job recruitment process of an elite college in India to quantify mechanisms driving labor market disparities and evaluate policies to promote hiring diversity. I employ novel administrative data which includes rich student-level information on every step of job search, including job applications, pre-interview screening tests, job interviews, job offers, and job choices. I show that the compositions of job applications and job choices do not explain the earnings gap across castes. Pre-interview screening tests including written aptitude tests (first round) and group discussion based "soft skills" tests (second round) explain only a small fraction of the drop off in earnings. Therefore, almost all of the earnings drop off occurs between one-on-one interviews (third round) and job offers. These findings suggest that policies which provide information about jobs, modify preferences, or improve performance at university are unlikely to close the earnings gap. Using a model of the job placement process, I evaluate three policies to promote hiring diversity. I show that directly compensating employers to make them indifferent between castes can be twice as cost-effective as improving pre-college achievement. Unlike these policies, a quota which mandates an equal caste-share of hires acts like a net tax on hiring and increases overall unemployment.

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1 Introduction

In India's urban labor markets, disadvantaged castes earn 15% less than comparable advantaged castes, with the largest disparities concentrated in the private sector (Madheswaran and Attewell, 2007). Such disparities remain pronounced despite widespread and effective affirmative action policies in college admissions. Still, there are no compensatory hiring practices for disadvantaged castes in the private sector. To address this gap, my paper studies the job recruitment process of an elite college in India to quantify mechanisms driving labor market disparities and evaluate policies to promote hiring diversity.

Current policy proposals to mitigate caste disparities in private sector hiring lack formal evidence. These policies largely fall under three broad groups. Some argue that reducing gaps in pre-college skills between advantaged and disadvantaged castes is paramount (Bagde et al., 2016; Newman and Thorat, 2010). Improving student test scores has also been one of the primary goals of numerous pre-college interventions in the developing world (McEwan, 2015). In contrast, others argue that imposing hiring quotas or making discriminatory hiring illegal would have larger and more long-lasting effects (Madheswaran, 2008; Verma, 2012).[1] Finally, in addition to reserving a share of jobs for disadvantaged castes, incentive-based measures linked to the Ministry of Minority Affairs' Diversity Index have also been proposed as long-term solutions to reduce caste disparities in the workplace (Kundu, 2008; Sachar Committee, 2006).[2] However, there is no evidence comparing the potential of such policies in reducing workplace caste disparities. The Indian private sector employs more than 90% of all college graduates. Hence, comparing the relative efficacy of policies to reduce caste disparities in the private sector is essential.

Most college graduates in India navigate the job search process through career offices which act as liaisons between students and employers. Some career offices also collect information on job applications, pre-interview screening tests, job interviews, job offers and job choices. Detailed information on each stage of the job placement process allows for a better understanding not only of the roles played by workers and firms in determining labor

[1] Unlike the U.S., India does not have an Equal Employment Opportunity (EEO) Office.

[2] The Diversity Index quantifies the employment distribution of occupations by caste, gender and religion.

market outcomes but also of suitable channels for policy interventions to remedy potential disparities.

In this paper, I employ novel data on each stage of the job placement process of a leading technical college in India to make three main contributions. First, I quantify the earnings drop off across castes using administratively collected information on all steps of job search, including job applications, pre-interview screening tests, job interviews, job offers and job choices. In particular, I show that the compositions of job applications and job choices by students do not explain the earnings gap across castes. Pre-interview screening tests including written aptitude tests (first round) and group discussion based ”soft skills” tests (second round) explain only a small fraction of the drop off in earnings. Therefore, almost all of the earnings drop off occurs between one-on-one interviews (third round) and job offers. These findings suggest that policies which provide information about jobs, modify preferences, or improve performance at university are unlikely to close the earnings gap.

Second, guided by the sequential decomposition of the earnings gap, I build a model of the job placement process. The model is of general interest and can serve as a prototype for studies of the placement processes of engineering colleges, business schools, law schools, and other institutions that use formal job placement mechanisms. My estimates show that caste disparities in hiring are driven not by differential caste-preferences over job characteristics but by hiring decisions of firms. Additionally, modelled unobservables play an economically small role in jointly determining observed choices.

Third, I evaluate three counterfactual policies to promote hiring diversity. In the first policy, I consider a subsidy in which firms are compensated by the cash-equivalent amount that makes them indifferent between hiring an observably identical advantaged or disadvantaged caste. In the second policy, I consider a “pre-college intervention” which equalizes the distribution of pre-college test scores across castes. Counterfactual simulations show that cash subsidies to employers fare substantially better in improving earnings and job assignments of disadvantaged castes in absolute terms. To compare cost-effectiveness of both policies, I use the model estimates and calculate the change in test scores required to induce the same employment gains for the disadvantaged caste as those under the direct subsidy.

The change in test scores is large because the model estimates imply that test scores play only a small role in hiring. Even under extremely conservative assumptions, a back-of-the-envelope calculation based on cost estimates of improving student test scores in India shows that cash subsidies to employers can be twice as cost-effective as the "pre-college intervention" policy. Finally, in the third policy, I consider a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes. However, unlike the previous two policies, quotas act like a net tax on hiring. In particular, a hiring quota which equalizes the caste-share of employed students leads to a 7% increase in the fraction of students who are not recruited through the formal placement process.

I now describe the main results in detail. I first document large gaps in earnings and job assignments across castes. I find that disadvantaged castes earn, on average, 11% less than comparable advantaged castes. There are no within-firm differences in pay by caste for a given job. So, the earnings gap arises due to differences in compositions of job offers across castes. Disparities in earnings and job assignments are most pronounced in the consulting sector and in client facing jobs. These findings are consistent with a Beckerian framework of labor market sorting in which job assignments are driven in part by the affinity of clients in some sectors, like consulting, to work with advantaged castes (Becker, 1971).

To better understand the mechanisms driving the earnings differentials, I also quantify the drop off in earnings at successive stages of job search. For this purpose, I use administrative data on job applications, pre-interview screening tests, job interviews, job offers and job choices. I show that the compositions of job applications and job choices do not explain the earnings gap. Pre-interview screening tests including written aptitude tests (first round) and group discussion based "soft skills" tests (second round) explain only a small fraction (14%) of the drop off in earnings. Therefore, almost all of the earnings drop off (86%) occurs between one-on-one interviews (third round) and job offers. These gaps persist despite detailed controls on pre-college skills, within-college academic performance and previous labor market experience.

Guided by the sequential decomposition of the earnings gap, I model the job placement process and study policies to promote hiring diversity. The model adapts the toolkit of related studies on college admissions and school choice to study something new: a job market. In particular, I build a model of job hiring and job choices. In the model, firms evaluate student characteristics and make job offers subject to bounds on their hiring size. Once job offers have been made, students make job choices by evaluating job characteristics, which include salaries and non-pecuniary amenities. I estimate the model and recover the "caste penalty" imposed by firms on disadvantaged castes.[3] Using the model, I evaluate policies for promoting hiring diversity.

The model bounds job placements of disadvantaged castes and job displacements of advantaged castes under counterfactual policies which explicitly improve employers' valuation of students. In the model, firms follow cutoff hiring rules which change in response to counterfactual hiring policies. Allowing firms to adjust cutoff hiring rules can be used to bound counterfactual outcomes. The bounds depend upon the elasticity of supply of job slots. When the supply of job slots is perfectly elastic, firms do not adjust cutoffs and can hire everyone who qualifies. However, when the supply of job slots is perfectly inelastic, firms adjust cutoffs to hire the same total number of students. Consider counterfactual policies which explicitly improve employers' valuation of disadvantaged castes, relative to the baseline. Under such policies, when cutoffs do not adjust, the number of disadvantaged caste hires is at least as large as when cutoffs increase to hire the same total number of students. Displacements of advantaged castes from jobs are bounded similarly.

The model also captures aspects most salient to the growing deliberations on advancing compensatory hiring practices for disadvantaged castes: advancement into and displacement from jobs. Concerns regarding potentially large displacements of advantaged castes have been major barriers in advancing compensatory hiring practices for disadvantaged castes in the Indian private sector (Verma, 2012). Hence, evaluating the aggregate and distributional consequences of affirmative action policies in hiring is essential.

As an intermediate step toward evaluating counterfactual policies, I assign dollar amounts to non-pecuniary characteristics which enter the utility functions of students and firms.

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

First, I quantify the "caste penalty" imposed by firms on disadvantaged castes. I find that firms need to be compensated 4.8% of average salary ($2721) to remain indifferent between hiring an observably identical advantaged or disadvantaged caste. Next, I quantify the value of non-pecuniary amenities in the utility functions of students. For example, all things equal, students need to be compensated 5.1% of average salary ($2909) for jobs which offer stock options and 6.5% of average salary ($3683) for jobs which offer signing bonuses. I find no differences between castes in preferences over job characteristics. This result is in contrast with the literature documenting differences between groups (especially, between gender) in preferences over job characteristics (Goldin, 2014; Altonji and Blank, 1999; Buser et al., 2014; Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Zafar and Wiswall, 2018). In my institutional setting, differences between castes in preferences over job characteristics do not explain caste disparities in earnings and job assignments. I also find that, conditional on observables, econometrician-unobservables play only modest roles in determining both job hiring and job choices.

Finally, I evaluate three counterfactual policies for promoting hiring diversity. I begin by comparing the effects of two counterfactual policies, both of which explicitly improve employers' valuation of disadvantaged castes. In the first such policy, I consider a subsidy in which firms are compensated by the cash-equivalent amount that makes them indifferent between hiring an observably identical advantaged or disadvantaged caste. In the second policy, I consider a "pre-college intervention" which equalizes the distribution of pre-college skills (college entrance exam test scores) across castes. Direct cash subsides to employers to hire more disadvantaged castes are worth 4.8% of average salary ($2721). The "pre-college intervention" policy is worth a much lower direct subsidy to employers. The subsidy-equivalent, implied by the model, of the "pre-college intervention" policy is only 0.6% of average salary ($337). Therefore, employer cash-subsidies increase job assignments and earnings of disadvantaged castes by substantially more than the "pre-college intervention" policy.

I also perform back-of-the-envelope calculations to compare the cost-effectiveness of both policies considered above. In particular, I calculate the cost of improving college entrance exam scores to achieve changes in job assignments and earnings of disadvantaged castes equivalent to those induced by direct cash subsidies to employers. For this purpose, I use estimates from a meta-analysis which evaluated the effects of pre-college intervention programs spanning nearly two decades on test scores of primary and secondary school students in India (Asim et al., 2015). Even under extremely conservative assumptions, my calculations show that cash subsidies to employers are twice as cost-effective as the "pre-college intervention" policy. The lower cost-effectiveness of the "pre-college intervention" policy is primarily driven by the modest effects of test scores on hiring.

The third, and final, counterfactual policy for diversity is a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes. In India, private sector firms do not hire in accordance with government-mandated quotas (Madheswaran, 2008; Newman and Thorat, 2010; Verma, 2012). However, quotas or reservation-based policies have been extensively used to improve the representation of disadvantaged castes in government jobs and educational institutions. Therefore, due to familiarity with reservation-based hiring policies, imposing hiring quotas in the private sector could be a politically more feasible alternative to promote diversity. However, unlike the previous two policies, quotas act like a net tax on hiring. In particular, a hiring quota which equalizes the caste-share of employed students leads to a 7% increase in the fraction of students who are not recruited through the formal placement process.

The paper contributes to several strands of the economics literature, especially in labor economics. The paper presents unique descriptive facts on the decomposition of earnings differentials. Decomposing the earnings gap across race or gender has a long tradition in economics and serves as a useful starting point to examine the mechanisms driving labor market disparities (Oaxaca, 1973; Neal and Johnson, 1996; Neal, 1996; Altonji and Blank, 1999; Fortin et al., 2011; Blau and Kahn, 2017). However, earnings decompositions do not necessarily recover behavioral relationships thereby limiting the scope of counterfactual analyses (Fortin et al., 2011). Moreover, such decompositions are often not robust (Huber and Solovyeva, 2020). To my knowledge, this is the first paper to document drop off in earnings at successive stages of job search. An earnings decomposition which accounts for every step of job search can map more closely to behavioral relationships obtained through a structural model. Determining the role of different stages of job search in explaining the earnings gap is also a crucial step in understanding effective policy responses to redress disparities (in this case, across castes). For example, if students apply to almost all jobs, the lack of variation in job applications implies that policies aimed at inducing changes in job application behavior would not mitigate workplace caste disparities. If firm hiring exclusively explains caste disparities, policy responses which directly incentivize firms to hire more disadvantaged castes will be more effective in improving both earnings and job assignments of disadvantaged castes.

My policy proposals to improve the share of disadvantaged castes in the private sector can help evaluate the redistributive impacts of affirmative action policies. Existing studies on the empirical effects of affirmative action in education and labor markets have provided mixed conclusions. In the US, affirmative action in education has increased minority representation in the top decile of educational institutions, but with significant negative effects on students' performance and graduation rates (Kane, 1994; Long, 2004; Arcidiacono et al., 2016). On the other hand, affirmative action in labor markets has increased minority representation in the workforce, typically without much negative impact on the job performance of targeted minorities (Holzer and Neumark, 2000a,b). In India, studies evaluating the effects of affirmative action admissions policies at elite engineering colleges have found that minorities from poorer backgrounds have been effectively targeted (Robles and Krishna, 2015). However, targeted minorities are more likely to get worse jobs during graduation with the marginal disadvantaged caste entrant earning almost twice as less as the marginal advantaged caste entrant (Bertrand et al., 2010). Displacement effects are also important considerations in debates about affirmative action, subsides or quotas which favor one group (Fryrer and Loury, 2005). Ambiguity regarding the distributional effects of affirmative action policies has been a primary driver behind India's decision to exclude almost all of the private sector from delineating compensatory hiring practices for disadvantaged castes (Madheswaran, 2008). Assessing the redistributive effects of compensatory hiring practices would facilitate in championing their expansion to previously secluded avenues.

The paper also contributes to the personnel economics literature. To my knowledge, this is the first paper to study a formal job placement mechanism. My structural model of the job placement process can also serve as a prototype for studies of the placement processes used by engineering schools, business schools, law schools, and other institutions that use formal job placement mechanisms. Job placement processes proposed by career offices often dictate how a college graduate obtains his first job. The initial job placement of a college graduate plays a crucial role in his future job mobility and career growth. Poor initial placements can lead to lasting impediments by placing college graduates in jobs with limited room for training or promotion (Kahn et al., 2014). Evaluating the aggregate and distributional consequences of such job placement processes is, therefore, an important step in understanding how the education and talent of individuals is linked to the types of jobs they obtain early in their careers, and their overall labor market success.

Finally, the paper adds to the growing, but relatively thin, empirical literature on quantifying preferences for non-pecuniary amenities in the workplace (Goldin and Katz, 2011; Flabbi and Moro, 2012; Mas and Pallais, 2017; Zafar and Wiswall, 2018). Experimental studies based on surveys are less informative than observed choices in an actual job market. I also account for a key factor — firm preferences over workers — that typically breaks the direct connection between worker preferences and observed job choices. By doing so, I empirically isolate the role of worker preferences over job attributes from firm preferences over workers in determining equilibrium matching of jobs to workers. Differences in willingness-to-pay for non-pecuniary amenities might also explain differences in occupational choices, lifetime earnings, and even human capital investments as workers prepare to enter professions compatible with their multi-faceted preferences for jobs.

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

2 Caste and Affirmative Action in India

This section provides a brief overview of the origin of caste-based affirmative action policies in India.

In 1914, when India was still under British rule, the Madras Legislative Council deliberated upon the communal representation of registered students in the University of Madras. Out of a total of 650 students enrolled in the university, 452 were Brahmin and 12 were non-Brahmin Hindus. However, only 74 students belonged to the non-advantaged communities (Bayly, 2008). The deliberations of the Madras Legislative Council paved the way for compensatory practices for disadvantaged groups, which over several decades became solidified as reservation-based (quota) policies in legislative services, government jobs and educational institutions in present-day India.

In 1918, The Maharaja (Supreme King) of Mysore, Krishna Raja Wadiyar IV, received a petition from "depressed" classes in India. "Depressed" classes primarily belonged to socio-economically disadvantaged groups. The petition elaborated upon their grievances regarding lack of representation in both government educational institutions and government jobs. Based on the petition, the Maharaja of Mysore appointed the Miller Committee, headed by Justice Leslie Miller. The purpose of the Miller Committee was to determine whether the non-Brahmin community had adequate representation in state services. Meanwhile, the British Government, eager to elicit Indian support in its efforts during the First World War, had already accepted India's long-standing request of establishing self-governing institutions i.e. provincial assemblies and central legislative assemblies. Self-governing institutions were formally introduced by the Government of India Act, 1919, under the Montague-Chelmsford Reforms. The first provisions for uplifting depressed classes of Indian society were passed under the Government of India Act, 1919 (Bayly, 2008; Gilmour, 2019; Lee, 2020).

The provisions of the Government of India Act, 1919, begged a key question: how does the government identify depressed sections of society? For this purpose, the British Government appointed the Simon Commission to assess Indian society and suggest reforms. The

Simon Commission recommended "the need to safeguard the minorities, and other socially and politically depressed classes of people" (Bakshi, 1977). In 1923, the British Government decided not to extend grants to schools which refused admissions to children belonging to depressed classes. The depressed classes, under the leadership of Dr. B.R. Ambedkar, who later became one of the leading architects of independent India's constitution, demanded reservation of seats (quotas) for depressed classes in legislative bodies, special educational concessions and recruitment in public sector jobs. The depressed classes also demanded a separate electorate but the Simon Commission did not accept this request (Jenkins, 2003).

The demands of the depressed classes were formally discussed in the Round Table Conference of 1930 convened by the British Government. Shortly after, the Prime Minister of the British Government, Ramsay MacDonald, granted the Communal Award upon India, partitioning it into separate electorates for Muslims, Sikhs, Indian-Christians, Anglo-Indians, Europeans and depressed classes. Mahatma Gandhi, who by then had established himself as the leader of the Civil Disobedience Movement against the British Government, was opposed to reservations of any kind. He was especially opposed to the provision of granting a separate electorate to the depressed classes, and branded it as the "divide and rule" policy of the British Government. However, B.R. Ambedkar was more sympathetic towards reservations for depressed classes, including the provision of a separate electorate. A comprise was reached between Mahatma Gandhi and B.R. Ambedkar under the Poona Pact of 1932, which was signed in Yerwada Central Jail on 24th September, 1932 (Roy, 2017). The Poona Pact agreed upon a single general electorate to govern British India and the new central legislatures. As a result of the pact, 141 seats were reserved for depressed classes in provincial councils. In contrast, MacDonald's award promised only 71. Depressed classes also received a representation of 18% in central assemblies. The Poona Pact was finally ratified by the Government of India Act, 1935, which also replaced the words "depressed classes" with "Scheduled Castes".

From 1942-1946, B.R. Ambedkar served as a member of the British Viceroy's Executive Council as a Minister for Labour. He used this position to further the interests of depressed classes and demanded reservations in government educational institutions, in addition to government jobs. His demands became the foundation of affirmative action policies for depressed classes (Scheduled Castes) in independent India (Ambedkar, 2016).

In December 1946, almost a year before India gained independence, the first Constituent Assembly, which included B.R. Ambedkar, deliberated upon the key features of the Indian constitution. The framers wanted to set up an egalitarian society with special protections for the "socially, educationally and politically" disadvantaged communities. The Constituent Assembly comprised different committees to address different societal issues. The Minority Committee Report argued for reservations (quotas) for disadvantaged groups in proportion to their representation in the population. The report argued for representation in legislatures, higher educational institutions and government jobs. The Constituent Assembly also accepted the provision of a joint electorate but was opposed to reservation on the basis of religion. Interestingly, reservations for depressed classes were originally intended as *temporary* provisions subject to a review every ten years, during which it would be open to the Indian Parliament to either renew or abolish it (Khosla, 2020).

Many articles of the Indian constitution formalized affirmative action policies for disadvantaged groups. The articles were broadly aimed at forwarding the representation of "backward classes", which not only included members of Scheduled Castes (SCs) and Scheduled Tribes (STs) but also those from the Other Backward Classes (OBCs). These provisions begged an obvious question: what determines "backwardness"? In 1953, the Kelkar Committee recommended caste as the basis for determining "backwardness". However, the Union Government did not accept the recommendation. In *M.R. Balaji v. State of Mysore* (1963), the Supreme Court ruled that "backward" classes should be classified on the basis of caste, but social and educational backwardness should also be considered. Moreover, the Court ruled that "backwardness" of OBCs should be comparable to that of the SCs and STs (Khosla, 2020).

In 1979, the Second Backward Classes Commission was setup under the chairmanship of B.P. Mandal. The commission, also called The Mandal Commission, recommended caste as the basis for reservation. The commission also recommended 27% reservation (quota) in central and state services, public undertakings and educational institutions for OBCs. Given the already existing 22.5% reservation for SCs and STs, the fraction of reserved seats for disadvantaged castes (SCs, STs and OBCs) was brought up to 49.5%. The Mandal Commission Report was subject to widespread student protests in 1990. Nearly 200 college students committed self-immolation, and 62 succumbed to their burns. Despite these protests and a temporary stay order on the report issued by the Supreme Court in 1992, the recommendations of the Mandal Commmsion were formally implemented in 1993 (Panandiker, 1997).

Interestingly, none of the current constitutional provisions extend to providing compensatory hiring practices for disadvantaged castes in private sector jobs (Madheswaran and Attewell, 2007; Madheswaran, 2008). The focus of this paper is to assess the potential of such policies in promoting hiring diversity.

3 Setting and Data

3.1 Post-Secondary College Placements in India

Career offices in post-secondary educational institutions in India act as liaisons between students and employers. Employers are invited by career offices to recruit from college campuses following which firms conduct pre-interview screening tests involving written and verbal components, on-campus interviews and make job offers. Career offices also collect information pertaining to the entire job placement process. In particular, career offices collect information on job applications, pre-interview screening tests, job interviews, job offers and final job choices. Moreover, career offices make rules regarding the job placement process and require that students and firms abide by them. In the following section, I describe the job placement process in my institutional setting.

3.2 The Placement Process

The job placement process involves the following steps: 1) the career office invites firms, 2) invited firms post their job positions and compensation packages, 3) students apply for jobs, 4) firms determine eligibility for on-campus interviews by conducting pre-interview screening tests comprising both written and verbal components, 5) firms interview students on campus during slots (interview days) allotted to them by the career office, 6) after conducting interviews, firms make job offers, and 7) after receiving job offers, students make final job choices.

Figure 1 below shows a diagrammatic representation of the placement process.

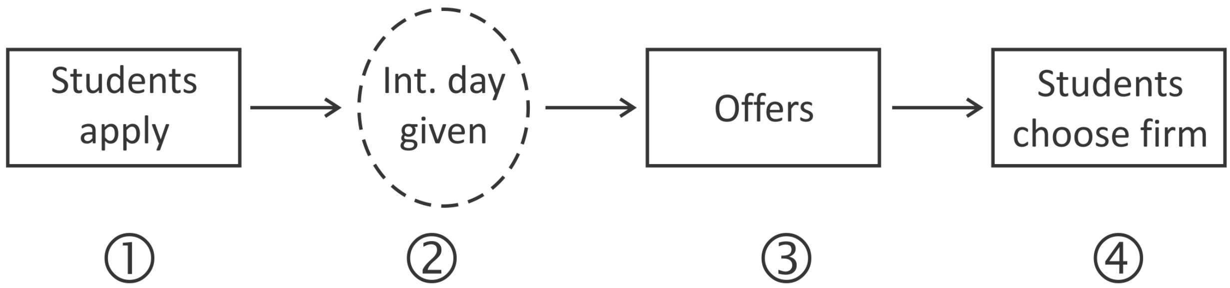

Figure 1: The Placement Process

A particular rule of the job placement process states that conditional on getting a job offer on a given interview day, a student can no longer participate in interviews on future interview days. At best, a student can receive multiple job offers within a given interview day. If a student does not get any job offer on a particular interview day, he can participate in interviews on future interview days.[4] All job offers are announced within a short interval of time at the end of the interview day, typically late in the evening to prevent firms from coordinating on whom to hire.

3.3 Data Overview

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

[4]I deal with how this affects strategic behavior of firms to compete for better interview slots in Section 5.

3.3.1 Sample Selection

I omit students pursuing the Master of Science (M.Sc.) degree and those in other smaller degree programs. Such students are much fewer in number relative to those pursuing other degrees. Moreover, these students are much less likely to make use of the career office in their job search. I omit firms belonging to the public sector. Such firms comprise less than 4% of all jobs available to students in the degree programs included in the sample. Public sector firms are also quite different than their private sector counterparts, especially in salary structure (pay-scales for different job ranks with a substantial portion of the perks in the form of allowances for transportation, phone bills, medical needs etc.), job stability etc.

3.3.2 Students

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

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

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

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

There are 4207 students in the sample. 2167 students belong to advantaged castes and 2040 belong to disadvantaged castes. Due to affirmative action (quota) policies in college admission, disadvantaged castes are represented in nearly equal proportion as advantaged castes. Both Bachelor of Technology (B.Tech.) and Dual degree students are admitted to the institution through a common entrance exam. A Dual degree integrates undergraduate and post-graduate studies and is completed a year after the conventional four-year B.Tech.

degree. In the B.Tech. degree, the proportion of students belonging to advantaged castes is 0.45. In the Dual degree, an almost equal proportion of students belong to each caste. Master of Technology (M.Tech.) and Master of Science (M.S.) degree students are also admitted through a common entrance exam. In the M.Tech. degree, a roughly equal proportion of students belong to each caste. The M.S. degree has a substantially larger proportion of advantaged castes relative to disadvantaged castes indicating that despite admissions quotas, some college degrees may not be able to fill up all college seats reserved for disadvantaged castes.

3.3.3 Differences Across Castes in Baseline Characteristics

In this section, I document differences in baseline characteristics across castes. The largest differences are concentrated in pre-college skills, especially in college entrance exam scores. There are also large differences across castes in college GPA. However, I find only modest differences across castes in previous labor market experience. Previous labor market experience includes 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, sectors of internship employment and employment in startups. For students pursuing Master's degrees, the dataset also includes other measures of employer-relevant experience like specialization within the major (e.g. aerodynamics, computational fluid mechanics etc.) and software programming skills etc.

A) Pre-college Skills

There are substantial differences in pre-college skills across castes, especially in college entrance exam scores. Table 2 reports differences in pre-college skills across castes. The largest differences in pre-college skills are in college entrance exam scores. Appendix Figure A.1 shows common support for students belonging to either disadvantaged or advantaged castes within each entrance exam score decile.

The differences in 10th and 12th grade national level examination scores are substantially smaller. College entrance exam scores are the basis of college admissions while test scores in

Table 2: Differences in Pre-College Skills Across Castes

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

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

10th and 12th grade national level examinations are not. Therefore, students have a larger incentive to differentiate themselves on college entrance exam scores. Hence, differences across castes in college entrance exam scores correspond to relatively smaller gaps in scores on 10th and 12th national level examination.

B) Within-College Academic Performance

There are also large differences across castes in college GPA. Table 3 reports differences in overall college GPA (not adjusted for major) across castes. Differences in overall college GPA are largest in the B.Tech. and Dual degrees. Appendix Figure A.1 shows common support for students belonging to either disadvantaged or advantaged castes within each college GPA decile.

Table 4 shows that college GPA and entrance exam scores are negatively correlated. College entrance exams determine whether students get assigned to selective majors.[5] Selective

[5] In Appendix Tables E.24 and E.25, I show that student characteristics, like entrance exam score and caste, are almost perfectly predictive of major assignments.

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

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

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

majors are Computer Science, Electrical Engineering, Mechanical Engineering, Civil Engineering and Chemical Engineering. These majors have more challenging workloads making it harder to get high grade point averages. Hence, the regressions reported in Table 4 allow for a mean-shift in college GPA by major. Still, I find that a higher college entrance exam score is associated, on average, with a lower college GPA.

Column (1) in Table 4 reports the negative correlation between GPA and entrance exam scores for B.Tech. degree students. A one-standard deviation higher college entrance exam score is associated with an average decrease of 2.5% in college GPA.

Columns (2) and (3) in Table 4 report the relationship between GPA and entrance exam scores for B.Tech. degree students in selective and non-selective majors, respectively. Within selective majors, entrance exam scores and GPA are not correlated. In contrast, within non-selective majors, a one-standard deviation higher college entrance exam score is associated with an average decrease of 6% in college GPA.

Overall these patterns indicate that low entrance exam scorers who get assigned less selective majors have a strong incentive to signal their "type" by raising their within-major academic performance. These students perform better than their comparatively higher scoring peers in the same major. On the other hand, high entrance exam rank scorers in selective majors may not have a strong incentive to differentiate themselves further, at least academically. These students appear to drop off compared to their lower scoring peers in the same major. The negative relationship between entrance exam scores and GPA persists across all

Table 4: GPA for B.Tech. Degree Students Negatively Correlated with Entrance Exam Score

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

Notes: Table 4 includes estimates from a regression of grade point averages (GPA) of B.Tech. degree holders on student characteristics. Dependent variable is (log) GPA. Controls include college major, entrance exam score (standardized) and grades in 10th and 12th grade national level examinations (standardized). College major includes dummies for each major. College entrance exam scores have been re-normalized so that higher numbers are better. In column (1), I report results for all students. In column (2), I report results only for students in non-selective majors. In column (3), I report results only for students in selective majors. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

college degrees (see, Appendix Tables E.1, E.2 and E.3).

The results above could also be explained by random variation in entrance exam scores conditional on ability (proxied by GPA). Students at the top of the distribution will have more positive error in their entrance exam scores conditional on ability. This will be less true for students in the lower range of the ability distribution. However, the overall effect is likely much stronger at the top of the distribution because the pool of students entering the college is truncated at relatively high entrance exam scores.

C) Previous Labor Market Experience

Table 5: Differences in Previous Labor Market Experience Across Castes

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

Notes: Table 5 documents differences in previous labor market experience across castes. Previous labor market experience includes internship duration (weeks), part-time or full-time employment duration (weeks), total pay during internships, total pay during part-time or full-time employment, sectors of employment and employment in startups. Standard errors are reported in parenthesis. All dollar amounts are in puchasing power parity (PPP) units. T-tests are conducted for differences in overall means. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

I find only modest differences across castes in previous labor market experience. Table 5 reports differences in previous labor market experience across castes.

On average, disadvantaged castes are statistically indistinguishable from advantaged castes in weeks of former employment, total pay during internships, total pay during part-time or full-time employment and employment in startups.

Among B.Tech. and Dual degree students, disadvantaged castes are also similar to advantaged castes in sectors of former employment. Among M.Tech and M.S. degree students, disadvantaged castes are less likely to be previously employed in the technology sector, as likely to be previously employed in the consulting sector and more likely to be previously employed in the manufacturing sector.

For students pursuing Master's degrees, I do not find significant differences across castes in specialization within major (e.g. aerodynamics, computational fluid mechanics etc.) and software programming skills (not shown).

The absence of prohibitively large caste disparities in previous labor market experience is surprising since disadvantaged castes have substantially lower test scores and college GPA than advantaged castes.

3.3.4 Firms

In the sample, a job designation (henceforth, "job") means a job title within a firm. For example, a firm can hire a Product Manager and a Software Engineer. Firms offer different salaries to different college degrees for the same jobs. B.Tech. degree holders will typically get paid lower salaries than M.Tech. degree holders for the same jobs. Firms do not pay different salaries to different majors within the same college degree. There is no differential pay across castes or gender within the same jobs. Some firms pay the same salaries for the same jobs across college degrees, despite some college degrees having one or more additional years of education.

Table 6 shows the distribution of firms by sector, the fraction of non-domestic jobs by sector and the average salary across all jobs by sector. 52% of all jobs belong to the technology sector, 20% belong to the consulting sector and 28% belong to the manufacturing sector. Among all non-domestic jobs, 85% belong to the technology sector and 15% belong

Table 6: Firm Sectors, Location and Average Salary

Sector	Total (Fraction)	Fraction Non-Domestic	Avg. Salary ($)
Technology	335 (0.52)	0.85	67302.64
Consulting	129 (0.20)	0.00	63544.02
Manufacturing	180 (0.28)	0.15	43525.25

Notes: Table 6 shows the distribution of firms by sector, the fraction of non-domestic jobs by sector and the average salary across all jobs by sector. Column (1) shows the number of firms in each sector, with their proportions in parenthesis. Column (2) shows the fraction of non-domestic jobs belonging to each sector. Column (3) shows the average salary of all jobs in a given sector. All dollar amounts are in purchasing power parity (PPP) terms.

to the manufacturing sector. The average salary across all jobs in the technology sector is $67,302.64 (PPP). The average salary across all jobs in the consulting sector is $63,544.02 (PPP). Manufacturing jobs pay much less than jobs in either consulting or technology. The average salary across all jobs in the manufacturing sector is $43,525.25 (PPP).

In addition to salaries, compensation bundles for jobs include stock options, signing bonuses, performance bonuses, relocation allowances, medical insurance etc. Like salaries, these other forms of compensation vary across but not within college degrees. The administrative dataset comprises information on over 40 different types of non-pecuniary amenities offered by firms.[6] Therefore, firms horizontally differentiate themselves along many characteristics, besides pay, to attract their favorite candidates.

Table 7: Select Non-Pecuniary Amenities by Job Sector

Non-Pecuniary Amenity	Technology	Consulting	Manufacturing
Stock Options	29.52	27.00	17.85
Signing Bonus	25.58	24.77	22.08
Mediclaim Insurance	18.00	15.75	20.28
Relocation Allowance	36.78	40.95	28.80
401 Benefits/EPF	26.01	34.24	23.80
Confirmation Bonus	37.80	32.44	31.35
Retention Bonus	32.76	22.50	36.60
Travel Allowance	37.26	46.80	43.02
Annual Bonus	37.83	36.04	34.35
Performance Bonus	30.60	36.45	29.80

Notes: Table 7 shows the fraction of firms in each sector offering a select subset of non-pecuniary amenities. EPF stands for Employees' Provident Fund.

Table 7 shows the fraction of firms in each sector offering a select subset of non-pecuniary

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

amenities. On average, a given non-pecuniary amenity is offered by a larger proportion of firms in the technology or consulting sectors than those in the manufacturing sector.

Importantly, firms are required by the placement office to commit to the compensation bundles they advertise for each job *before* the start of the job search process i.e. before students start applying. Therefore, salaries and non-pecuniary amenities posted by jobs are non-negotiable at any of the stages before the job offer stage (especially, at the one-on-one interview) and even after the job offer has been made. Commitment on job characteristics is enforced by the placement office by requiring employers to fill an employer registration form detailing compensation packages, and also requiring that students submit a copy of the job offer letter to match against what was previously advertised by the employer. Ex-ante commitment and ex-post verification of job characteristics rules out differences in negotiation skills as a potential source of disparities across castes. Differences in negotiation ability have been a well documented source of labor market disparities in other contexts, especially across gender (Babcock and Laschever, 2003; Gneezy and Croson, 2009; Bertrand, 2011; Blau and Kahn, 2017; Recalde and Vesterlund, 2020).

4 Descriptive Facts

Before proceeding to the model, I establish key descriptive facts specific to my institutional setting. These descriptive facts establish caste disparities in earnings and job assignments. Moreover, these descriptive facts also shed light on promising channels for policy intervention and inform modeling choices. In all of the regression results shown below, I run different regression specifications at the student-level controlling for GPA, degree, major and entrance exam scores both linearly and through flexible polynomials. For Bachelor's degree holders, I also control for previous internship experience, including detailed job descriptions, duration of employment, total internship pay, sectors of employment and employment in startups. For students pursuing Master's degrees, I control for undergraduate degree, undergraduate major, undergraduate GPA, previous internship experience, previous part-time or full-time job experience, total pay during former part-time or full-time employment, sectors of former part-time or full-time employment, specialization within college degree (e.g, aerodynamics, computational fluid mechanics etc.) and software programming skills.

4.1 Large Earnings Gap Between Castes

Using data on job placements, I first document large earnings disparities between advantaged and disadvantaged castes. I run different specifications of the following regression:

$$\log(\text{earnings}_i) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \tag{1}$$

Table 8: Earnings Gap

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

Notes: Table 8 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), GPA and entrance exam scores enter as quadratic polynomials while other controls enter linearly. In column (3), GPA and entrance exam scores enter as cubic polynomials while other controls enter linearly. In column (4), estimates are reported from a fully-flexible quadratic polynomial regression with all possible interactions between controls. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

The coefficient of interest is β, which is reported in Table 8 for four alternative specifications. The unconditional earnings gap across castes is -0.174 (0.016) log points, or 17.4%. After including detailed controls for pre-college skills, within-college academic performance and previous labor market experience, I find that disadvantaged castes earn, on average, 0.113 (0.014) log points, or 11%, less than comparable advantaged castes. The results are robust to many different specifications (see, Appendix Tables E.4 and E.5).

The earnings gap reported in Table 8 is conservative. Table 8 only includes those students who got jobs through the career office. Appendix Tables E.6 and E.7 show that disadvantaged castes are much more negatively selected out of this sample on GPA and entrance exam scores than advantaged castes. Since average earnings are increasing in GPA and entrance exam scores (not shown), the earnings gap reported in Table 8 is conservative.

4.2 Job Applications Do Not Explain the Earnings Gap

Using data on job applications, I show that the composition of job applications does not explain the earnings gap reported in Table 8. Figure 2 below shows the raw distribution of salaries of jobs to which students applied.

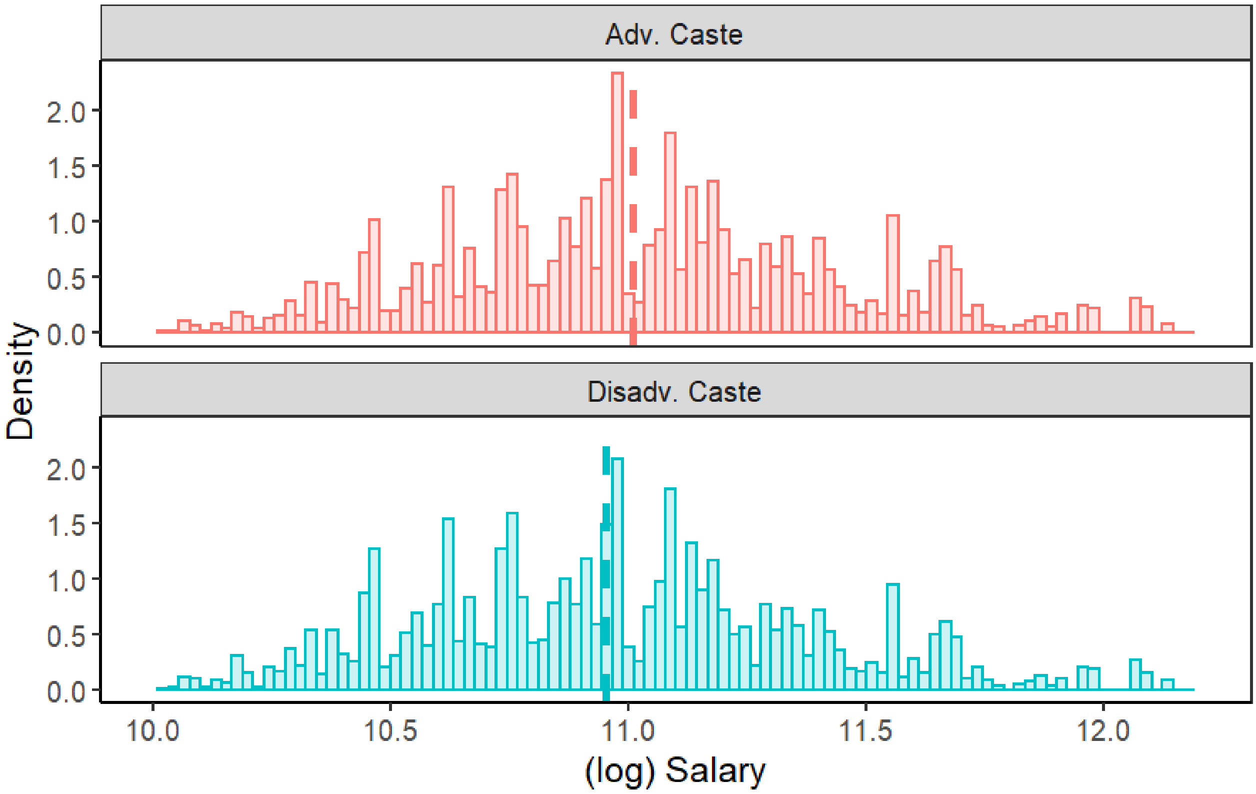

Figure 2: Distribution of Salaries of Jobs to Which Students Applied

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

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

$$\log(\text{Avg. Salary of Jobs Applied to}_i) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \quad (2)$$

Table 9: Salaries of Jobs to Which Students Applied

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

Notes: Table 9 includes estimates from a regression run on the sample of all students who applied for jobs. Dependent variable is log average salary of jobs to which students applied. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), GPA and entrance exam score enter as quadratic polynomials while other controls enter linearly. In column (3), GPA and entrance exam score enter as cubic polynomials while other controls enter linearly. In column (4), estimates are reported from a fully-flexible quadratic polynomial regression with all possible interactions between controls. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The coefficient of interest is β, which is reported in Table 9 for four alternative specifications. Table 9 shows that the difference between castes in the average salary of jobs to which students applied is only -0.001 (0.007) log points, or 0.1%. The difference is economically very small, and statistically insignificant. Therefore, the composition of job applications does not explain the earnings gap across castes. The results are robust to many different specifications (see, Appendix Tables E.8 and E.9).

Table 10 shows that disadvantaged and advantaged castes submit, on average, the same number of job applications.

Table 10: No. of Jobs to Which Students Applied Fully-Flexible Polynomials

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

Notes: Table 10 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log number of firms to which students applied. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), estimates from a natural cubic spline with three degrees of freedom are reported. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available on request. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The absence of differences between castes in both job application salaries and the number of job applications has immediate policy implications. In particular, policies which induce changes in job application behavior will not mitigate caste disparities in earnings.

4.3 Almost All of the Earnings Gap is at the Hiring Stage

In this section, I lay out one of the key contributions of the paper. In particular, I quantify the role of each step of the job placement process in explaining the earnings gap reported in Table 8. To my knowledge, this is the first paper documenting the incremental drop off in earnings at successive stages of job search.

I show that almost all of the earnings gap reported in Table 8 is at the hiring stage. In my institutional setting, firms conduct pre-interview screening tests often comprising both written and verbal components. The written component (first round) is a timed aptitude test. The verbal component (second round), also called group discussion (GD), tests students' abilities to effectively communicate among their peers on a given topic. Firms conduct one-on-one interviews (third round) based on outcomes from pre-interview screening tests and, ultimately, make job offers.

To show that almost all of the earnings gap is at the hiring stage, I run different specifications of the following regression:

$$\log(\text{Avg. Salary of Jobs}_i^{\text{Job Search Stage}}) = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \quad (3)$$

where Job Search Stage $\in$ {Application, Aptitude Test, Group Discussion (GD), Interview, Offers, Accepted Offers}. The coefficient of interest is β, which is shown in Figure 3 for each successive stage of job search.

There is a substantial winnowing down in the number of jobs available at each successive stage of job search. The number of jobs available to each student reduces by about 35% between any two stages, except between job interviews and job offers where the drop-off is much sharper due to the rules of the job placement process (see, Section 3.2).

Figure 3 shows that almost all of the earnings gap is at the hiring stage. As reported in Table 9, job applications do not explain the earnings gap. Pre-interview screening tests

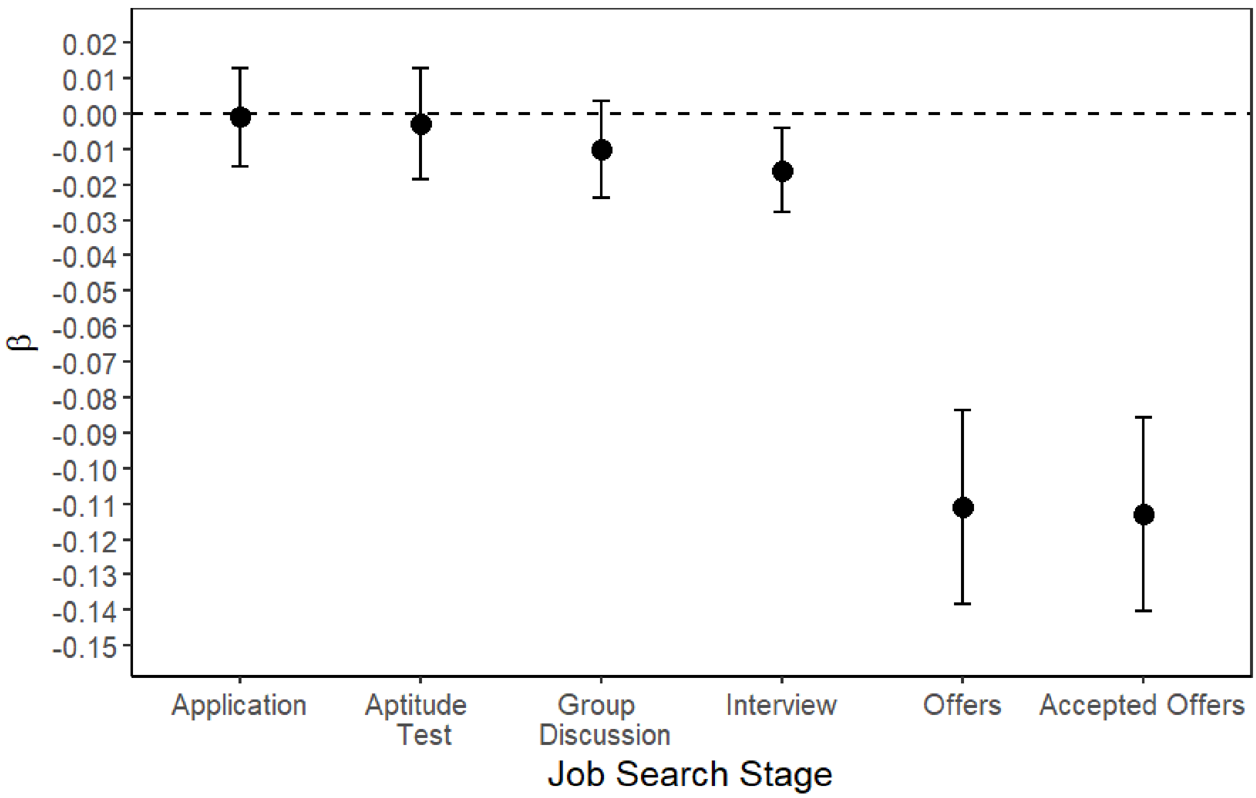

Figure 3: Earnings Gap Across Castes at Each Job Search Stage

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

account for only 14% of overall earnings gap. The remaining 86% of the earnings gap is concentrated between job interviews and job offers.

The earnings gap decomposition is also informative of effective policies to mitigate caste disparities in earnings. Since firm hiring exclusively drives the earnings gap, policy responses would be most effective if they directly incentivize firms to hire more disadvantaged castes. However, understanding worker choice is still important. Workers may have preferences over job characteristics, besides pay, which drive final job choices. Quantifying preferences of workers over such characteristics is necessary to fully account for the effects of policy responses aimed at firms to hire more disadvantaged castes.

The large drop off in earnings at the offer stage raises the possibility that differences in socio-emotional skills may be driving some of the observed earnings gap across castes. However, it is not clear whether these "social skills" represent caste cues or are genuinely valuable skills (Mamidi, 2010). Moreover, the drop off in earnings occurs among students who were selected for one-on-one interviews (third round) after group discussion based "soft skills" tests (second round). In my institutional setting, nearly 85% of the jobs are non-client facing (see, Section 4.4), which suggests that employers may not have a substantial preference for students on the right tail of the socio-emotional skills distribution compared to those closer to the mean. In a different context, I study the role of socio-emotional skills in determining college investment, job search behavior and labor market outcomes in an elite MBA program in the U.S. (Humphries and Shukla, 2020).

Another possible explanation for the earnings drop off at the offer stage is that employers may not make high paying job offers to disadvantaged castes because advantaged castes may have better "outside options." For example, such "outside options" may represent aspects of broader discrimination, like better job offers procured from outside of the centralized placement process. However, nearly 99% of all graduating students in this college participate in searching for jobs through the help of the placement office. If students are discovered to be searching for jobs "offline" i.e. outside of the centralized placement process, they are debarred from the services of the placement office in their on-campus job search. Hence, in this context, the lack of "offline" job opportunities limits the possibility of advantaged castes leveraging employers for high paying job offers.

4.3.1 The Differential Role of the Group Discussion Stage Across Sectors

Figure 3 shows that the initial drop off in earnings across castes occurs at the group discussion stage. On average, disadvantaged castes perform similarly to advantaged castes in written aptitude tests. The drop off at the group discussion stage raises the possibility that disadvantaged castes have worse communication skills, on average, than advantaged castes. Alternatively, it is possible that while differences in communication skills across castes are not substantial, these skills are valued differently in different sectors. For example, firms in the consulting sector may place a large weight on communication skills while making interview decisions and exacerbate small initial differences in communication skills across castes.

In this section, I study whether the drop off in earnings across castes at the group discussion stage shown in Figure 3 varies by sector. I find that the drop off in earnings across castes at the group discussion stage occurs only among consulting jobs and not among jobs in either technology or manufacturing.

Figure 4 shows the decomposition of the earnings gap in the manufacturing sector. There is no drop off in earnings across castes at the group discussion stage. The point estimate of the earnings gap across castes among manufacturing jobs is about 4%, and the upper bound of the 95% confidence interview is slightly above zero (see also, Appendix Table E.10).

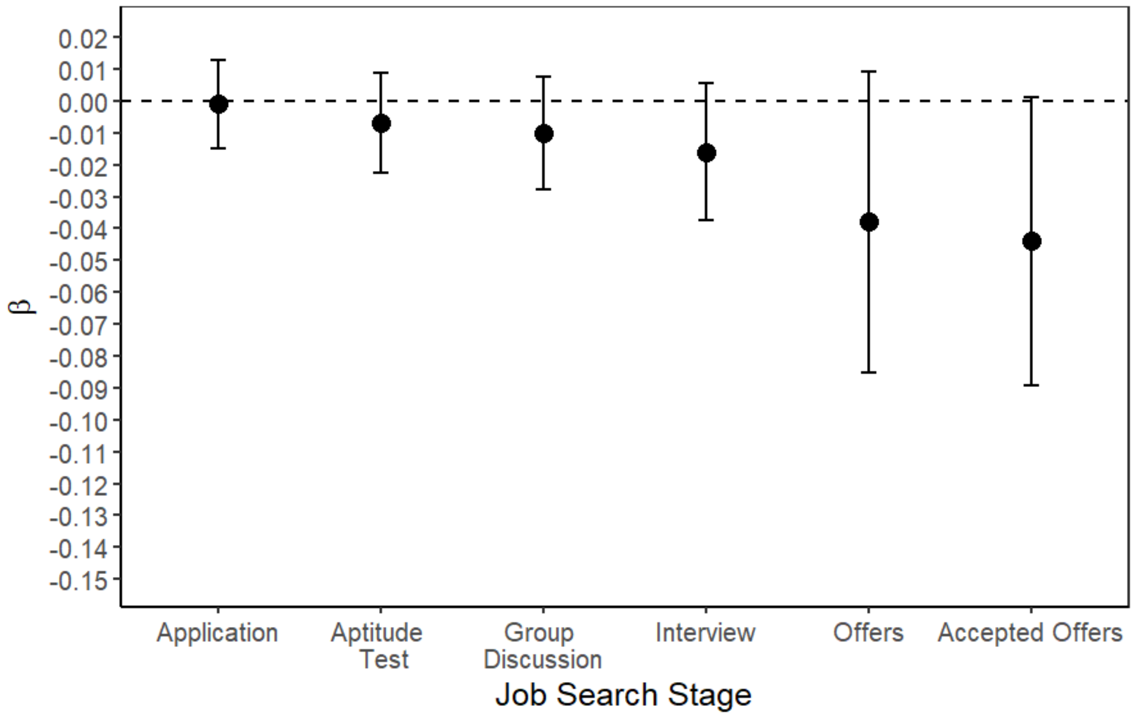

Figure 4: Earnings Gap Across Castes at Each Job Search Stage in the Manufacturing Sector

Notes: Figures 4 shows the coefficient β corresponding to the regression in Equation 3 among jobs in the manufacturing sector. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

Figure 5 shows the decomposition of the earnings gap in the technology sector. Notably, there is still no drop off in earnings across castes at the group discussion stage. However, the point estimate of the earnings gap across castes among jobs in technology is about 8% (see also, Appendix Table E.11).

Figure 6 shows the decomposition of the earnings gap in the consulting sector. Unlike in manufacturing or technology jobs, there is a drop off in earnings across castes at the group

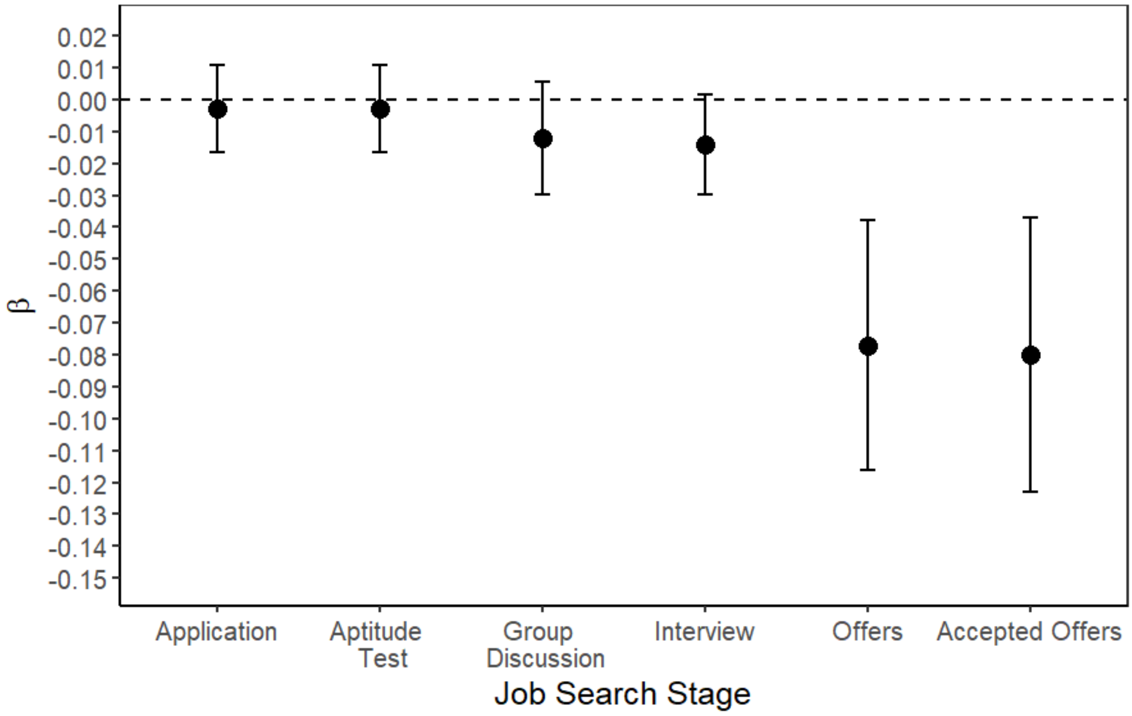

Figure 5: Earnings Gap Across Castes at Each Job Search Stage in the Technology Sector

Notes: Figures 5 shows the coefficient β corresponding to the regression in Equation 3 among jobs in the technology sector. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

discussion stage among consulting jobs. The point estimate of the earnings gap across castes among jobs in consulting is about 10% (see also, Appendix Table E.12).

Overall, these findings indicate that the drop off in earnings across castes at the group discussion stage, shown in Figure 3, is exclusively driven by the consulting sector. These results suggest the possibility that communication skills are valued differently by consulting jobs. However, based on the absence of an earnings drop off at the group discussion stage among jobs in technology and manufacturing, it seems unlikely that average differences in communication skills across castes are prohibitively large. After all, verbal skills are part of the pre-interview screening mechanisms of most jobs in technology and manufacturing. Therefore, it is reasonable to assume such firms value communication skills to some degree. Still, it is challenging to formally disentangle differences in communications skills across castes from the weights placed on them by firms in different sectors.

It is also challenging to formally separate the role of caste in firm hiring from differences in communication skills across castes. One could identify a random effect on the odds

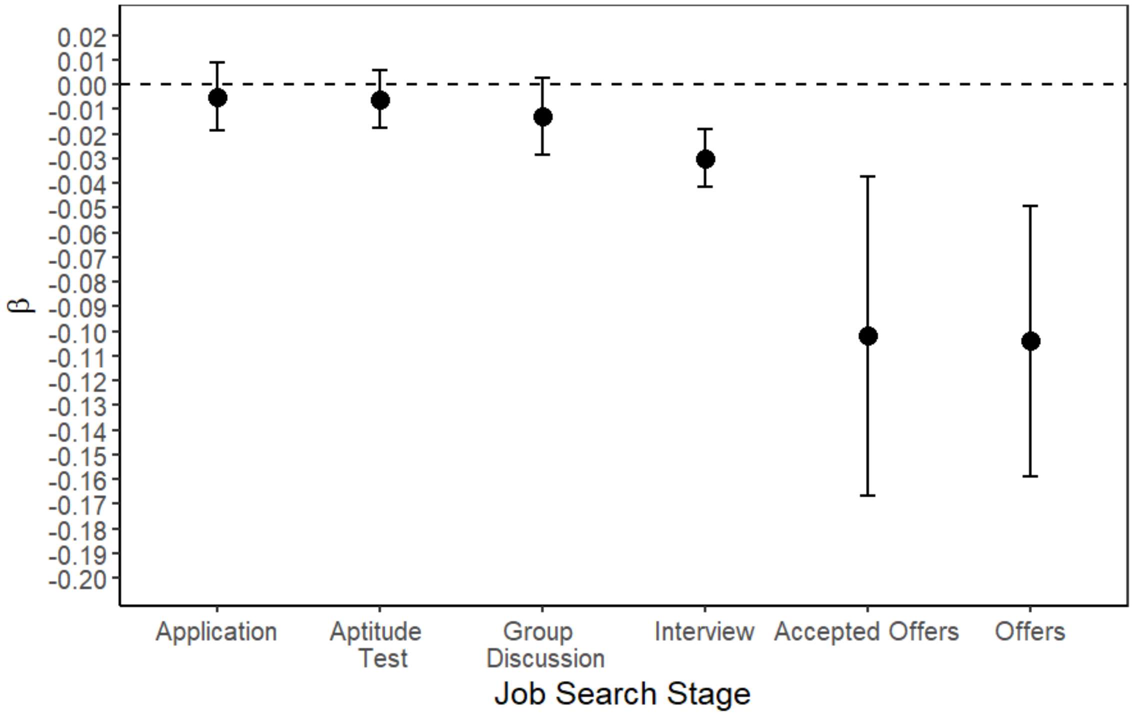

Figure 6: Earnings Gap Across Castes at Each Job Search Stage in the Consulting Sector

Notes: Figure 6 shows the coefficient β corresponding to the regression in Equation 3 among jobs in the consulting sector. β represents the percentage difference in the average salary at each job search stage between advantaged and disadvantaged castes. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

of getting through different types of interviews, with factor loadings that depend on job sectors. However, the random effect may not be communication skills. Moreover, by definition, such a specification would be uninformative regarding caste-related differences in the distribution of communication skills.

4.4 Differences in Job Assignments Are Most Pronounced in the Consulting Sector and in Client Facing Jobs

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

(Becker, 1971).

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

$$\mathbb{1}\{i \text{ hired in the } j \text{ sector}\} = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \tag{4}$$

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

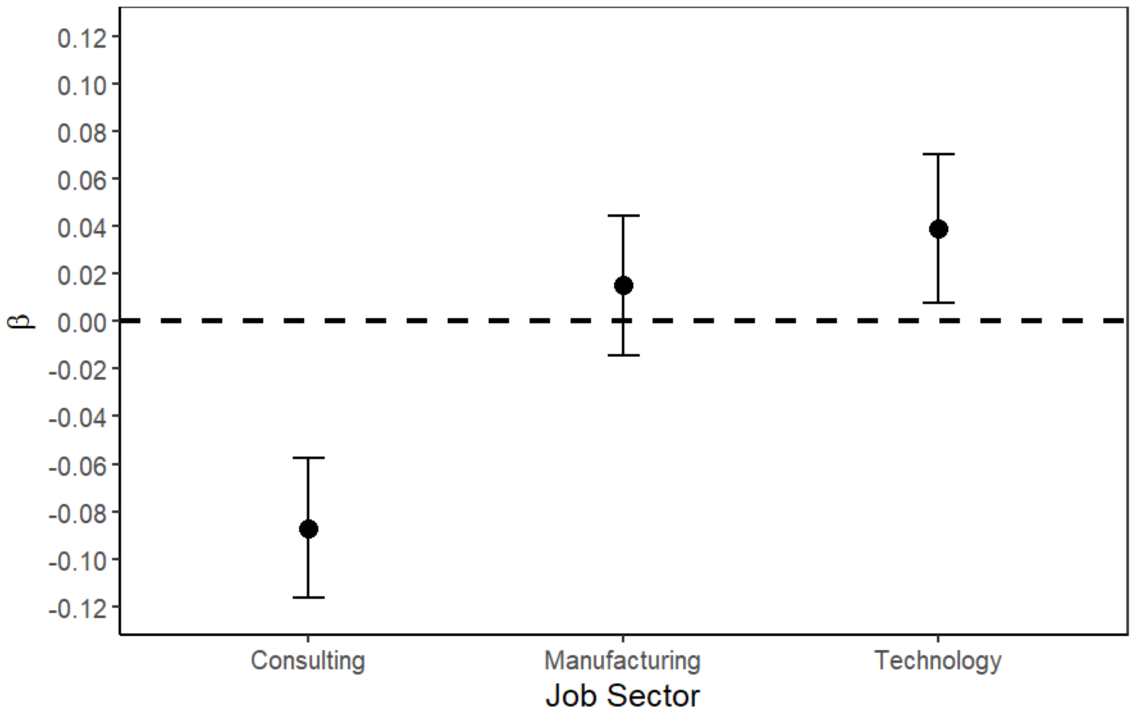

Figure 7: Differences in Job Offer Probabilities Across Caste by Job Sector

Notes: Figure 7 shows the coefficient β corresponding to the regression in Equation 4. β represents the difference between advantaged and disadvantaged castes in the probability of getting a job offer from either the consulting, manufacturing or technology sector. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

Figure 7 shows that differences in job assignments between advantaged and disadvantaged castes are most pronounced in the consulting sector. On average, disadvantaged castes are 8% less likely to get consulting jobs than advantaged castes.

The trends are reversed in the manufacturing and technology sectors. Disadvantaged castes are as likely as advantaged castes to get jobs in manufacturing. Disadvantaged castes are 4% more likely to get jobs in technology than advantaged castes (see, Appendix Tables E.13, E.14 and E.15).

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

$$\mathbb{1}\{i \text{ got a } k \text{ job}\} = \alpha + \beta \times \text{Disadv. Caste}_i + \text{Controls}_i + \epsilon_i. \quad (5)$$

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

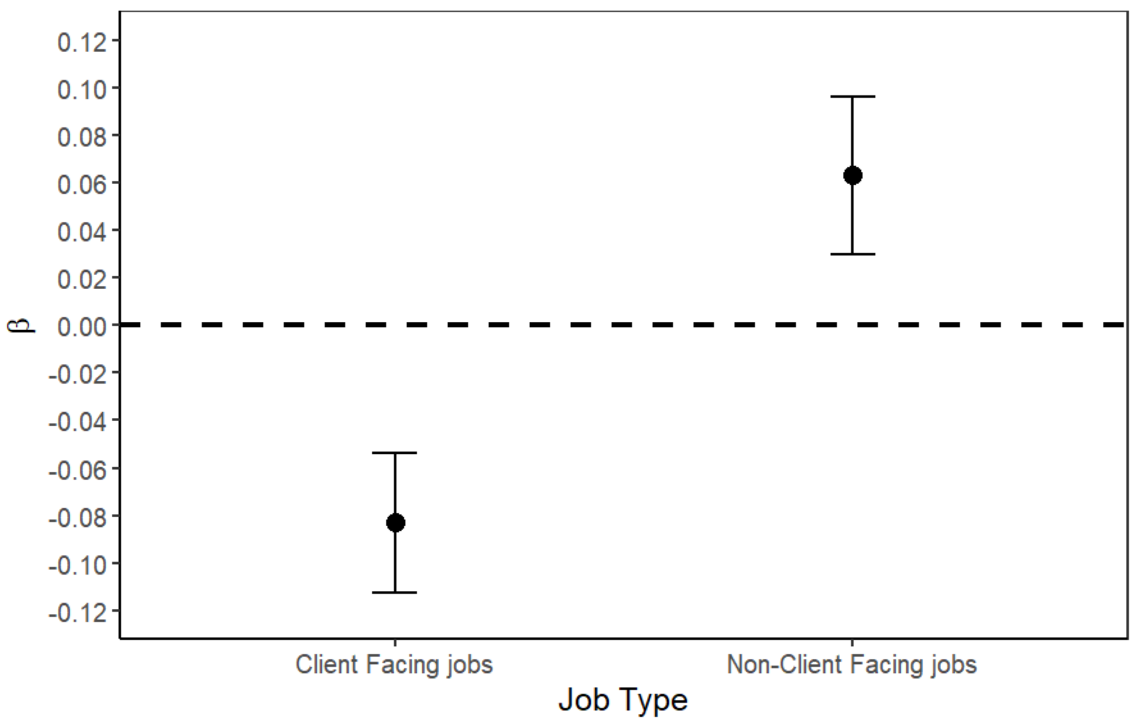

Figure 8: Differences in Job Offer Probabilities Across Caste by Job Type

Notes: Figure 8 shows the coefficient β corresponding to the regression in Equation 5. β represents the difference between advantaged and disadvantaged castes in the probability of getting a job offer from either a client facing or a non-client facing job. Each dot is the coefficient β from a separate regression. The vertical bars are 95% confidence intervals. These regressions include controls.

Figure 8 shows that differences in job assignments between advantaged and disadvantaged castes are most pronounced within client facing jobs. On average, client facing jobs are 8% less likely to hire disadvantaged castes than advantaged castes. In contrast, non-client facing jobs are 6% more likely to hire disadvantaged castes than advantaged castes (see, Appendix Tables E.16, E.17, E.18 and E.19).

Overall, the descriptive facts shown in Section 4 serve two main purposes. First, they uncover the mechanisms behind observed earnings differentials across castes. Second, they shed light on promising channels for policy intervention and inform modeling choices. Policies which provide information about jobs, improve performance at university, or modify preferences are unlikely to close the earnings gap. Counterfactual policies to address hiring disparities will be more effective if they directly incentivize firms to hire more disadvantaged castes.

5 A Model of the Job Placement Process

Guided by the sequential decomposition of the earnings gap, I build a model of the job placement process. In particular, I build a model of job hiring and job choices. I estimate the model and recover the "caste penalty" imposed by firms on disadvantaged castes.[7] Finally, to mitigate the effect of caste on firm hiring, I propose and evaluate policies for promoting hiring diversity.

A model of job hiring and job choices allows us to fully account for the effects of counterfactual hiring policies. In particular, the model allows firms to respond by changing their hiring strategies under counterfactual policies. Given the counterfactual distribution of job offers, students then choose jobs in accordance with their multi-faceted preferences over job characteristics.

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

5.1 Setup and Notation

Given that most students apply everywhere conditional on eligibility, I omit job applications from the model (see, Section 4.2; Appendix Tables E.8 and E.9). In Appendix Section C, I show how the model can be extended to incorporate job application behavior, which may be important in other settings.

I also take the interview days allotted to firms as exogenous. Past interview day allocations and job characteristics are almost perfectly predictive of current interview day allocations (see, Appendix Tables E.20 and E.21). Among these job characteristics, job salaries are the only significant determinants of interview day assignments. A one standard deviation increase in salary increases the probability of getting assigned the first interview slot (first interview day) by 8%. However, I take job salaries as exogenous. The assumption is plausible since the institution comprises a small fraction of a firm's total hiring pool. Hence, it is reasonable to assume that firms do not coordinate job salaries across universities. To provide some evidence, I scrape data from Glassdoor and Levels.fyi and show that average reported job salaries are very similar to the salaries offered for the same job-location combination in my institutional setting (see, Appendix Table E.22).[8] Since job salaries in my institutional setting — the only significant determinants of interview day assignments — are similar to those offered to other students in other universities, it is plausible to assume that interviews days are exogenous.

All things the same, a firm in the consulting sector has a 2% higher probability, relative to a firm in the manufacturing sector, of being assigned the first interview day. Conditional on observables, firms in the technology sector do not have a comparative advantage over manufacturing firms in interview day assignments. Compared to job salaries and sectors, job titles play an insignificant role in interview day assignments.

The binary variable A_{ij} indicates whether student i applies to job j.[9] The vector $A_i = (A_{i1}, \ldots, A_{iJ})$ collects these indicators for all jobs. Let A_i^k be a vector of indicators which takes the value 1 if student i applies to a job allotted interview day k. Similarly, let Z_i^k be

[8] For more details, visit www.glassdoor.com and www.levels.fyi.

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

a vector of indicators which takes the value 1 if student i gets accepted from a job allotted interview day k.

Taking student applications as given, job j accepts student i on interview day k with probability π_j^i, which depends upon both student and job characteristics. Let Z_{ij} be an indicator variable which takes the value 1 if student i receives an offer from job j and 0 otherwise. The vector $Z_i = (Z_{i1}, \ldots, Z_{iJ})$ collects all job offers for student i. Given job offers, students make final job choices.

5.2 Stage 2: Job Choices by Students

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

$$\mathcal{O}(Z_i) = \{0\} \cup \{j : Z_{ij} = 1\}. \tag{6}$$

where the outside option is denoted by $j = 0$. In this model, the outside option is indistinguishable from unemployment. Let U_{ij} be the utility of student i from job j. U_{ij} depends upon student and job characteristics, econometrician-unobserved random effect q_i and a job offer acceptance shock, ϵ_{ij}^1, realized after job offers are known but before final job choices are made. Mathematically,

$$U_{ij} = X_{ij}'\boldsymbol{\beta} + \mathrm{NP}_j'\boldsymbol{\Upsilon} + w_j\tau + q_i + q_i \times \sum_{m=1}^{M} \gamma_m \mathrm{NP}_{jm} + \epsilon_{ij}^1. \tag{7}$$

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

The value of the outside option at the job offer acceptance stage is given by

$$U_{i0} = \epsilon_{i0}^1. \tag{8}$$

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

$$C_i^* = \arg\max_{j \in \mathcal{O}(Z_i)} U_{ij} - U_{i0}. \tag{9}$$

5.3 Stage 1: Job Offers

Recall from Section 5.1 that Z_i^k denotes the offer vector of student i on interview day k. Similarly, A_i^k denotes the application vector of student i on interview day k.

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

$$f_k(Z_i^k | A_i^k) = \prod_{j=1}^{J} \left(A_{ij}^k \left[\pi_j^i Z_{ij}^k + (1 - \pi_j^i)(1 - Z_{ij}^k) \right] + (1 - A_{ij}^k)(1 - Z_{ij}^k) \right). \tag{10}$$

where π_j^i is the probability that job j accepts student i, which depends upon both student and job characteristics. A_{ij}^k is an indicator taking the value 1 if student i applied to job j allotted interview day k and 0 otherwise. Z_{ij}^k is an indicator taking the value 1 if student i received an offer from job j allotted interview day k and 0 otherwise. In Equation 10, I am assuming that a firm allotted interview day k makes job offers independently of any other firm allotted the same interview day. This assumption is plausible since the career office requires all firms conducting interviews on the same interview day to announce job offers within a very short interval of time at the end of the interview day, typically late in the evening to prevent firms from coordinating on whom to hire (see, Section 3.2).

Let $f(Z_i | A_i)$ denote the the probability of realizing a job offer vector Z_i given an application vector A_i. The formula for $f(Z_i|A_i)$ is shown in Appendix Section A.

5.3.1 Student Choice by Jobs

We now describe how jobs choose students in more detail. A job j accepts a student i with probability π_j^i, which depends upon both student and job characteristics.

Each job chooses an incoming cohort of students to maximize expected utility. For a job j, the utility from student i is given by

$$V_{ij} = S_{ij}'\boldsymbol{\alpha} + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta + \mu_{ij}. \tag{11}$$

where S_{ij} is a vector of student and job characteristics including dummies for whether or not a student qualified for the aptitude test (first round), group discussion based "soft skills" tests (second round) or the one-on-one interview (third round), w_j is the (log) salary offered by job j, q_i is econometrician-unobserved student-level attributes and μ_{ij} is an idiosyncratic match term, which is unobservable to student i but observable to job j. The vector S_{ij} also includes other controls for pre-college skills, within-college academic performance and previous labor market experience. We will assume that each μ_{ij} follows a standard logistic distribution and is independent across all students and jobs.

As shown in Equation 11, the probability of getting an offer from job j depends upon econometrician-unobserved q_i which is observable to student i. Therefore, from the student's perspective, job offer probabilities on a given interview day are independent based on the information available to him. However, job offer probabilities on a given interview day are not independent from the econometrician's perspective as they are all functions of q_i.

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

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

$$\overline{V}_j(C(j)) = \sum_{i \in C(j)} V_{ij}. \tag{12}$$

An economic interpretation of Equation 12 is that jobs do not focus on complementarities or team-building during hiring. The assumption is plausible since the university comprises a small fraction of a job's overall incoming cohort i.e. a job does not coordinate hiring across universities. Moreover, jobs select students for interviews based on written and verbal aptitude tests which are general in scope. The assumption of firms not focusing on complementarities or team-building during hiring is also common in the firm-worker matching literature (Chade et al., 2006).

In Equation 12 above, the utility of job j is defined for a *given* cohort $C(j)$. $C(j)$ is random from the perspective of job j when it is deciding which students to extend offers to. Accepting an offer from job j depends upon students' preferences over other jobs (through $\epsilon_{ij'}$ in Equation 7) while getting other jobs depends upon idiosyncratic match terms not observed by job j (through $\mu_{ij'}$ in Equation 11). While job j does not observe $\mu_{ij'}$ for $j' \neq j$, it observes $(S_{ij}, w_j, q_i, \mu_{ij})$ for each student i. Job j solves

$$Z^*(j) = \arg \max_{Z(j) \in \{0,1\}^{|A(j)|}} \mathbb{E}\left[\overline{V}_j(C(j))\right]. \tag{13}$$

$$\text{s.t. } \mathbb{E}(C(j)) \leq \overline{M_j}. \tag{14}$$

where the above expectation is taken over unknowns from the perspective of job j, $A(j)$ is the set of applicants to job j, $Z(j)$ is the set of applicants who receive offers from job j and Equation 14 is the ex-ante hiring constraint faced by job j. The left-hand side of Equation 14 is the expected size of the incoming cohort $C(j)$ for job j. We will assume that each job j has an ex-ante hiring cap which we denote by $\overline{M_j}$.

Note that econometrician-unobserved q enters the utility functions of both students and jobs. An economic interpretation of such a specification is that jobs may choose students either because they like high q students (see, Equation 11) or because high q students are more likely to accept an offer conditional on getting one (see, Equations 7 and 14). Hence, q acts as a productivity term while also affecting preferences over jobs.[10] Proposition 1 below shows that each job j follows a cutoff rule when deciding whether or not to hire student i.

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

Proof. The proof follows from Kapor (2020). We prove the proposition above by contradiction. Let $\texttt{Hire}\{j\} : \{1, \ldots, I\} \to [0, 1]$ be a hiring rule used by job j which satisfies Equation 14. Suppose it is not a cutoff rule. Then there exist two students i and i' such that $V_{ij} > V_{i'j}$ but $\texttt{Hire}\{j\}(i) < 1$ and $\texttt{Hire}\{j\}(i') > 0$. Let P_{ij} and $P_{i'j}$ denote the probabilities that students i and i' accept offers from job j. Then, for some $\epsilon > 0$, it is feasible for job j to increase $\texttt{Hire}\{j\}(i)$ by $\frac{\epsilon}{P_{ij}}$, reduce $\texttt{Hire}\{j\}(i')$ by $\frac{\epsilon}{P_{i'j}}$ and increase overall cohort quality. $\square$

The proposition above relies on the assumption that each job j observes $(S_{ij}, w_j, q_i, \mu_{ij})$ in Equation 11. The information observed by job j is sufficient for its valuation of the utility, V_{ij}, it gets from student i. Observing decisions of other jobs does not affect job j's best estimate of V_{ij}.

5.4 Equilibrium

An equilibrium is a tuple

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

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

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

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

solves

$$C_i^* = \arg\max_{j \in \mathcal{O}(Z_i)} U_{ij} - U_{i0}. \tag{15}$$

where U_{ij} and U_{i0} are given by Equations 7 and 8 respectively.

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

$$Z^*(j) = \arg\max_{Z(j) \in \{0,1\}^{|A(j)|}} \mathbb{E}\left[\overline{V}_j(C(j))\right]. \tag{16}$$

$$\text{s.t. } \mathbb{E}(C(j)) \leq \overline{M_j}. \tag{17}$$

where the expectation above is taken over unknowns from the perspective of job j, $C(j)$ is the incoming cohort for job j, $A(j)$ is the set of applicants to job j, $Z(j)$ is the set of applicants who receive offers from job j, Equation 17 is the ex-ante hiring constraint faced by job j and $\overline{M_j}$ is the ex-ante hiring cap for job j. As shown in Proposition 1, the decision problem of job j can be expressed as simply one of choosing a cutoff $\underline{k_j^*}$, which will be estimated for each job j. Note that $\underline{k_j^*}$ is not a structural parameter and will be allowed to change under counterfactuals.

6 Identification and Estimation

6.1 Identification

I assume that characteristics like caste, salaries, non-pecuniary amenities etc. entering the utility function of students are exogenous. Similarly, exogenous characteristics entering the utility functions of jobs include salaries, sector, caste, major and degree etc. Identification of the preference parameters comes from variation in the exogenous variables entering the utility functions of jobs and students. For example, variation in job choices of students and variation in job characteristics identify student preferences over salaries and other non-pecuniary amenities like stocks, signing bonuses, relocation allowances etc. Parameters describing interactions between student and job characteristics (like, caste $\times$ salary) are identified by variation in job choices of observably similar students belonging to different castes. Variation in student characteristics and variation in the decisions of jobs regarding whom to accept identify preferences of jobs over student characteristics like GPA, caste, major and degree.

Differences in job choices and job offers among observationally equivalent students and jobs identify the distributional parameters of unobservable preferences entering their utility functions. For example, conditional on having the same job offer sets, two observationally equivalent students making different job choices identifies differences in their unobservable preferences for jobs. Correlation in job offers within a student's job application portfolio identifies the variance of econometrician-unobserved q in the utility functions of jobs. Highly correlated job offer outcomes within a student's job application portfolio, conditional on observables, imply that q plays an important role in job hiring. The factor loading on q in the utility functions of jobs is identified by the variation in job offers across observationally equivalent students with observationally equivalent job application portfolios. Effectively, the factor loading on q allows for average effects of unobservable student-level attributes in the utility functions of jobs.

Identification of the caste parameter entering Equation 11 is crucial as counterfactual policies will aim to mitigate the "caste penalty" imposed by firms on disadvantaged castes. I assume that the caste coefficient entering the utility functions of jobs is causal. To address concerns regarding potential differences in unobservable ability by caste, I include detailed measures of pre-college skills, within-college academic performance and previous labor market experience. Pre-college skills include entrance exam ranks, scores on 10th grade national level examinations and scores on 12th grade national level examinations. Information on within-college academic performance includes details on coursework and college GPA, major and degree. Information on previous labor market experience includes duration of former employment, detailed job descriptions, total internship pay, total part-time or full-time employment pay, sectors of former employment and employment in startups. Additionally, for students pursuing Master's degrees, I include detailed measures of undergraduate education including undergraduate degree, undergraduate major, undergraduate

GPA, specialization within the degree (e.g., aerodynamics, computational fluid mechanics etc.) and software programming skills. Finally, in Equation 11, I also include dummies for whether or not a student qualified for the written aptitude test (first round), group discussion based "soft skills" test (second round) or the one-on-one interview (third round) in the vector of student and job characteristics, S_{ij}.

I also assume that econometrician-unobserved q is independent of caste and any other observables, where the observables include detailed controls, including selection into third-round interviews in the job search process. Appendix Tables E.23, E.24 and E.25 address whether it is plausible to assume q in the firm's hiring decision (Equation 11) as being orthogonal to student observables, especially major. For this purpose, I consider a subset of jobs which are "major-neutral" i.e. allow students from all majors to apply. Such jobs are typically in the consulting sector, although some are also in the technology and manufacturing sectors. If there is evidence that students in selective majors (like, Computer Science) are being selected at the same rates as those in less selective majors (like, Ocean Engineering), it would suggest that econometrician-unobserved q is orthogonal to major. Indeed, I find that non-selective majors are as likely to get hired as selective majors in "major-neutral" jobs. "Major-neutral" firms conduct written and verbal aptitude tests which are general in scope. Therefore, being in a more selective major does not necessarily improve the odds of being hired by such firms. Hence, it is unlikely that econometrician-unobserved q is a primary driver of selection into majors because, all things the same, high q students in more selective majors should have higher job offer rates in "major-neutral" jobs than low q students in less selective majors.

6.2 Estimation

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

6.2.1 Job Choice by Students

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

$$\Pr(C_i^* = j | X_{ij}, w_j, \text{NP}_j, q_i) = \frac{\exp(u_{ij})}{\sum_{k \in \mathcal{O}(Z_i)} \exp(u_{ik})}. \tag{18}$$

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

6.2.2 Job Offers

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

$$\pi_j^i(S_{ij}, w_j, q_i, \underline{k_j^*}) = \frac{\exp(S_{ij}'\boldsymbol{\alpha} + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta - \underline{k_j^*})}{1 + \exp(S_{ij}'\boldsymbol{\alpha} + \text{Disadv. Caste}_i \times \eta - w_j\phi + q_i\delta - \underline{k_j^*})}. \tag{19}$$

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

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

7 Parameter Estimates

As an intermediate step towards evaluating counterfactual policies, I assign dollar amounts to non-pecuniary characteristics which enter the utility functions of students and jobs. To do so, I scale the coefficients of interest by the coefficient on wage and express utility in wage units.

7.1 Student Preferences Over Job Characteristics

Table 11 shows select parameter estimates entering the utility functions of students. Unless otherwise stated, all compensation measures are interpreted for a student with mean q_i. All dollar amounts are in purchasing power parity (PPP) terms.

Table 11: Select Parameter Estimates (Student Utility)

Parameter Estimates (Student Utility)						
Parameter	Estimate	Std. Error	Compensation ($)	Std. Error ($)	Compensation (%)	Std. Error (%)
Salary (log), τ	2.482***	0.008	—	—	—	—
Signing Bonus	0.156***	0.005	+3683.111***	120.058	+6.489***	0.211
Performance Bonus	0.049***	0.008	+1132.033***	199.491	+1.994***	0.351
Medical Insurance	0.046***	0.010	+1062.080***	233.872	+1.871***	0.412
Relocation Allowance	0.078***	0.010	+1812.616***	246.859	+3.193***	0.434
Restricted Stock Units	0.124***	0.002	+2908.609***	50.599	+5.123***	0.089
Getting a Job in Technology	0.078***	0.005	+1812.616***	115.655	+3.193***	0.204
Getting a Job in Consulting	0.087***	0.006	+2025.454***	143.100	+3.567***	0.252
Unobserved heterogeneity, σ_q	0.042***	0.004	+968.942***	92.339	+1.706***	0.162
Disadv. Caste × Salary (log)	−0.013	0.099	—	—	—	—
Disadv. Caste × Signing Bonus	−0.026	0.061	-591.654	1380.824	−1.042	2.432
Disadv. Caste × Performance Bonus	−0.011	0.117	-251.072	2664.572	−0.442	4.693
Disadv. Caste × Medical Insurance	−0.013	0.134	-296.602	3049.280	−0.522	5.371
Disadv. Caste × Relocation Allowance	−0.039	0.131	-885.165	2949.910	−1.559	5.196
Disadv. Caste × Restricted Stock Units	−0.012	0.127	-273.842	2891.160	−0.482	5.093
Disadv. Caste × Technology	−0.046	0.065	-1042.574	1459.487	−1.836	2.571
Disadv. Caste × Consulting	0.016	0.079	+367.188	1818.833	+0.647	3.204

Average Salary = $56,767.29 (PPP), N = 4207 (no. of students), J = 644 (no. of jobs).
Notes: Table 11 includes estimates for select student preference parameters over job characteristics. The compensation terms are calculated for a person with average unobserved heterogeneity (q) in units of dollars (PPP). A positive compensation means, all things the same, a student needs to be paid that amount to remain indifferent between a job that has the non-pecuniary amenity versus one that does not. A negative compensation means, all things the same, a student can part with that amount and still remain indifferent between a job that has the non-pecuniary amenity versus one that does not. The standard errors for the compensation terms are calculated through the delta method. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%.

Stock options and signing bonuses are the most valuable non-pecuniary amenities.[11] All things the same, a student needs to be compensated 5.1% of average salary ($2909) to remain indifferent between a job that offers stock options versus one that does not. A student needs to be compensated 6.5% of average salary ($3683) to remain indifferent between a job that offers a signing bonus versus one that does not. Other non-pecuniary amenities like relocation allowance, medical insurance and performance bonuses are not valued as highly as stock options or signing bonuses.

A student needs to be compensated 3.2% of average salary ($1813) to remain indifferent between a job that offers relocation allowance versus one that does not. A student only needs to be compensated 1.9% of average salary ($1062) for the removal of medical insurance and 2% of average salary ($1132) for the removal of performance bonus.

There are no differences between castes in preferences over job characteristics, including non-pecuniary amenities and job sectors. The absence between groups in preferences over job characteristics is in contrast to those found in similar studies on labor market disparities, especially across gender (Altonji and Blank, 1999; Buser et al., 2014; Eriksson and Kristensen, 2014; Flory et al., 2014; Goldin, 2014; Mas and Pallais, 2017; Zafar and Wiswall, 2018). In my institutional setting, differences between castes in preferences over job characteristics do not explain caste disparities in earnings and job assignments.

Jobs in the consulting sector are the most preferred. A student needs to be compensated 3.6% of average salary ($2025) to give up a job in the consulting sector and take one in the manufacturing sector. A student needs to be compensated 3.2% of average salary ($1813) to give up a job in the technology sector and take one in the manufacturing sector. However, since first jobs may persist and disparities in starting salaries may have long term effects, these compensation measures may not fully capture the true willingness-to-pay to remain indifferent across sectors.

The average paying consulting job is typically preferred over the average paying manufacturing job. In fact, the average paying manufacturing job can almost never compete with the average paying consulting job. Ignoring the error terms, student utility from the average

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

paying manufacturing job with non-pecuniary amenities including signing bonus, performance bonus, medical insurance, relocation allowance and stock options will typically *still* be lower than student utility from the average paying consulting job without these non-pecuniary amenities. The average paying manufacturing job will typically offer a worse set of non-pecuniary amenities making the task of choosing between the average paying consulting or manufacturing job even easier (see, Table 7). The match-up between the average paying firms in the consulting and technology sectors is fairer. On average, firms in the technology sector offer a richer set of non-pecuniary amenities than those in the consulting sector (see, Table 7). Given a small pay differential between a job in the consulting sector or the technology sector, students will typically choose the latter.

Table 12: Select Random Marginal Effects for Non-Pecuniary Amenities

Parameter Estimates (Student Utility)		
Parameter	Estimate	Std. Error
$\gamma_{\text{Signing Bonus}}$	0.217***	0.053
$\gamma_{\text{Performance Bonus}}$	0.526***	0.049
$\gamma_{\text{Medical Insurance}}$	0.017	0.079
$\gamma_{\text{Relocation Allowance}}$	0.286***	0.051
$\gamma_{\text{Restricted Stock Units}}$	0.487***	0.104

Notes: Table 12 includes estimates for factor loadings (γ_m) in Equation 7, where m indexes non-pecuniary amenities or fringe benefits. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%.

Econometrician-unobserved q_i plays only a modest role in the utility functions of students. Consider a job that does not offer any non-pecuniary amenities. To get the same utility from that job as a student with one standard deviation higher q_i, a student with mean q_i needs to be compensated 1.7% ($969) of average salary. Table 12 shows random marginal effects over non-pecuniary amenities. To get the same utility as a student with one standard deviation higher q_i, a student with mean q_i needs to be compensated 6% of average salary ($3400) for the removal of stock options, 6.9% of average salary ($3906) for the removal of signing bonus, 3.7% of average salary ($3209) for the removal of relocation allowance and 2.9% of average salary ($1652) for the removal of performance bonus. Therefore, q_i not only shifts the value of all jobs relative to the value of unemployment but also drives preferential selection over job offers by making high q_i students value non-pecuniary amenities more than low q_i students (see, Equation 7).

7.2 Job Preferences Over Student Characteristics

Table 13 shows select parameter estimates entering the utility functions of jobs. All dollar amounts are in purchasing power parity (PPP) terms.

Table 13: Select Parameter Estimates (Job Utility)

Parameter	Estimate	Std. Error	Employer Subsidy ($)	Std. Error ($)	Employer Subsidy (%)	Std. Error (%)
Parameter Estimates (Job Utility)						
Salary (log), ϕ	1.893***	0.074	—	—	—	—
Disadv. Caste, η	-0.093***	0.030	+2721.486***	863.231	+4.794***	1.521
Unobserved heterogeneity, σ_q	0.042***	0.004	+1245.627***	125.895	+2.194***	0.222
Parameter on σ_q, δ	0.512***	0.024	—	—	—	—
Bachelor of Technology (B.Tech.) Degree						
College GPA	0.077***	0.023	+2262.744***	667.570	+3.986***	1.175
College GPA × Consulting	0.018**	0.010	+537.226**	299.516	+0.946**	0.522
College GPA × Technology	0.028**	0.012	+833.485**	357.073	+1.468**	0.630
Entrance Exam Score	0.022**	0.011	+655.917**	326.920	+1.155**	0.576
Dual Degree						
College Degree	0.039	0.033	+1157.567	972.072	+2.039	1.712
College GPA	0.121***	0.021	+3515.013***	604.677	+6.192***	1.065
College GPA × Consulting	0.012	0.076	+358.718	2264.842	+0.632	3.990
College GPA × Technology	0.014	0.052	+418.283	1548.101	+0.737	2.727
Entrance Exam Score	0.019**	0.010	+566.922**	297.577	+0.998**	0.524
Master of Technology (M.Tech.) Degree						
College Degree	0.203***	0.041	+5772.520***	1130.359	+10.169***	1.991
College GPA	0.123***	0.028	+3571.245***	796.479	+6.291***	1.403
College GPA × Consulting	0.038**	0.017	+1128.183**	503.132	+1.987**	0.886
College GPA × Technology	0.048	0.052	+1421.328	1521.945	+2.504	2.681
Entrance Exam Score	0.003***	0.001	+89.893***	29.988	+0.158***	0.053
Master of Science (M.S.) Degree						
College Degree	0.182***	0.063	+5203.660***	1727.431	+9.167***	3.043
College GPA	0.090***	0.022	+2635.767***	636.632	+4.643***	1.121
College GPA × Consulting	0.023	0.057	+685.550	1689.161	+1.207	2.976
College GPA × Technology	0.078	0.051	+2291.530	1472.316	+4.036	2.593
Entrance Exam Score	0.003***	0.001	+89.893***	29.998	+0.158***	0.053

Average Salary = $56,767.29 (PPP), N = 4207 (no. of students), J = 644 (no. of jobs).
Notes: Table 13 includes estimates for the preference parameters of jobs over student characteristics. A positive subsidy means an employer needs to be compensated by that amount to remain indifferent. Employer subsidy measures for entrance exam scores are calculated for a unit standard deviation decrease in entrance exam score. College entrance exam scores (ranks) have been re-normalized so that higher numbers are better. Employer subsidy measures for GPA are calculated for a unit standard deviation decrease in GPA. The standard errors for the employer subsidy terms are calculated through the delta method. Degree fixed effects are shown relative to the Bachelor's degree. College GPA and sector interactions are shown relative to manufacturing sector. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%.

Overall, firms need to be subsidized 4.8% of average salary ($2721) to remain indifferent between hiring, an observably identical disadvantaged or advantaged caste. This compensating amount is a one-time payment: 4.8% of first year salary in the first job instead of 4.8% of average salary paid during each year of the job tenure. The "caste penalty" imposed by firms for disadvantaged castes is consistent with descriptive facts which show the adverse effect of caste on firm hiring. The compensation required for employers to remain indifferent between, otherwise identical, advantaged or advantaged castes is much higher than the amount required to offset a one standard deviation decrease in college entrance exam scores and on par with the amount required to offset a one standard deviation decrease in college GPA.

College GPA is much more valuable to firms than college entrance exam scores. The following interpretation of estimates is for Bachelor's degree holders. A firm in the manufacturing sector needs to be subsidized 4% of average salary ($2263) to offset a one standard deviation decrease in GPA. Relative to a firm in the manufacturing sector, a firm in the consulting sector needs to be subsidized an additional 0.9 percentage points of average salary ($537) to offset a one standard deviation decrease in GPA. Overall, a firm in the consulting sector needs to subsidized 4.9% of average salary ($2800) to offset a one standard deviation decrease in GPA. Relative to a firm in the manufacturing sector, a firm in the technology sector needs to be subsidized an additional 1.5 percentage points of average salary ($833) to offset a one standard deviation decrease in GPA. Overall, a firm in the technology sector needs to subsidized 5.5% of average salary ($3096) to offset a one standard deviation decrease in GPA.

In contrast, employer compensations for reductions in college entrance exam scores are substantially lower. A firm in the manufacturing sector needs to a subsidized 1.2% of average salary ($655) for a one standard deviation decrease in entrance exam scores. The marginal effects of entrance exam ranks are statistically indistinguishable across sectors. The relative importance of GPA and entrance exam scores for other college degrees are reported in Table 13.

Econometrician-unobserved q_i plays only a modest role in the utility functions of jobs. A firm needs to be subsidized 2.2% of average salary ($1246) to offset a one standard deviation decrease in econometrician-unobserved q_i.[12]

[12] Assuming a factor loading of $\delta = 1$.

7.3 Job Cutoffs

Job cutoffs are consistent with descriptive evidence on selectivity. Table 14 shows job cutoffs by pay category, job sector and job title for aggregate firms.[13] As expected, cutoffs are increasing in pay category. The top 25% paying jobs have the highest cutoffs whereas the bottom 25% paying jobs have the lowest cutoffs.

To better understand differences in selectivity of jobs across sectors and job titles, consider a simple application portfolio with just one job application in the "aggregate" sector. Assume also that the student is eligible to get a job offer. Jobs in consulting are the hardest to get followed by jobs in manufacturing and technology, respectively. A marginal hire in a manufacturing job needs to be subsidized 5.6% of average salary ($3,176) to have the same odds of getting an offer as a marginal hire in a consulting job.[14] In contrast, a marginal hire in a technology job needs to be subsidized 36.7% of average salary ($20,840) to have the same odds of getting an offer as a marginal hire in a consulting job.

Table 14: Select Job Cutoffs by Pay Category, Job Sector and Job Title

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

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

Notes: Table 14 includes estimates of the job cutoffs by pay category, job sector and job title for aggregate firms. An "aggregate" firm in a given category (e.g. sector) has the hiring cutoff averaged over all firms in that category. Note that the job cutoff estimates are not structural parameters as they are allowed to change under counterfactual policies. Full estimation tables are available upon request. * significant at 10%, ** significant at 5%, *** significant at 1%.

[13] An "aggregate" firm in a given category (e.g. sector) has the hiring cutoff averaged over all firms in that category.

[14] A "marginal hire" has the same expected "score" implied by Equation 11 as the cutoff to get a job offer.

All things the same, managerial roles are the easiest to get followed by engineering and consulting roles, respectively. A marginal hire in a managerial role needs to be subsidized 35.8% of average salary ($20,305) to have the same odds of getting an offer as a marginal hire in a consultant role. A marginal hire in an engineering role needs to be subsidized 11.3% of average salary ($6,442) to have the same odds of getting an offer as a marginal hire in a consultant role.

Overall, job cutoffs are such that average students have a relatively low chance of success, with any specific application. However, with an average of a few hundred applications per job slot per year, strong students are not guaranteed offers either.

7.4 Model Fit

The model-simulated earnings gap across castes is close to the observed earnings gap across caste. Although I do not use moments designed to match observed earnings gap in the data, the model does a good job of matching the observed earnings gap. The model-simulated earnings gap across castes is 10.6%. The observed earnings gap across castes is 11%.

Table 15: Model Fit — Job Offer and Job Choice Probabilities

Model Fit		
Job Offer		
	Data	Model
Consulting	0.25	0.23
Technology	0.48	0.51
Manufacturing	0.27	0.26
Job Choice		
	Data	Model
Consulting	0.24	0.22
Technology	0.49	0.51
Manufacturing	0.27	0.27
Unemployed		
	Data	Model
—	0.30	0.31

Notes: Table 15 compares the empirical job offer and job choice probabilities to the corresponding model-simulated probabilities. Model-simulated probabilities are computed by simulating the model using the MSL estimates 300 times for each observation in the sample, and then averaging over the number of observations and the number of simulation draws.

The model also matches observed job choices and job offers in the data well. Table 15 shows empirical job offer and job choice probabilities along with the corresponding model-simulated predictions.

The model slightly under-predicts job offers and job choices belonging to the consulting and manufacturing sectors. The model slightly over-predicts job offers and job choices belonging to the technology sector. In the sample, 30% of all students are unemployed, while the model predicts an unemployment rate of 31%.

8 Counterfactuals

As shown in Section 7.2, caste has a significant impact on firm hiring. To mitigate the role of caste on firm hiring, I propose and evaluate the effects of three counterfactual policies. First, I consider a policy in which firms are subsidized by the cash-equivalent amount that makes them indifferent between hiring an observably identical advantaged or disadvantaged caste. Next, I consider a "pre-college intervention" which equalizes the distribution of pre-college skills (college entrance exam scores) across castes. Finally, I consider a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes.

The cash-equivalent subsidy will be one common subsidy given to all firms, regardless of firm characteristics, like sector. This common subsidy will be a one-time payment of nearly 5% of first year salary in the first job. Estimating differing weights on caste by firm characteristics, like sector, is more of a theoretical curiosity, since subsidizing firms in proportion to the magnitudes of their discrimination may lead to perverse incentives, especially since my model does not distinguish between taste-based or statistical discrimination. For example, seen through the lens of my model, it would not be inconsistent to view a higher subsidy for consulting firms, compared to firms in technology, as a compensation for their higher animus toward disadvantaged groups.

The "pre-college intervention" policy encompasses different types of interventions in India which focus on improving pre-college test scores. Such policies typically use randomized controlled trials (RCTs) to induce (plausibly) exogenous changes in test scores. Examples of such policies include hiring tutors, paying teachers bonuses, redesigning school curricula etc., which are then evaluated through the changes they induce in learning outcomes, like test scores (Asim et al., 2015).

The quota policy will require firms to hire an equal share of advantaged and disadvantaged castes. Quotas or reservation-based policies have been extensively used in government jobs and educational institutions (Madheswaran, 2008; Newman and Thorat, 2010; Verma, 2012). However, there are no quota policies for private sector hiring in India.

Crucially, the composition of advantaged and disadvantaged castes remains fixed under all counterfactual policies. Affirmative action policies in college admissions equalize the distribution of castes within each major, and, therefore, within each cohort. I also keep GPA fixed in the counterfactuals, an assumption which *overestimates* the effects of the "pre-college intervention" policy (see, Table 4; Appendix Tables E.1, E.2 and E.3).

8.1 Hiring Subsidies and Pre-College Intervention

In the next few sections, I only focus on comparing the effects of hiring subsidies to those of the "pre-college intervention" policy. Note that both of these counterfactual policies explicitly improve employers' valuation of disadvantaged castes (see, Equation 11).

8.1.1 Counterfactuals: Intuition

To build some intuition regarding the effects of these two counterfactual policies, I consider two extreme strategies by jobs in response to improvements in their valuation of disadvantaged castes.

8.1.1.1 Perfectly Elastic Supply of Jobs

In the first case, jobs hire everyone who qualifies. This strategy corresponds to the supply of job slots being perfectly elastic. As shown in Figures 9 and 10, when jobs do not adjust cutoffs, disadvantaged caste hires are at least as large as in the baseline. There is also no displacement of advantaged castes from jobs.

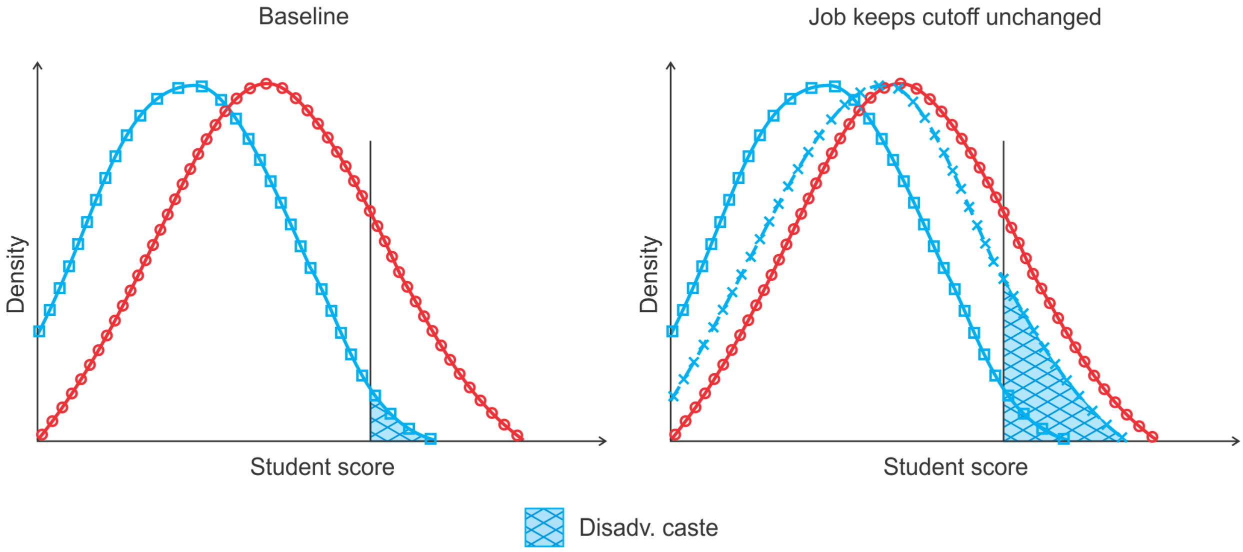

Figure 9: Disadvantaged Caste Hires under Perfectly Elastic Supply of Jobs

Notes: In Figure 9 the distribution of advantaged caste "scores" are to the right of the distributions of disadvantaged caste "scores". "Scores" can be calculated from Equation 11. As shown in Figure 9, the distribution of disadvantaged caste "scores" shifts to the right. In the absence of jobs adjusting cutoffs, disadvantaged caste hires, depicted by the shaded area in the top panel, are at least as large as in the baseline.

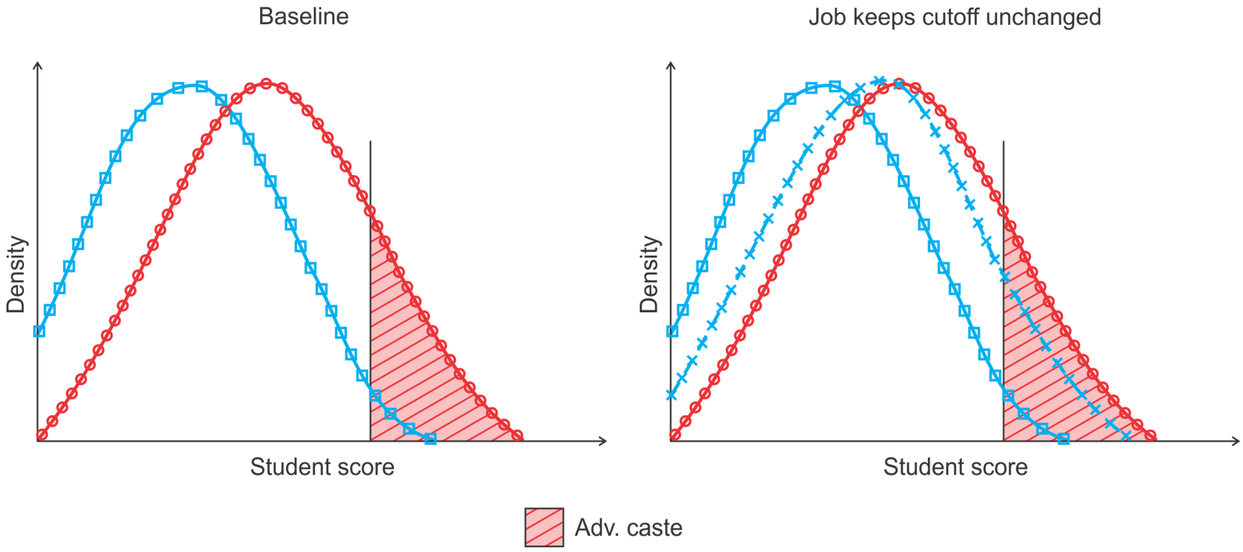

Figure 10: Advantaged Caste Hires under Perfectly Elastic Supply of Jobs

Notes: In Figure 10, the distributions of advantaged caste "scores" are to the right of the distributions of disadvantaged caste "scores". "Scores" can be calculated from Equation 11. As shown in Figure 10, the distribution of advantaged caste "scores" stays the same. In the absence of jobs adjusting cutoffs, advantaged caste hires, depicted by the shaded area in the bottom panel, are the same as in the baseline. When the supply of job slots is perfectly elastic, there is no displacement of advantaged castes from jobs.

8.1.1.2 Perfectly Inelastic Supply of Jobs

In the second case, jobs adjust cutoffs to hire the same total number of students (in expectation) as in the baseline. This strategy corresponds to the supply of job slots being perfectly inelastic.

As shown in Figures 11 and 12, when the supply of job slots is perfectly inelastic, the number of disadvantaged caste hires is at least as large as in the baseline. However, the number of disadvantaged caste hires is bounded above by the number of disadvantaged caste hires when the supply of job slots is perfectly elastic.

The number of advantaged caste hires is lower than in the baseline. The number of advantaged caste hires is bounded below by the number of advantaged caste hires when the supply of job slots is perfectly inelastic. There is no displacement of advantaged castes when the supply of job slots is perfectly elastic, which provides an upper bound of the number of advantaged caste hires.

Hence, by allowing jobs to respond to new hiring policies by adjusting cutoffs, the model captures the most salient aspects of the growing deliberations on advancing compensatory hiring practices for disadvantaged castes: advancement into and displacement from jobs.

The viewpoint of allowing firms to choose between one of two extreme hiring rules is also a natural way to bound plausible responses under counterfactual policies which explicitly increase employers' valuation of disadvantaged castes. If firms derive higher value from a proportion of the population, they would typically do a combination of increasing the hiring threshold a little and hiring a few more people.

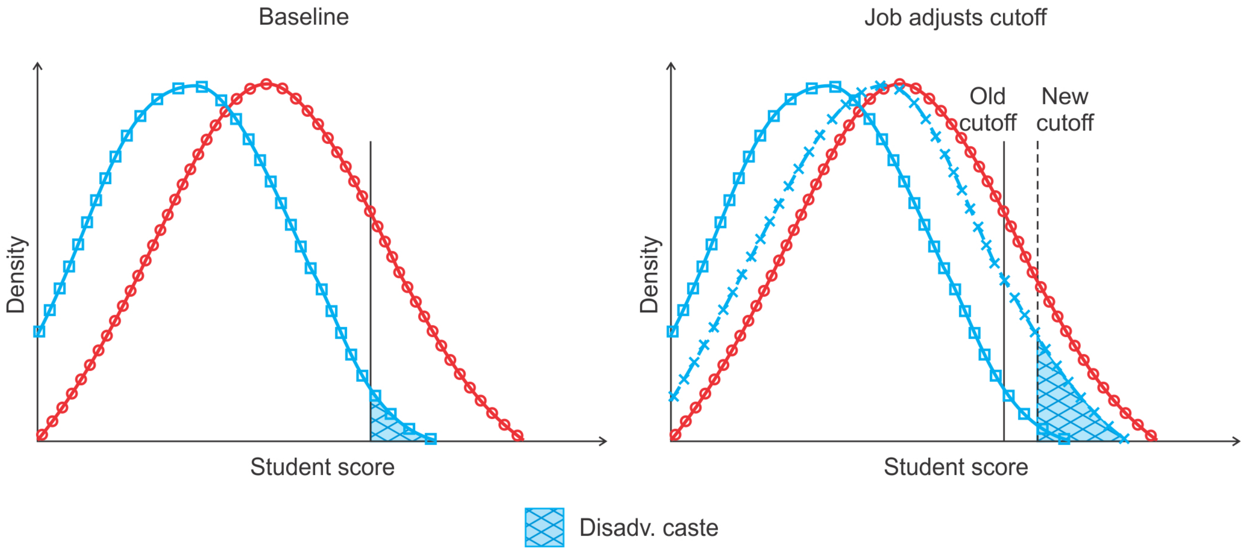

Figure 11: Disadvantaged Caste Hires under Perfectly Inelastic Supply of Jobs

Notes: In Figure 11, the distributions of advantaged caste "scores" are to the right of the distributions of disadvantaged caste "scores". "Scores" can be calculated from Equation 11. Under both counterfactual policies, the distribution of disadvantaged caste "scores" shifts to the right. When jobs adjust cutoffs to hire the same total number of students (in expectation) as in the baseline, the number of disadvantaged caste hires is at least as large as in the baseline. As shown in Figures 9 and 11, the number of disadvantaged caste hires when the supply of job slots is perfectly inelastic can be no more than the number disadvantaged caste hires when the supply of job slots is perfectly elastic. The number of disadvantaged caste hires is bounded above by the number of disadvantaged caste hires when the supply of job slots is perfectly elastic. The number of disadvantaged caste hires is bounded below by the number of disadvantaged caste hires when the supply of job slots is perfectly inelastic. Therefore, when jobs follow cutoff hiring rules, the model bounds the effects of both counterfactual policies on job placements of disadvantaged castes.

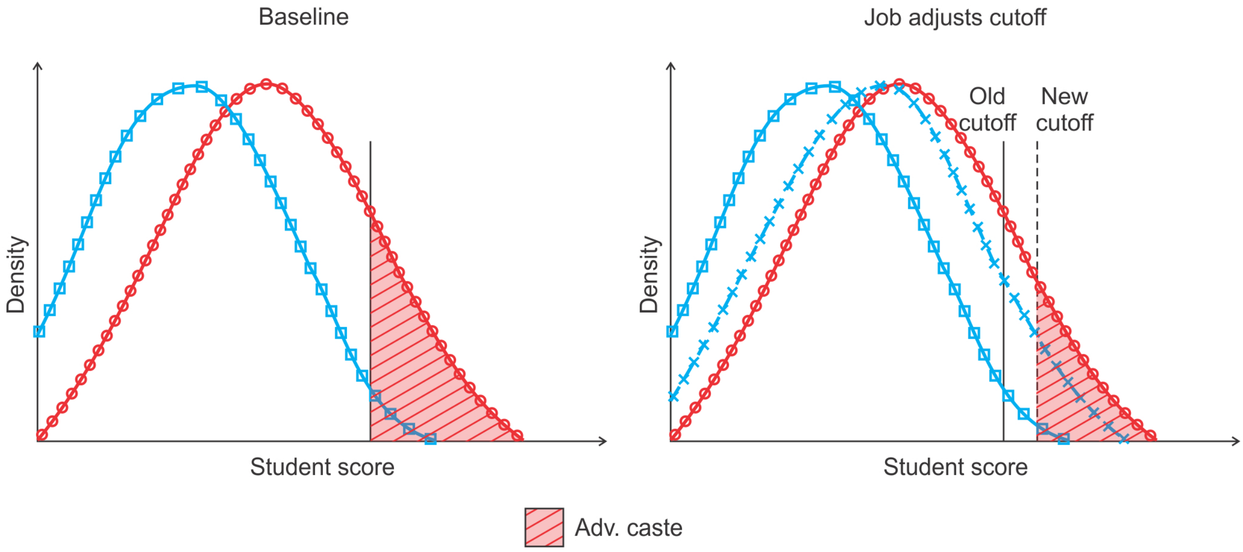

Figure 12: Advantaged Caste Hires under Perfectly Inelastic Supply of Jobs

Notes: In Figure 12, the distributions of advantaged caste "scores" are to the right of the distributions of disadvantaged caste "scores". "Scores" can be calculated from Equation 11. Under both counterfactual policies, the distribution of disadvantaged caste "scores" shifts to the right. As shown in Figure 12, the distribution of advantaged caste "scores" stays the same. When jobs adjust cutoffs, the number of advantaged caste hires falls compared to the number of advantaged caste hires in the baseline. As shown in Figures 10 and 12, the number of advantaged caste hires is bounded above by the number of advantaged caste hires when supply job slots is perfectly elastic. The number of advantaged caste hires is bounded below by the number of advantaged caste hires when the supply of job slots is perfectly inelastic. The displacement of advantaged castes from jobs is the highest when the supply of job slots is perfectly inelastic and lowest when the supply of job slots is perfectly elastic. Therefore, when jobs follow cutoff hiring rules, the model bounds the effects of both counterfactual policies on job displacements of advantaged castes.

8.1.2 Counterfactual Results

In this section, I compare the reductions in workplace caste disparities from a policy which provides direct cash subsidies to employers to those from a policy which improves the pre-college skills (college entrance exam scores) of disadvantaged castes.

8.1.2.1 Job Offers

The subsidy-equivalent for employers to remain indifferent between hiring an observably identical disadvantaged or advantaged caste is 4.8% of average salary ($2721). In contrast, using the weights on college entrance exam scores reported in Table 13, I find that the subsidy-equivalent for employers of a policy which equalizes the distribution of college entrance exam scores across castes is only 0.6% of average salary ($337). Equalizing the distribution of college entrance exam scores is worth about 8 times less to employers than direct compensation to hire more disadvantaged castes. Therefore, employer cash-subsidies increase job assignments and earnings of disadvantaged castes by substantially more than the "pre-college intervention" policy in absolute terms.

As an example to compare performances across policies, we will focus on the technology sector. The relative performances of both policies in the technology sector can be better understood through the lens of the model. From the perspective of a disadvantaged caste student, an increased job cutoff is equivalent to an increase in the salary paid by the same job. Both lower the probability of getting a job offer (see, Equation 18 and Table 13). Therefore, an increased job cutoff offsets some of the positive effect of the direct subsidy or the increase in entrance exam scores on hiring.

When cutoffs do not adjust under the "pre-college intervention" policy, the "subsidy" to hire disadvantaged castes is about 0.6% of average salary ($337). When cutoffs adjust under the policy of providing direct cash subsidies to employers, the net effect of the subsidy to hire disadvantaged castes, averaged over all jobs in the technology sector, is about 2% of average salary ($1135). The net effect of the subsidy when employers are provided cash subsidies is still more than three times the direct subsidy-equivalent of the "pre-college intervention" policy. Therefore, among jobs in the technology sector, even the lowest effects of employer cash-subsidies on job assignments of disadvantaged castes will typically be larger than the highest effects of the ”pre-college intervention” policy.

Table 16 shows the effects on job hiring in the technology sector under both policies. Under the policy of providing cash-subsidies to employers, job assignments of disadvantaged castes increase between 5% to 13% when cutoffs adjust and do not adjust, respectively. The effects on jobs assignments of disadvantaged castes under the “pre-college intervention” policy are substantially lower. Under the “pre-college intervention” policy, job assignments of disadvantaged castes increase between 2% to 5% when cutoffs adjust and do not adjust, respectively. Similar reasoning explains the relative performances of both policies among jobs in other sectors and pay categories.

Table 16: Job Offers by Sector in Baseline and Counterfactuals

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

Notes: Table 16 shows the fraction of job offers by caste in each sector under both baseline and counterfactuals.

The effects of employer cash subsidies in increasing job assignments of disadvantaged castes are most pronounced in the consulting sector. I focus on the more interesting case in which jobs adjust cutoffs. Table 14 shows that, on average, firms in the technology or manufacturing sectors have lower hiring cutoffs than those in the consulting sector. Hence, when cutoffs do not adjust under both policies, firms in the technology and manufacturing sectors draw a larger number of disadvantaged castes above their hiring thresholds than those in the consulting sector. On average, there is a larger excess supply of candidates above the hiring thresholds of firms in the manufacturing and technology sectors than those of firms in the consulting sector. Hence, to hire the same total number of students as before, firms in the technology and manufacturing sectors will increase hiring cutoffs by more, on average, than firms in the consulting sector (see, Appendix Tables E.26 and E.27). A larger increase in cutoffs implies a smaller net effect of the subsidy for hiring disadvantaged castes. Due to the smaller net effect of the subsidy for hiring disadvantaged castes, firms in the manufacturing and technology sectors will typically hire fewer disadvantaged castes, as a proportion of previous hires, than those in the consulting sector.

Table 16 shows the effects on job hiring in the consulting sector under the policy of providing direct cash subsidies to employers. Under this policy, job assignments of disadvantaged castes increase between 18% to 29% when cutoffs adjust and do not adjust, respectively. The effects of employer cash subsidies on disadvantaged caste hires in the technology and manufacturing sectors are smaller.

Details regarding relative performances of both policies on job offers within pay categories can be found in Appendix Table E.28.

8.1.2.2 Job Choices

The effects of employer cash subsidies in improving final job choices of disadvantaged castes are most pronounced in the consulting sector.

Two complementary mechanisms explain the result above. First, as a proportion of previous hires, direct cash subsidies to employers lead to substantially more disadvantaged castes hires in consulting jobs than the "pre-college intervention" policy (see, Table 16). Second, the effect of more disadvantaged caste hires on final job choices is amplified by both stronger student affinity for consulting jobs (see, Table 11) and the rich bundle of non-pecuniary amenities offered by such jobs as part of their overall compensation packages (see, Table 7).

Table 17 shows the effects on final job choices in the consulting sector under the policy of providing direct cash subsidies to employers. Under this policy, final job choices of disadvantaged castes improve between 22% to 29% when cutoffs adjust and do not adjust, respectively. The effects of employer cash subsidies on final job choices of disadvantaged castes in the technology and manufacturing sectors are smaller.

Table 17: Job Choices by Sector in Baseline and Counterfactuals

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

Notes: Table 17 shows the fraction of job choices by caste in each sector under both baseline and counterfactuals.

Details regarding relative performances of both policies on final job choices within pay categories can be found in Appendix Table E.29.

8.1.2.3 Unemployment

The policy of providing employers cash subsidies leaves fewer disadvantaged castes without jobs than the "pre-college intervention" policy.[15] As stated before, employer cash-subsidies ($2721) are worth more than 8 times the subsidy-equivalent of equalizing the distribution of college entrance exam scores ($337). Therefore, considerably more disadvantaged castes find jobs when employers are provided direct cash subsidies than under the "pre-college intervention" policy.

Table 18 shows the effects of counterfactual hiring policies on unemployment across castes. In the baseline, 36% of disadvantaged castes do not find jobs. Under the policy of providing cash-subsidies to employers, unemployment among disadvantaged castes is between 24% to 28% when cutoffs do not adjust and adjust, respectively. Under the "pre-college intervention" policy, unemployment among disadvantaged castes is between 31% to 33% when cutoffs do not adjust and adjust, respectively.

Table 18: Unemployment in Baseline and Counterfactuals

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

Notes: Table 18 shows unemployment in the baseline and counterfactuals for advantaged and disadvantaged castes. "PCI" stands for the pre-college intervention policy.

8.1.2.4 Earnings

Two complementary mechanisms explain the reduction in the earnings gap under both policies. First, there are large increases in disadvantaged caste hires in both the technology and consulting sectors (see, Table 16). Moreover, displaced advantaged castes get, on average, slightly "worse" jobs under both policies. Second, the comparatively higher pay and better

[15] I abstract away from aggregate disemployment effects financing such a policy may have.

bundle of non-pecuniary amenities offered by jobs in the technology and consulting sectors lead to more disadvantaged castes choosing such jobs (see, Tables 6 and 7). Overall, both mechanisms combine to explain the reduction in the earnings gap across castes under both policies.

Since direct cash subsidies to employers are worth almost 8 times the subsidy-equivalent of the "pre-college intervention" policy, the former policy reduces the earnings gap across castes by substantially more than the latter policy.

Figures 13 and 14 shows the earnings gap in the baseline and the counterfactuals. In the baseline, the earnings gap across castes is 11%. Under the policy of providing direct cash-subsidies to employers, the earnings gap across castes is between 6% to 8%, when cutoffs do not adjust and adjust, respectively. Under the "pre-college intervention" policy, the earnings gap across castes is between 9% to 10%, when cutoffs do not adjust and adjust, respectively.

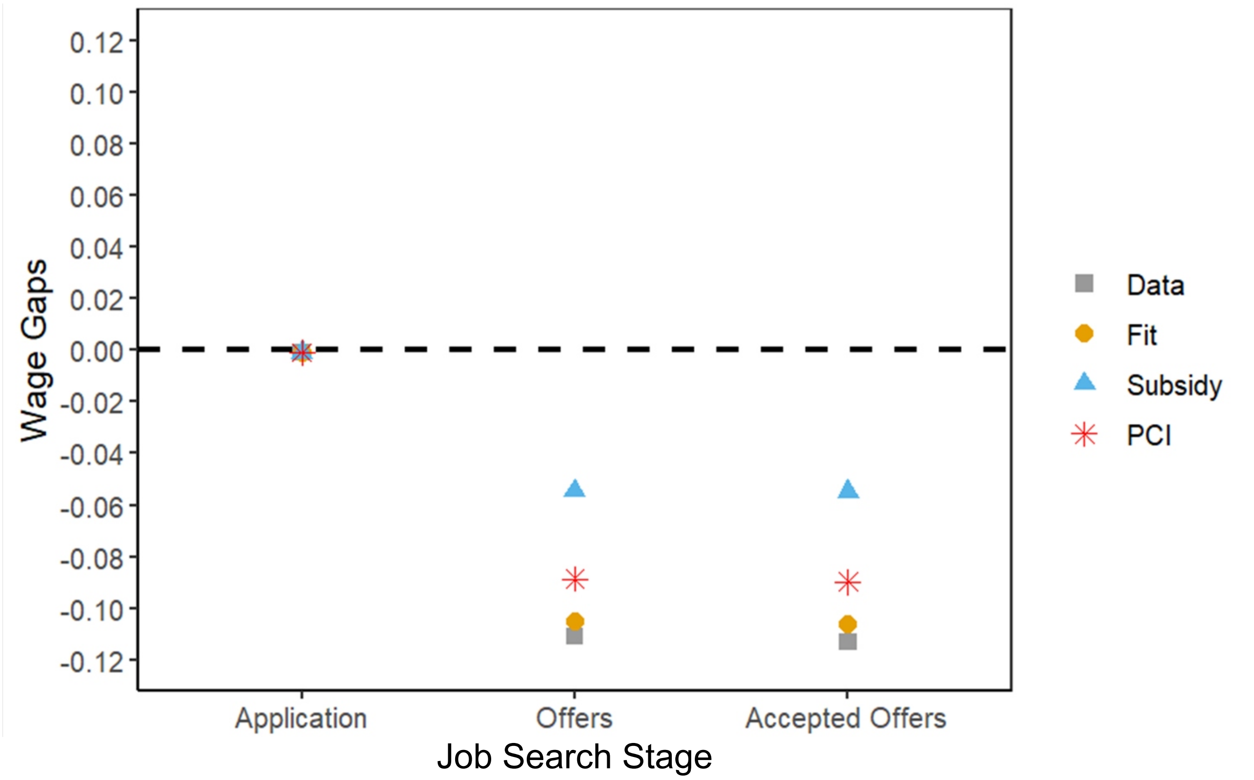

Figure 13: Model Fit and Counterfactual Wage Gaps When Supply of Jobs is Perfectly Elastic

Notes: Figure 13 shows model fit and counterfactual wage gaps under both policies. "Subsidy" refers to the policy of providing employers cash subsidies to make them indifferent between hiring an observably identical disadvantaged and advantaged caste. "PCI" refers to the "pre-college intervention" policy of equalizing the distribution of pre-college skills (entrance exam scores) across caste.

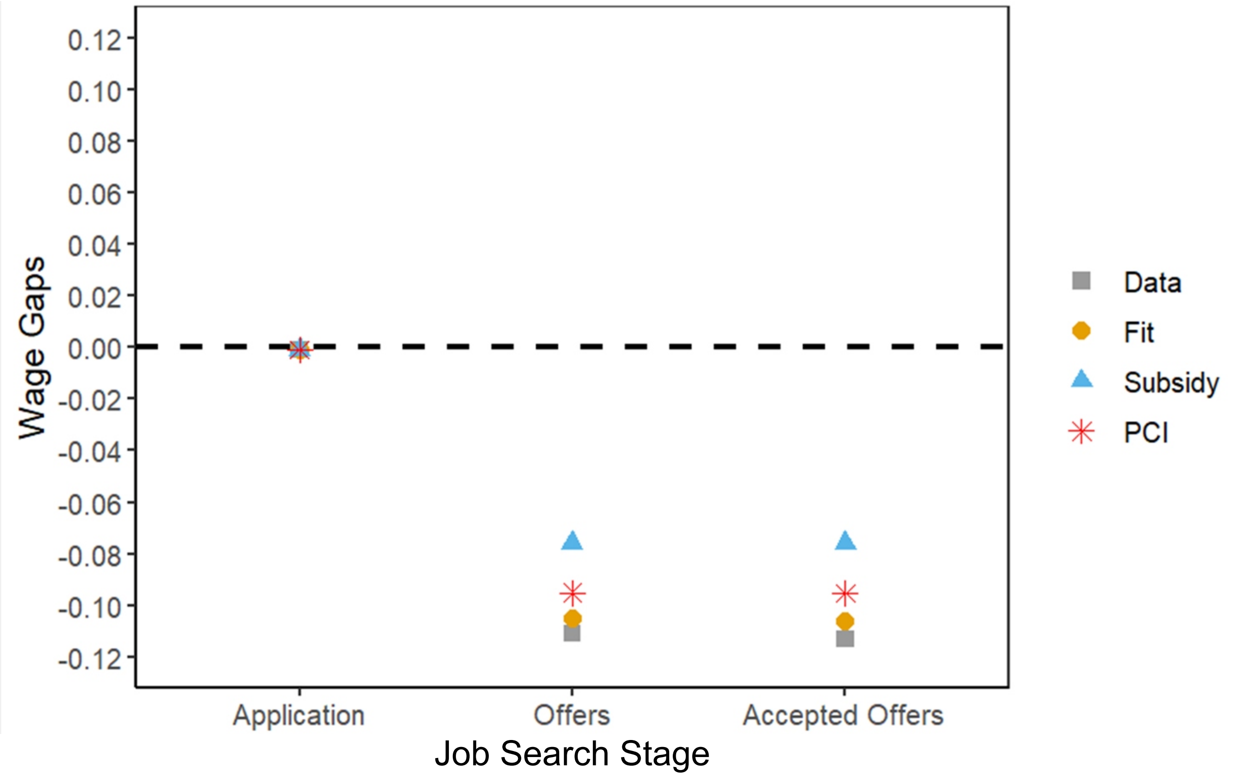

Figure 14: Model Fit and Counterfactual Wage Gaps When Supply of Jobs is Perfectly Inelastic

Notes: Figure 14 shows model fit and counterfactual wage gaps under both policies. "Subsidy" refers to the policy of providing employers cash subsidies to make them indifferent between hiring an observably identical disadvantaged and advantaged caste. "PCI" refers to the "pre-college intervention" policy of equalizing the distribution of pre-college skills (entrance exam scores) across caste.

8.1.2.5 Discussion

Subsidizing employers to hire members of disadvantaged groups has parallels in many countries, particularly in the U.S. and India. For example, The Work Opportunity Tax Credit (WOTC) in Wisconsin subsidies employers to hire welfare recipients, young food stamp recipients, poor veterans and youth from disadvantaged geographic areas. The subsidy varies according to the number of hours worked by the employee and can be as high as 40% of the first $6,000 in earnings, resulting in a maximum potential subsidy of $2,400 per new hire (Hamersma, 2005). In early 2020, the government of Kerala, a large southern state in India, announced a wage-subsidy scheme to promote women employment in new industries (ET Bureau, 2020). However, no such scheme exists in India for high-skilled workers belonging to historically disadvantaged groups.

While the policy of providing cash subsidies to employers increases job assignments and earnings of disadvantaged castes by more than the "pre-college intervention" policy, the two policies are not necessarily independent. Improvements in pre-college skills might also be a consequence of incentivizing firms to hire more disadvantaged castes. Theoretical works have posited that affirmative action policies might unintentionally lead to an equilibrium in which negative perceptions regarding abilities of intended beneficiaries might prevail (Coate and Loury, 1993; Craig and Fryer, 2018). However, empirical evidence on the effects of affirmative action policies have suggested that such concerns might be misplaced. Akhtari et al. (2018) show the affirmative action educational policies in the U.S. led to an increase in pre-college human capital investment as students anticipated increased returns to effort. In the Indian context, Khanna (2018) shows that affirmative action policies in government jobs increased schooling, with the average disadvantaged caste receiving an additional 0.8 years of education. Therefore, improvements in pre-college skills might also be induced by directly providing cash subsidies to employers as disadvantaged castes, anticipating larger returns in the labor market, increase pre-college human capital investment.

The "pre-college intervention" policy equalizes the distribution of college entrance exam scores across castes but keeps college GPA and the distribution of castes within college majors the same. Keeping GPA fixed in the counterfactuals is conservative since college GPA and college entrance exam scores are slightly negatively correlated (see, Table 4; Table 4; Appendix Tables E.1, E.2 and E.3). Moreover, improving the college entrance exam scores of disadvantaged castes does not improve their representation in more selective majors since affirmative action policies in college admissions equalize the distribution of castes within each major and, therefore, within each cohort.

8.1.2.6 Cost-Effectiveness

The previous sections focused on comparing the absolute effects of both counterfactual policies. However, policymakers might be more interested in the costs relative to welfare gains of policies. In this section, I perform back-of-the-envelope calculations to compare the cost-effectiveness of both policies. For this purpose, I use estimates from a meta-analysis comprising randomized experiments, spanning over two decades, which evaluated the effects of pre-college intervention programs on test scores of primary and secondary school students in India (Asim et al., 2015). From this study, I find that it costs about $45 (PPP) per student to achieve an average increase of 0.13 standard deviations in test scores. Using these estimates, I calculate the cost of improving test scores (college entrance exam scores) to achieve changes in job assignments and earnings of disadvantaged castes equivalent to those induced by direct cash subsidies to employers.

Even under extremely conservative assumptions, my results show that employer cash subsidies can be twice as cost-effective as the "'pre-college intervention" policy. From Table 13, I calculate improvements in college entrance exam scores (measured in standard deviation units) that would be equivalent to providing employers direct cash subsidies of 4.8% of average salary ($2721) to hire more disadvantaged castes. Given the weights on college entrance exam scores shown in Table 13, improvements in college entrance exam ranks equivalent to $2721 in direct cash subsidies are extremely large. For B.Tech. and Dual Degree students, improvements in college entrance exam scores of 4 and 5 standard deviations, respectively, are equivalent to $2721 in employer subsidies. For both M.Tech. and M.S. students, improvements in college entrance exam scores of a staggering 30 standard deviations are equivalent to $2721 in employer subsidies!

For the sake of argument, we will assume such large changes in college entrance exam scores are actually possible. To extrapolate costs of improvements in college entrance exam scores equivalent to $2721 in employer subsidies, I will use the cost estimate of test score increases calculated from Asim et al. (2015). Even under the *extremely conservative* assumption that costs are linear in test score improvements (Duflo et al., 2011; Costrell et al., 2008), employer cash-subsidies are twice as cost-effective as the "pre-college intervention" policy.

Alternatively, one could also price the "pre-college intervention" policy in the model and compare the model implied subsidy-equivalent to the cost of changing test scores calculated from the meta-analysis done by Asim et al. (2015). The "pre-college intervention" policy is worth a direct employer subsidy of 0.6% of average salary ($337). Improvements in college entrance exam scores equivalent to a direct employer subsidy of $337 can be calculated from Table 13. For B.Tech. and Dual Degree students, improvements in college entrance exam scores of 0.5 and 0.6 standard deviations, respectively, are equivalent to $337 in direct employer subsidies. For both M.Tech. and M.S. students, improvements in college entrance exam scores of approximately 4 standard deviations are equivalent to $337 in direct employer subsidies. Using cost estimates from Asim et al. (2015) and maintaining the assumption that costs are linear in test score improvements, direct cash subsidies to employers will still be twice as cost-effective as the "pre-college intervention" policy.

While improvements in college entrance exam scores presumably increase student productivity, providing cash-subsidies to employers does not. The cost-effectiveness calculations above do not take into account the productivity offset of improving college entrance exam scores. However, given the coefficients on college entrance exam scores reported in Table 13, my estimates suggest that the productivity offset is very small. These estimates complement recent studies evaluating labor market outcomes for college graduates in India which show that pre-college test scores play only modest roles in determining earnings upon graduation (Sekhri, 2020).

The cost-effectiveness comparison of the two policies reemphasises the potency of providing direct cash subsidies to employers to hire more disadvantaged castes. However, one must be judicious in drawing policy recommendations from this paper. An erroneous conclusion to draw from the paper would be that policies for improving pre-college skills are unnecessary. As shown in this paper, improvements in pre-college skills (college entrance exam scores) can still play an important role in improving job assignments and earnings of disadvantaged castes. However, at least in the short-run, this paper argues that employer cash-subsidies are the most cost-effective methods to improve hiring diversity.

8.2 Hiring Quotas

In this section, I evaluate the effects of a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes. Since the proportion of final hires are balanced on caste, I only evaluate the effects of quotas on the fraction of students who are not recruited through the formal placement process.

In India, private sector firms do not hire in accordance with government-mandated quotas (Madheswaran, 2008; Newman and Thorat, 2010; Verma, 2012). However, quotas or reservation-based policies have been extensively used to improve the representation of disadvantaged castes in government jobs and educational institutions. Therefore, due to familiarity with reservation-based hiring policies, imposing hiring quotas in the private sector could be a politically more feasible alternative to promote diversity.[16]

8.2.1 Implementation and Results

8.2.1.1 Implementation

My model of the job placement process can readily accommodate hiring quotas. In contrast to firm responses to alternative hiring policies considered in this paper, firms now explicitly decide on two hiring thresholds: one for the advantaged castes and vice-versa.[17]

Solving for two cutoffs per job, instead of just one, introduces additional computational

[16]Hiring quotas have also made headway in the developed world. Finland requires state-owned enterprises to reserve 40% of board seats for females (Bertrand et al., 2019). In 2020, Nasdaq Inc., a U.S. based corporation, filed a proposal with the Securities and Exchange Commission requiring listed companies to have "at least one woman on their boards, in addition to a director who is a racial minority or one who self-identifies as lesbian, gay, bisexual, transgender or queer" (Osipovich and Otani, 2020).

[17]I use the word "explicitly" because, under previous counterfactual policies, firms implicitly solved for two hiring thresholds. The cutoffs for disadvantaged castes were shifted up by the common intercept term ("caste penalty") in Equation 11.

complexity. The computational challenge can be overcome due to a key institutional feature of the job placement process, which prevents students from attending interviews on future interview days conditional on receiving job offers on the current interview day (see, Section 3.2). Hence, firms allotted the first interview day can ignore firms allotted the second interview day onward as legitimate competition. Firms allotted the second interview day can, therefore, take the decisions of firms allotted the first interview day as given, and can ignore firms allotted the third interview day onward as legitimate competition, and so on.[18]

8.2.1.2 Results

By construction, hiring quotas equalize the composition of employed advantaged and disadvantaged castes. However, unlike the direct subsidy or the "pre-college intervention" policy, quotas lead to an *increase* in the fraction of students who are unemployed through the formal placement process as firms counteract the policy by making fewer job offers in total.[19]

Under the quota policy, a firm needs to balance hiring of advantaged and disadvantaged castes. All things equal, if a firm derives substantially lower utility from disadvantaged castes, then it may be willing to hire an additional disadvantaged caste only if the accompanying advantaged caste hire gives it sufficiently high utility. Conversely, hiring an additional advantaged caste comes at the price of going further to the left of the skill distribution of disadvantaged castes (see, Equation 11; Figures 9, 10, 11 and 12). A job slot is no longer filled if marginal utility of filling it exceeds marginal cost, but instead if the average marginal utility of filling two job slots — one filled by an advantaged caste and the other by a disadvantaged caste — exceeds the average marginal cost. It is worth noting that if a firm does not have a hard constraint on its hiring size, then quotas may either increase or decrease the fraction of students who are not recruited through the formal placement process.[20] If the penalty on disadvantaged castes is large enough to make the average marginal

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

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

[20]In my model, a firm's hiring cap is denoted by $\overline{M_j}$ (see, Equation 14), which is *not* treated as a parameter.

utility lower than the average marginal cost, a firm will counteract the quota policy by reducing aggregate hiring, even though the composition of total hires is balanced on caste.

Table 19: Unemployment in Baseline and Under Hiring Quotas

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

Notes: Table 19 shows unemployment in the baseline and under hiring quotas.

Table 19 shows the effect of hiring quotas on unemployment of advantaged and disadvantaged castes. As expected, more disadvantaged castes find jobs under quotas. The proportion of unemployed disadvantaged castes falls from 36% to 31%. However, the disemployment effects of quotas on advantaged castes are severe. On average, nearly two advantaged castes become unemployed for a newly employed disadvantaged caste. The proportion of unemployed advantaged castes increases from 25% to 35%. Overall, quotas act like a net tax on hiring and increase the overall fraction of students who are not recruited through the formal placement process by nearly 7%, relative to the baseline.

Appendix Table E.30 shows the hiring cutoffs for advantaged and disadvantaged castes under the quota policy for each pay category, job sector and job title.

9 Conclusion

To my knowledge, this is the first paper to formally study a job placement process. Quantifying the aggregate and distributional consequences of job placement processes is crucial. Job placement processes proposed by college career offices serve as a critical segue between college and the first job, the long term consequences of which have been extensively documented (Kahn et al., 2014). Therefore, studies of job placement processes allow for a better understanding not only of the roles played by workers and firms in determining labor market outcomes but also of suitable channels for policy interventions to remedy potential disparities.

This paper studies the entire job recruitment process of an elite college to quantify mechanisms driving labor market disparities and evaluate policies to promote hiring diversity. To do so, I employ novel data on every stage of the job placement process of a leading technical college in India, half of which is comprised of students from historically disadvantaged groups or disadvantaged castes. The administrative data includes rich student-level information on all stages of job search, including job applications, pre-interview screening tests, job interviews, job offers, and job choices. I make three main contributions. First, I quantify the earnings drop off across castes at each stage of job search. In particular, I show that the compositions of job applications and job choices by students do not explain the gaps in earnings across castes. Pre-interview screening tests including written aptitude tests (first round) and group discussion based "soft skills" tests (second round) explain only a small fraction of the drop off in earnings. Therefore, almost all of the earnings drop off occurs between one-on-one interviews (third round) and job offers. These findings suggest that policies which provide information about jobs, modify preferences, or improve performance at university are unlikely to close the earnings gap.

Second, guided by the sequential decomposition of the earnings gap, I build a model of the job placement process. The model is of general interest and can serve as a prototype for the studies of the placement processes of engineering schools, business schools, law schools, and other institutions that use formal job placement mechanisms. My estimates show that caste disparities in hiring are driven not by differential caste-preferences over job characteristics but by hiring decisions of firms. Additionally, modelled unobservables play an economically small role in jointly determining observed choices.

Third, I study three counterfactual policies to promote hiring diversity. In the first policy, I consider a subsidy in which firms are compensated by the cash-equivalent amount that makes them indifferent between hiring an observably identical advantaged or disadvantaged caste. In the second policy, I consider a "pre-college intervention" which equalizes the distribution of pre-college test scores across castes. Counterfactual simulations show that cash subsidies to employers fare substantially better in improving earnings and job assignments of disadvantaged castes in absolute terms. To compare cost-effectiveness of both policies, I use the model estimates and calculate the change in test scores required to induce the same employment gains for the disadvantaged caste as those under the direct subsidy. The change in test scores is large because the model estimates imply that test scores play only a small role in hiring. Even under extremely conservative assumptions, a back-of-the-envelope calculation based on cost estimates of improving student test scores in India shows that cash subsidies to employers can be twice as cost-effective as the "pre-college intervention" policy. Finally, in the third policy, I consider a government-mandated hiring quota in which firms are required to hire an equal proportion of advantaged and disadvantaged castes. However, unlike the previous two policies, quotas act like a net tax on hiring. In particular, a hiring quota which equalizes the caste-share of employed students leads to a 7% increase in the fraction of students who are not recruited through the formal placement process.

This paper also opens up many avenues for further research. For example, one could ask what the optimal job placement mechanism would be. Theoretical first-best mechanisms, like the one proposed by Kelso and Crawford (1982), may not be well-suited for distributional welfare (or, equity). However, ad-hoc job placement processes might sacrifice substantial aggregate welfare (or, efficiency) for modest improvements in distributional welfare. An ideal job placement process would balance both distributional and aggregate welfare of participants. Another study could involve quantifying the inefficiencies (if, any) due to early matching or unraveling. In the job placement process I study, students cannot participate in job interviews scheduled on the next interview day conditional on receiving job offers from firms interviewing them on the current interview day. However, it is not obvious if such a job placement process is sub-optimal, especially if the job placement process has distributional goals. While theoretical works positing the inefficiencies of unraveling in labor markets have been large, they have been so far accompanied by a very slim body of empirical evidence. In future work, I plan to pursue these and other related avenues of research.

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A Appendix I: Calculation of Job Offer Probabilities

The formula for $f_k(Z_i^k|A_i^k)$ (see, Equation 10) can be illustrated through a simple example. Suppose there are only two interview days and two jobs. Let $A_i = (1,1)$ and $Z_i = (1,0)$ i.e. student i applied to both jobs and received an offer only from job $j = 1$. With two jobs and two days, the sets D^1 and D^2 comprising vectors of indicator variables for the interview day allotment for each job have $2^J = 2^2 = 4$ elements in total i.e.

$$D^1 = D^2 = \Big\{D_1^1, D_2^1, D_3^1, D_4^1\Big\} = \Big\{(1,0), (0,1), (0,0), (1,1)\Big\}.$$

Consider an element $D_1^1 = (1,0) \in D^1$ which denotes the event that job $j = 1$ was given interview day $k = 1$ while job $j = 2$ was not. Then, $A_i^1 = A_i \times D_1^1 = (1,0)$, $Z_i^1 = Z_i \times D_1^1 = (1,0)$ and

$$\begin{aligned} f_k(Z_i^k|A_i^k) &= f_1(Z_i^1|A_i^1) = f_1((1,0)|(1,0)). \\ &= \pi_1^i \cdot 1. \\ &= \pi_1^i. \end{aligned}$$

where the third equality above follows from Equation 10. In the above example, even though the student applied to both jobs *overall*, the day 1 application set of student i is $A_i^1 = (1,0)$ i.e. the student applied to only one job ($j = 1$) which was given a day 1 interview slot. Given his day 1 application set, the student gets an offer from job $j = 1$ with probability π_1^i and does not get an offer from job $j = 2$ with probability 1 since his *day 1 application set* has no application for job $j = 2$. Note that in the formula for $f_k(Z_i^k|A_i^k)$ we are assuming that jobs allotted the same interview day make offers independently (see, Equation 10). The assumption of independent offers on the same interview day is plausible since all daywise offers are announced within a short interval of time after all jobs have conducted their interviews (see, Section 3.2).

As another example, consider another element $D^1_4 = (1,1) \in D^1$ which denotes the event that both jobs were given a day 1 interview slot. Then, $A^1_i = A_i \times D^1_4 = (1,1)$, $Z^1_i = Z_i \times D^1_4 = (1,0)$ and

$$\begin{aligned} f_k(Z^k_i | A^k_i) &= f_1(A^1_i | Z^1_i) = f_1((1,0)|(1,1)). \\ &= \pi^i_1 \cdot (1 - \pi^i_2). \end{aligned}$$

where the third equality above follows from Equation 10. In this example, the day 1 application set of student i is $A^1_i = (1,1)$ which coincides with his overall application set. Given his day 1 application set, the student gets an offer from job $j = 1$ with probability π^i_1 and does not get an offer from job $j = 2$ with probability $(1 - \pi^i_2)$.

A.1 Job Offer Probabilities

For this section, suppose there are only 2 jobs and 2 interview days. From Appendix Section E.9, it is reasonable to assume interview day allotments to jobs as exogenous. However, for the purposes of the illustration of the formula for job offer probabilities, it will be easier to also assign probabilities to interview day allotments. Recall that Z_i the offer vector for student i and A_i is the application vector for student i. Let $f(Z_i|A_i)$ denote the probability of realizing Z_i given A_i. Then, $f(Z_i|A_i)$ is defined as

$$f(Z_i|A_i) = \begin{cases} \prod_{l=0,1,\dots,K} \widetilde{f}_l(\underbrace{(0,0,\dots,0)}_{J}|A_i) & \text{if } Z_{ij} = 0 \ \forall j \\ \sum_{k=1}^{K} \left(\prod_{l=0,1,\dots,k-1} \widetilde{f}_l(\underbrace{(0,0,\dots,0)}_{J}|A_i) \right) \left[\sum_{\{m: Z_i \times D^k_m = Z_i\}} \Pr(D^k_m) f_k(Z^k_i|A^k_i) \right] & \text{else.} \end{cases} \tag{20}$$

where $\widetilde{f}_l(\underbrace{(0,0,\dots,0)}_{J}|A_i) = \sum_{\{m:\underbrace{(0,0,\dots,0)}_{J} \times D^l_m = \underbrace{(0,0,\dots,0)}_{J}\}} \Pr(D^l_m) f_l(Z^l_i|A^l_i)$ is the probability of not getting any offer on interview day l, $m = 1, \dots, 2^{|\{1,\dots,J\}|}$ and D^l_m is defined as in section A.

For completeness,

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

- If, for a given k, there is no such m such that $Z_i \times D^k_m = Z^k_i$, then set $\sum_{\{m:Z_i\times D^k_m=Z^k_i\}} \Pr(D^k_m) f_k(Z^k_i|A^k_i) = 0$.

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

I take an example to illustrate the formula for $f(Z_i|A_i)$. Let $A_i = (1,1)$. I will show that

$$\sum_{Z_i} f(Z_i|A_i) = 1. \tag{21}$$

For convenience, I set some values for each of $\Pr(D^k_l)$ where $k = 1,2$ and $l = 1,\ldots,2^2 = 1,2,3,4$ (the example goes through with arbitrary values for these probabilities).

$$\begin{aligned} D^1 &= \left\{D^1_1, D^1_2, D^1_3, D^1_4\right\} = \left\{\underbrace{(1,0)}_{0.2}, \overbrace{(0,1)}^{0.4}, \underbrace{(0,0)}_{0.2}, \overbrace{(1,1)}^{0.2}\right\}. \\ D^2 &= \left\{D^2_1, D^2_2, D^2_3, D^2_4\right\} = \left\{\overbrace{(1,0)}^{0.4}, \underbrace{(0,1)}_{0.2}, \overbrace{(0,0)}^{0.2}, \underbrace{(1,1)}_{0.2}\right\}. \end{aligned} \tag{22}$$

The probabilities are denoted above each element belonging to the interview allotment set D^k for $k = 1,2$. For example, $\Pr(D^1_1) = 0.2$, $\Pr(D^2_1) = 0.4$ and so on. Note that with 2 jobs and 2 interview days, the event $(0,1)_1$[21] is the same as the event $(1,0)_2$ i.e. if job $j = 2$ gets allotted the first interview day and job $j = 1$ does not, then job $j = 1$ will get allotted the second interview day since each job must get allotted one (and, only one) interview day. Additionally, we will assume that $\pi^i_1 = \pi^i_2 = \pi$ where π^i_j is the probability that jobs $j = 1,2$ make offers to applicant i (this is not essential but makes the exposition which follows simpler). We use the formula for $f_k(Z^k_i|A^k_i)$ in Equation 10 to calculate $f(Z_i|A_i)$ in Equation 20 for each of the following cases:

[21] $(1,0)_1$ is shorthand for $(1,0) \in D^1$. Similarly, $(1,0)_2$ is shorthand for $(1,0) \in D^2$.

(1) $Z_i = (1, 0)$.

Following Equation 20, I first calculate the inner sum i.e. $\sum_{\{m:Z_i\times D_m^k = Z_i\}} \Pr(D_m^k) f_k(Z_i^k|A_i^k)$ for each $k = 1, 2$. From the definitions of D^1 and D^2 in Equation 22 above, it follows that

- For $k = 1$

$$\begin{aligned}
&\sum_{\{m:Z_i\times D_m^1=(1,0)\}} \Pr(D_m^1) f_1((1,0)|A_i^1).\\
&= \Pr(D_1^1) f_1((1,0)|A_i^1) + \Pr(D_4^1) f_1((1,0)|A_i^1).\\
&= 0.2 f_1((1,0)|(1,0)) + 0.2 f_1((1,0)|(1,1)).\\
&= 0.2\pi + 0.2\pi(1-\pi) = 0.4\pi - 0.2\pi^2.
\end{aligned}$$

- For $k = 2$

$$\begin{aligned}
&\sum_{\{m:Z_i\times D_m^2=(1,0)\}} \Pr(D_m^2) f_2((1,0)|A_i^2).\\
&= \Pr(D_1^2) f_2((1,0)|A_i^2) + \Pr(D_4^2) f_2((1,0)|A_i^2).\\
&= 0.4 f_2((1,0)|(1,0)) + 0.2 f_2((1,0)|(1,1)).\\
&= 0.4\pi + 0.2\pi(1-\pi) = 0.6\pi - 0.2\pi^2.
\end{aligned}$$

Recall that $\widetilde{f}_0((0,0)|A_i) = 1$.

To calculate $\widetilde{f}_1((0,0)|A_i)$, I use the following formula:

$$\begin{aligned}
\widetilde{f}_1((0,0)|A_i) = &\sum_{\{m:(0,0)\times D^1_m=(0,0)\}} \Pr(D^1_m) f_1((0,0)|A^1_i). \\
&= \Pr(D^1_1) f_1((0,0)|A^1_i) + \Pr(D^1_2) f_1((0,0)|A^1_i). \\
&+ \Pr(D^1_3) f_1((0,0)|A^1_i) + \Pr(D^1_4) f_1((0,0)|A^1_i). \\
&= 0.2 f_1((0,0)|(1,0)) + 0.4 f_1((0,0)|(0,1)) + 0.2 f_1((0,0)|(0,0)) + 0.2 f_1((0,0)|(1,1)). \\
&= 0.2(1-\pi) + 0.4(1-\pi) + 0.2 + 0.2(1-\pi)^2. \\
&= 1 - \pi + 0.2\pi^2.
\end{aligned}$$

Hence, for $A_i = (1,1)$ and $Z_i = (1,0)$

$$\begin{aligned}
&f((1,0)|(1,1)). \\
&= \sum_{k=1}^{K=2} \left(\prod_{l=0,1,\ldots,k-1} \widetilde{f}_l((0,0)|A_i) \right) \left[\sum_{\{m:Z_i\times D^k_m=(1,0)\}} \Pr(D^k_m) f_k(Z^k_i|A^k_i) \right]. \\
&= \underbrace{\widetilde{f}_0((0,0)|A_i) \left[\sum_{\{m:Z_i\times D^1_m=(1,0)\}} \Pr(D^1_m) f_1((1,0)|A^1_i) \right].}_{k=1} \\
&\underbrace{+ \widetilde{f}_1((0,0)|A_i) \left[\sum_{\{m:Z_i\times D^2_m=(1,0)\}} \Pr(D^2_m) f_2((1,0)|A^2_i) \right].}_{k=2} \\
&= (0.4\pi - 0.2\pi^2) + [1 - \pi + 0.2\pi^2](0.6\pi - 0.2\pi^2).
\end{aligned}$$

(2) $Z_i = (1,1)$.

Following Equation 20, I first calculate the inner sum i.e. $\sum_{\{m:Z_i\times D^k_m=Z_i\}} \Pr(D^k_m) f_k(Z^k_i|A^k_i)$ for each $k = 1,2$. From the definitions of D^1 and D^2 from Equation 22, it follows that

- For $k = 1$

$$\sum_{\{m: Z_i \times D_m^1 = (1,1)\}} \Pr(D_m^1) f_1((1,1)|A_i^1).$$
$$= \Pr(D_4^1) f_1((1,1).|A_i^1)$$
$$= 0.2 f_1((1,1)|(1,1)).$$
$$= 0.2\pi^2.$$

- For $k = 2$

$$\sum_{\{m: Z_i \times D_m^2 = (1,1)\}} \Pr(D_m^2) f_2((1,1)|A_i^2).$$
$$= \Pr(D_4^2) f_2((1,1)|A_i^2).$$
$$= 0.2 f_2((1,1)|(1,1)).$$
$$= 0.2\pi^2.$$

Recall that $\widetilde{f}_0((0,0)|A_i) = 1$.

To calculate $\widetilde{f}_1((0,0)|A_i)$, I use the following formula:

$$\begin{aligned}
\widetilde{f}_1((0,0)|A_i) &= \sum_{\{m:(0,0)\times D^1_m=(0,0)\}} \Pr(D^1_m) f_1((0,0)|A^1_i). \\
&= \Pr(D^1_1) f_1((0,0)|A^1_i) + \Pr(D^1_2) f_1((0,0)|A^1_i). \\
&+ \Pr(D^1_3) f_1((0,0)|A^1_i) + \Pr(D^1_4) f_1((0,0)|A^1_i). \\
&= 0.2 f_1((0,0)|(1,0)) + 0.4 f_1((0,0)|(0,1)) + 0.2 f_1((0,0)|(0,0)) + 0.2 f_1((0,0)|(1,1)). \\
&= 0.2(1-\pi) + 0.4(1-\pi) + 0.2 + 0.2(1-\pi)^2. \\
&= 1 - \pi + 0.2\pi^2.
\end{aligned}$$

Hence, for $A_i = (1,1)$ and $Z_i = (1,1)$

$$\begin{aligned}
& f((1,1)|(1,1)). \\
&= \sum_{k=1}^{K=2} \left(\prod_{l=0,1,\ldots,k-1} \widetilde{f}_l((0,0)|A_i) \right) \left[\sum_{\{m:Z_i \times D^k_m=(1.1)\}} \Pr(D^k_m) f_k(Z^k_i|A^k_i) \right]. \\
&= \underbrace{\widetilde{f}_0((0,0)|A_i) \left[\sum_{\{m:Z_i \times D^1_m=(1.1)\}} \Pr(D^1_m) f_1((1,1)|A^1_i) \right].}_{k=1} \\
&\underbrace{+ \widetilde{f}_1((0,0)|A_i) \left[\sum_{\{m:Z_i \times D^2_m=(1,1)\}} \Pr(D^2_m) f_2((1,1)|A^2_i) \right].}_{k=2} \\
&= 0.2\pi^2 + [1 - \pi + 0.2\pi^2] 0.2\pi^2.
\end{aligned}$$

(3) $\underline{Z_i = (0,1)}$.

Following Equation 20, I first calculate the inner sum i.e. $\sum_{\{m:Z_i \times D^k_m=Z_i\}} \Pr(D^k_m) f_k(Z^k_i|A^k_i)$ for each $k = 1,2$. From the definitions of D^1 and D^2 from Equation 22 above, it follows that

- For $k = 1$

$$\sum_{\{m:Z_i \times D_m^1 = (0,1)\}} \Pr(D_m^1) f_1((0,1)|A_i^1).$$

$$= \Pr(D_2^1) f_1((0,1)|A_i^1) + \Pr(D_4^1) f_1((0,1)|A_i^1).$$

$$= 0.4 f_1((0,1)|(0,1)) + 0.2 f_1((0,1)|(1,1)).$$

$$= 0.4\pi + 0.2\pi(1-\pi) = 0.6\pi - 0.2\pi^2.$$

- For $k = 2$

$$\sum_{\{m:Z_i \times D_m^2 = (0,1)\}} \Pr(D_m^2) f_2((0,1)|A_i^2).$$

$$= \Pr(D_2^2) f_2((0,1)|A_i^2) + \Pr(D_4^2) f_2((0,1)|A_i^2).$$

$$= 0.2 f_2((0,1)|(0,1)) + 0.2 f_2((0,1)|(1,1)).$$

$$= 0.2\pi + 0.2\pi(1-\pi) = 0.4\pi - 0.2\pi^2.$$

Recall that $\widetilde{f}_0((0,0)|A_i) = 1$.

To calculate $\widetilde{f}_1((0,0)|A_i)$, I use the following formula:

$$\widetilde{f}_1((0,0)|A_i) = \sum_{\{m:(0,0) \times D_m^1 = (0,0)\}} \Pr(D_m^1) f_1((0,0)|A_i^1).$$

$$= \Pr(D_1^1) f_1((0,0)|A_i^1) + \Pr(D_2^1) f_1((0,0)|A_i^1).$$

$$+ \Pr(D_3^1) f_1((0,0)|A_i^1) + \Pr(D_4^1) f_1((0,0)|A_i^1).$$

$$= 0.2 f_1((0,0)|(1,0)) + 0.4 f_1((0,0)|(0,1)) + 0.2 f_1((0,0)|(0,0)) + 0.2 f_1((0,0)|(1,1)).$$

$$= 0.2(1-\pi) + 0.4(1-\pi) + 0.2 + 0.2(1-\pi)^2.$$

$$= 1 - \pi + 0.2\pi^2.$$

Hence, for $A_i = (1,1)$ and $Z_i = (0,1)$

$$
\begin{aligned}
& f((0,1)|(1,1)). \\
& = \sum_{k=1}^{K=2} \Bigg(\prod_{l=0,1,\ldots,k-1} \widetilde{f}_l((0,0)|A_i) \Bigg) \Bigg[\sum_{\{m: Z_i \times D_m^k = (0.1)\}} \Pr(D_m^k) f_k(Z_i^k|A_i^k) \Bigg]. \\
& = \underbrace{\widetilde{f}_0((0,0)|A_i) \Bigg[\sum_{\{m: Z_i \times D_m^1 = (0.1)\}} \Pr(D_m^1) f_1((0,1)|A_i^1) \Bigg].}_{k=1} \\
& \underbrace{+ \widetilde{f}_1((0,0)|A_i) \Bigg[\sum_{\{m: Z_i \times D_m^2 = (0,1)\}} \Pr(D_m^2) f_2((0,1)|A_i^2) \Bigg].}_{k=2} \\
& = (0.6\pi - 0.2\pi^2) + [1 - \pi + 0.2\pi^2](0.4\pi - 0.2\pi^2).
\end{aligned}
$$

(4) $Z_i = (0,0)$.

From Equation 20 above, it follows that

$$
\begin{aligned}
f((0,0)|(1,1)) &= \prod_{l=0,1,2} \widetilde{f}_l((0,0)|A_i). \\
&= \widetilde{f}_0((0,0)|A_i) \times \widetilde{f}_1((0,0)|A_i) \times \widetilde{f}_2((0,0)|A_i). \\
&= \widetilde{f}_1((0,0)|A_i) \times \widetilde{f}_2((0,0))|A_i). \\
&= (1 - \pi + 0.2\pi^2) \cdot (1 - \pi + 0.2\pi^2).
\end{aligned}
$$

since

$$
\begin{aligned}
\widetilde{f}_2((0,0)|A_i) = & \sum_{\{m:(0,0) \times D_m^2 = (0,0)\}} \Pr(D_m^2) f_2((0,0)|A_i^2). \\
& = \Pr(D_1^2) f_2((0,0)|A_i^2) + \Pr(D_2^2) f_2((0,0)|A_i^2). \\
& + \Pr(D_3^2) f_2((0,0)|A_i^2) + \Pr(D_4^2) f_2((0,0)|A_i^2). \\
& = 0.4 f_2((0,0)|(1,0)) + 0.2 f_2((0,0)|(0,1)) + 0.2 f_2((0,0)|(0,0)) + 0.2 f_2((0,0)|(1,1)). \\
& = 0.4(1 - \pi) + 0.2(1 - \pi) + 0.2 + 0.2(1 - \pi)^2. \\
& = 1 - \pi + 0.2\pi^2.
\end{aligned}
$$

Also, $\widetilde{f}_1((0,0)|A_i) = 1 - \pi + 0.2\pi^2$ from the calculations above. Collecting all terms and recalling that $A_i = (1,1)$, it follows that

$$
\begin{aligned}
&\sum_{Z_i} f(Z_i|A_i) = f((1,0)|(1,1)) + f((1,1)|(1,1)) + f((0,1)|(1,1)) + f((0,0)|(1,1)).\\
&= \underbrace{(0.4\pi - 0.2\pi^2) + [1-\pi+0.2\pi^2](0.6\pi - 0.2\pi^2)}_{f((1,0)|(1,1))} + \underbrace{0.2\pi^2 + [1-\pi+0.2\pi^2](0.2\pi^2)}_{f((1,1)|(1,1)))}\\
&+ \underbrace{(0.6\pi - 0.2\pi^2) + [1-\pi+0.2\pi^2](0.4\pi - 0.2\pi^2)}_{f((0,1)|(1,1))} + \underbrace{(1-\pi+0.2\pi^2)\cdot(1-\pi+0.2\pi^2)}_{f((0,0)|(1,1))}.\\
&= [1-\pi+0.2\pi^2]\Bigg(\underbrace{0.6\pi - 0.2\pi^2 + 0.2\pi^2 + 0.4\pi - 0.2\pi^2 + 1 - \pi + 0.2\pi^2}_{=1}\Bigg).\\
&+ 0.4\pi - 0.2\pi^2 + 0.2\pi^2 + 0.6\pi - 0.2\pi^2.\\
&= 1 - \pi + 0.2\pi^2 + 0.4\pi - 0.2\pi^2 + 0.2\pi^2 + 0.6\pi - 0.2\pi^2 = 1.
\end{aligned}
$$

Clearly, $f(Z_i|A_i) \geq 0$ for any offer vector Z_i and any application vector A_i.

B Appendix II: Estimation Details and Standard Errors

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

$$\mathcal{L}_i(Z_i^*, C_i^* | A_i, \overline{X_i}, \theta) = \int_q f(Z_i^* | A_i, \overline{X_i}, q, \theta) \times \Pr(C_i^* = j | Z_i^*, \overline{X_i}, q, \theta)\, dF(q|\theta). \tag{23}$$

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

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

$$\widehat{\mathcal{L}}_i(\theta) = \frac{1}{R} \sum_{r=1}^{R} \mathcal{L}_i^r(\theta). \tag{24}$$

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

$$\widehat{\theta}_{MSL} = \arg\max_\theta \frac{1}{N} \sum_{i=1}^{N} \log \widehat{\mathcal{L}}_i(\theta) = \arg\max_\theta \left(\frac{1}{N} \sum_{i=1}^{N} \log \left[\frac{1}{R} \sum_{r=1}^{R} \mathcal{L}_i^r(\theta) \right] \right). \tag{25}$$

If R rises at any rate with N, the MSL estimator is consistent. If R rises faster than $\sqrt{N}$, the MSL estimator is $\sqrt{N}$-consistent and has the same distribution as the conventional maximum likelihood estimator (Train, 2003).

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

$$\widehat{H} = \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \log \widehat{\mathcal{L}}_i(\widehat{\theta}_{MSL}) \nabla_\theta \log \widehat{\mathcal{L}}_i(\widehat{\theta}_{MSL})'. \tag{26}$$

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

C Appendix III: Modeling Job Applications

The presence of a large number of jobs in my institutional setting makes it challenging to incorporate job application behavior in the main model. As shown in Section 4.2, the differences in the compositions of job applications across castes are not economically significant. Hence, I do not model job applications in the main model. However, I show below that the model can be extended to incorporate job application behavior as well. Therefore, the decision to omit job applications is not a restriction on the generality of the model of the job placement process.

C.1 Choosing Jobs Instead of Job Portfolios

The key trick in modeling job application behavior is to convert the student's search from one over potential *job application portfolios* to one over *jobs*. The intuition is simple: for any job a student applied to, the expected marginal benefit from adding the job to his application vector should exceed the cost of applying to the job. Similarly, for any job a student did not apply to, the expected marginal benefit from adding the job to his application vector should be lower than the cost of applying to the job.

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

$$A_{i/k} = \begin{cases} \{m | m \in A_i, m \neq k\} & \text{if } k \in A_i \\ \{m | m \in A_i\} \cup \{k\} & \text{if } k \notin A_i \end{cases} \tag{27}$$

Then, it must be true that

$$MV_{i/k} > 0 \quad \forall k \in A_i \tag{28}$$

$$MV_{i/p} < 0 \quad \forall p \notin A_i \tag{29}$$

To make the computation tractable, one proceeds by reducing the search space by eliminating dominated strategies. Following Howell (2010), we categorize strategies into four main categories: adjacent, non-adjacent, single-swap and multiple-swap strategies. Consider an application vector, $A_i = \{\text{Goldman Sachs}, \text{Microsoft}, \text{Google}\}$. Then,

(i) Removing "Goldman Sachs" from the application vector is an *adjacent strategy*.

(ii) Removing both "Goldman Sachs" and "Google" from the application vector is a *non-adjacent strategy*.

(iii) Replacing "Goldman Sachs" with "Facebook" in the application vector is a *single-swap strategy*.

(iv) Replacing "Goldman Sachs" and "Microsoft" with "Facebook" and "Uber" in the application vector is a *multiple-swap strategy*.

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

The cost of job applications can be modeled in the following manner. The cost function $c(a, \overline{X_i}, \eta_i)$ comprises a fixed and a marginal cost component. In particular,[22]

$$c(a, \overline{X_i}, \eta_i) = \underbrace{1\{|a| > 0\} \times \exp(\delta_0^f + \overline{X_i}' \delta_1^f)}_{\text{fixed cost}} + |a| \times \underbrace{\exp(\delta_0^m + \overline{X_i}' \delta_1^m)}_{\text{marginal cost}} + \sum_{j=1}^{J} a_j \eta_{ij} \tag{30}$$

[22]Note that modeling application behavior à la Howell (2010) would not identify fixed costs. However, I include the fixed cost term in Equation 30 above for illustrative purposes.

where $\overline{X_i}$ are the covariates of student i and $|a| = \sum_{j=1}^{J} a_j$ is the total number of applications. The unobserved cost η_{ij} is incurred for all applications in which $a_j = 1$ i.e. for all firms j to which a student submits an application.

Then, by using a logit kernel smoother (Train, 2003), one can show that

$$\Pr(A_i^* = a|\theta, \overline{X_i}, q_i) = \prod_{j\in A_i^*}\left[\frac{\exp\{\frac{MV_{i/j}(\theta,q,\overline{X_i})}{\lambda}\}}{1+\exp\{\frac{MV_{i/j}(\theta,q,\overline{X_i})}{\lambda}\}}\right]\prod_{k\notin A_i^*}\left[\frac{1}{1+\exp\{\frac{MV_{i/k}(\theta,q,\overline{X_i})}{\lambda}\}}\right] \tag{31}$$

where $\lambda > 0$ is a scale parameter chosen by the researcher.

Finally, following Kapor (2020), we can extend the definition of the equilibrium in Section 5.4 and include application choices as part of the equilibrium tuple.

D Appendix IV: Institutional Setting and Data

This paper uses administrative data collected by the career office of a leading post-secondary educational institution in India. The career office collects information on job applications, pre-interview screening tests, job interviews, job offers and job choices. The career office also makes rules regarding the job placement process and requires that students and firms abide by them. Section 3.2 lays out the rules of the job placement process in my institutional setting. The job placement rules delineated by the career office are similar to those followed by most post-secondary and post-graduate engineering institutions, M.B.A. programs and law schools in India. The administrative dataset has detailed information on students and firms.

Pre-College Skills

The administrative dataset has detailed information on the pre-college skills of students. Pre-college skills include entrance exam scores which are the basis of admissions to the post-secondary educational institution. These entrance exam scores are analogous to S.A.T. and A.C.T. scores used for undergraduate admissions in the United States. I also have information on scores from national-level board examinations completed in the 10th and the 12th grades.

Within-College Performance

The administrative dataset has detailed information on within-college performance of students. Measures of within-college performance include college GPA, college major and college degree and coursework. For Master's degree holders, I have additional information on undergraduate institution, undergraduate degree, undergraduate major and specialization within degree (e.g. computational fluid mechanics, solid mechanics, aircraft propulsion etc.). Most Master's degree students choose to write senior projects on their degree specialization. I have information on the main focus of their senior projects ("experimental fluid mechanics with a focus on interfacial phenomena"), keywords from their senior projects ("surface phenomena contact, angle hysteresis, wetting angle characterization"), whether the projects were experimental or analytical or both ("experimental and analytical") and their software programming skills ("Fortran and MATLAB"). Bachelor's degree holders do not have additional specialization within the major but sometimes combine their Bachelor's degree with a one-year Master's program, and graduate in five years. While I do not have measures of software programming skills or degree specialization for Bachelor's degree holders, I can directly proxy for relevant on-the-job skills by including dummies for getting past the written test, group discussion and the one-on-one interview stages.

Previous Labor Market Experience

For both Bachelor's and Master's degree holders, I have detailed information on both summer and winter internships completed by students. Internship information includes employment durations, job salaries, job locations, job sectors and detailed job descriptions. Internship job descriptions include eligibility criterion, desired skills and expectations on the job etc. For Master's degree holders, I also have information on previous full-time job employments, including employment durations, job salaries, job locations, job sectors, detailed job descriptions, specialization within the major (like, computational fluid mechanics) and software programming skills.

Job Characteristics

A "job" means a job designation within a firm. For example, a firm can hire for both engineering and managerial positions. I have access to detailed job descriptions. Job descriptions include job designations, job salaries, job locations, desired skills, expectations on the job and details on non-pecuniary amenities. Job salaries typically vary across but not within college degrees (see, 3.3.4). Job salaries do not vary across majors, caste or gender. Non-pecuniary amenities or fringe benefits include stocks, signing bonuses, performance bonuses, medical insurance, relocation allowances etc. I also have dollar amounts for how much a job pays as a signing bonus, stock options, performance bonus etc. although this information is incomplete.

Demographics

Key demographic variables include gender and caste.

Job Applications

The administrative dataset has detailed information on job applications. Students apply for jobs through a centralized job application portal. Applying to a job involves clicking on the name of the job in the application portal. Job applications do not require additional cover letters or other statements. Employers only request curriculum vitae which are uploaded by students on the centralized application portal. Eligibility for a job depends upon a combination of major, degree and GPA. We also have information regarding each job's eligibility criterion.

Pre-Interview Screening Tests

Pre-interview screening tests often involve both written and verbal components. The written component is a timed aptitude test. The verbal component, also called group discussion (GD), tests students' ability to effectively communicate among their peers on a given topic. While I do not have access to scores on pre-interview screening tests, I have data on the final outcomes i.e. whether or not the student progressed forward. (see, Section 4.3).

Job Interviews

I have access to data on outcomes from job interviews (see, Section 4.3). Job interviews are typically taken after one or two rounds of pre-interview screening tests.

Job Offers and Job Choices

I have access to data on job offers and final job choices. Job offers are given to students in accordance with the rules of the placement process (see, Section 3.2).

E Appendix V: Tables and Figures

E.1 GPA is Negatively Correlated with Entrance Exam Score

Table E.1: GPA for Dual Degree Students is Negatively Correlated with Entrance Exam Score

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

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

Table E.2: GPA for M.Tech. Degree Students is Negatively Correlated with Entrance Exam Score

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

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

Table E.3: GPA for M.S. Degree Students is Negatively Correlated with Entrance Exam Score

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

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

E.2 Large Earnings Gap Between Castes

Table E.4: Earnings Gap with Score Quantiles

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

Notes: Table E.4 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), dummies for entrance exam score quartiles are included. In column (3), dummies for entrance exam score quintiles are included. In column (4), dummies for entrance exam score deciles are included. Full regression results are available on request. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.5: Earnings Gap with Fully-Flexible Polynomials

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

Notes: Table E.5 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a natural cubic spline regression with three degrees of freedom is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available on request. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E.3 The Earnings Gap is Conservative

Table E.6: Average GPA of Students versus those of Students Without Jobs

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

Notes: Table E.6 compares the average GPA of students versus those of students without jobs. T-tests are conducted for differences in overall means versus means of students without jobs within each caste. Significance denoted by asterisks are shown in the third and fourth columns. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.7: Average Entrance Exam Scores of Students versus those of Students Without Jobs

Bachelor of Technology (B.Tech.) Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-1617.89	-3707.45	−1879.32*	−4315.18**
Dual Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-2096.60	-4067.13	−2602.79***	−5743.80***
Master of Technology (M.Tech.) Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-653.94	-2445.64	−1052.61***	−3310.677**
Master of Science (M.S.) Degree			
Overall		Students Without Jobs	
Adv. Caste	Disadv. Caste	Adv. Caste	Disadv. Caste
-558.94	-1416.09	-642.18	-1411.26

Notes: Table E.7 compares the average entrance exam scores (ranks) of students versus those of students without jobs. Ranks have been re-normalized so that higher numbers are better. T-tests are conducted for differences in overall means versus means of students without jobs within each caste. Significance denoted by asterisks are shown in the third and fourth columns. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E.4 Job Applications Do Not Explain the Earnings Gap

Table E.8: Salaries of Jobs to Which Students Applied with Fully-Flexible Polynomials

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

Notes: Table E.8 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log average salary of jobs to which students applied. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), estimates from a natural cubic spline with three degrees of freedom are reported. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available on request. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table E.9: No. of Jobs to Which Students Applied Fully-Flexible Polynomials

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

Notes: Table E.9 includes estimates from an earnings regression run on the sample of all students who graduated with jobs. Dependent variable is log number of firms to which students applied. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), estimates from a natural cubic spline with three degrees of freedom are reported. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available on request. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

E.5 Earnings Gap Most Pronounced in the Consulting Sector

Table E.10: Earnings Gap in the Manufacturing Sector

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

Notes: Table E.10 includes estimates from an earnings regression run on the sample of all students who graduated with jobs in the technology sector. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.11: Earnings Gap in the Technology Sector

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

Notes: Table E.11 includes estimates from an earnings regression run on the sample of all students who graduated with jobs in the technology sector. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.12: Earnings Gap in the Consulting Sector

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

Notes: Table E.12 includes estimates from an earnings regression run on the sample of all students who graduated with jobs in the consulting sector. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E.6 Job Offer Disparities Most Pronounced in Consulting Jobs

Table E.13: Offer Probabilities for Jobs in the Technology Sector

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

Notes: Table E.13 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got an offer from a job in the technology sector. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table E.14: Offer Probabilities for Jobs in the Consulting Sector

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

Notes: Table E.14 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got an offer from a job in the consulting sector. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table E.15: Offer Probabilities for Jobs in the Manufacturing Sector

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

Notes: Table E.15 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got an offer from a job in the manufacturing sector. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E.7 Job Offer Disparities Most Pronounced in Client Facing Jobs

Table E.16: Offer Probabilities in Client Facing Jobs

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

Notes: Table E.16 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got a client facing job. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.17: Offer Probabilities in Non-Client Facing Jobs

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

Notes: Table E.17 includes estimates from linear probability, logit and probit models. Dependent variable is whether or not a student got a non-client facing job. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E.8 Earnings Gap Most Pronounced in Client Facing Jobs

Table E.18: Earnings Gap in Client Facing Jobs

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

Notes: Table E.18 includes estimates from an earnings regression run on the sample of all students who graduated with client facing jobs. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table E.19: Earnings Gap in Non-Client Facing Jobs

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

Notes: Table E.19 includes estimates from an earnings regression run on the sample of all students who graduated with non-client facing jobs. Dependent variable is log earnings. Controls include college GPA, college degree, college major, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College major includes dummies for each major. College degree includes dummies for each degree. Each column is a separate regression. In column (1), all controls enter linearly. In column (2), a fully-flexible quadratic polynomial regression is estimated with all possible interactions between controls. In column (3), a fully-flexible cubic polynomial regression is estimated with all possible interactions between controls. In column (4), a fully-flexible natural cubic spline regression is estimated with all possible interactions between controls. The results are robust to other reasonable choices of degrees of freedom. Full regression results are available upon request. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

E.9 Interview Days Can be Predicted Using Firm Characteristics

Table E.20: Predicting Interview Days with Job Characteristics Only

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

Notes: Table E.20 includes measures of predictive accuracy of interview day assignments given firm characteristics. Dependent variable is the interview day assigned to a firm. Controls include job salaries, job sectors and job titles. In column (1), an ordered logistic model is estimated. In column (2), a random forest model is estimated. In column (3), a decision tree model is estimated. Accuracy is the total number of correct predictions divided by the total number of observations. The Kappa statistic, which lies between 0 and 1, measures how classification results compare to values assigned by chance. Full regression results are available on request.

Table E.21: Predicting Interview Days with Job Characteristics and "Firm Identity"

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

Notes: Table E.21 includes measures of predictive accuracy of interview day assignments given firm characteristics and measures of "firm identity". "Firm identity" is proxied by previous interview day assignment of the same firm. Other controls include job salaries, job sectors and job titles. Dependent variable is the interview day assigned to a firm. In column (1), an ordered logistic model is estimated. In column (2), a random forest model is estimated. In column (3), a decision tree model is estimated. Accuracy is the total number of correct predictions divided by the total number of observations. The Kappa statistic, which lies between 0 and 1, measures how classification results compare to values assigned by chance. Full regression results are available on request.

E.10 Salaries for Select Firms in the Same Location

Table E.22: Salaries for Select Firms in the Same Location

Firm Name	Job Designation	Job Type	Glassdoor Salary ($ PPP)	Sample Salary ($ PPP)
McKinsey & Company	Business Analyst	Domestic	76,741.4	83,452.6
Microsoft Corporation	Software Engineer	Domestic	70,165.3	70,838.2
Amazon.com, Inc.	Software Engineer	Domestic	70,188.3	82,644.6
Microsoft Corporation	Software Engineer	Non-Domestic	126,839	136,000

Notes: Table E.22 includes salaries in USD (PPP) of select firms in the sample. Column (1) includes the firm name, column (2) includes job desgination, column (3) includes the job type, column (4) includes salary from Glassdoor or Levels.fyi and column (5) includes salary in the sample. The PPP conversion factor is taken from the OECD website. Domestic salaries are taken from the Glassdoor website. Non-domestic salaries are taken from the Levels.fyi website.

E.11 Non-Selective Majors Are As Less Likely As Selective Majors to Get Major-Neutral Jobs

Table E.23: Offer Probabilities in Major-Neutral Jobs for Selective Versus Non-Selective Majors

	Dependent Variable: Got an Offer		
Coefficient	LPM	Logit	Probit
Non-Selective Majors	-0.023 (0.014)	-0.023 (0.014)	-0.019 (0.013)
N	4189	4189	4189
R^2	0.122	0.137	0.136
Adjusted R^2	0.118	0.129	0.128

Notes: Table E.23 includes estimates from linear probability, logit and probit models. Major-neutral jobs are those which hire across all majors within a college degree. Dependent variable is whether or not a student a student got a job offer. Controls include college GPA, college degree, entrance exam score, pre-college skills including grades in 10th and 12th grade national level examinations and previous labor market experience including details of summer and winter internships. College degree includes dummies for each degree. In column (1), a linear probability model (LPM) is estimated. In column (2), a logit model is estimated. In column (3), a probit model is estimated. Pseudo R^2 is reported for logit and probit regressions. Full regression results are available on request. $p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

E.12 Major Assignments Can be Predicted Using Student Characteristics

Table E.24: Predicting Major Choice for B.Tech. and Dual Degree Students

Dependent Variable: Assigned a Selective Major		
Coefficient	B.Tech.	Dual Degree
Accuracy	0.904	0.948
95% CI	[0.841, 0.948]	[0.896, 0.979]
Kappa	0.768	0.892

Notes: Table E.24 includes measures of predictive accuracy of major assignments given student characteristics. Dependent variable is whether or not a student was assigned a selective major. Controls include caste, college entrance exam scores, scores on 10th and 12th grade national level examinations. Bachelor of Technology (B.Tech.) and Dual Degree students are admitted through a common entrance exam. Selective majors are Computer Science, Electrical Engineering, Mechanical Engineering, Civil Engineering and Chemical Engineering. Both columns report estimates from separate logistic regressions. Accuracy is the total number of correct predictions divided by the total number of observations. The Kappa statistic, which lies between 0 and 1, measures how classification results compare to values assigned by chance. Full regression results are available on request.

E.13 Major Assignments Can be Predicted Using Student Characteristics

Table E.25: Predicting Major Choice for M.Tech. and M.S. Degree Students

Dependent Variable: Assigned a Selective Major		
Coefficient	M.Tech.	M.S.
Accuracy	0.932	0.929
95% CI	[(0.875, 0.969]	[0.841, 0.976]
Kappa	0.841	0.852

Notes: Table E.25 includes measures of predictive accuracy of major assignments given student characteristics. Dependent variable is whether or not a student was assigned a selective major. Controls include caste, college entrance exam scores, scores on 10th and 12th grade national level examinations and undergraduate GPA. Master of Technology (M.Tech.) and Master of Science (M.S.) Degree students are admitted through a common entrance exam. Selective majors are Computer Science, Electrical Engineering, Mechanical Engineering, Civil Engineering and Chemical Engineering. Both columns report estimates from separate logistic regressions. Accuracy is the total number of correct predictions divided by the total number of observations. The Kappa statistic, which lies between 0 and 1, measures how classification results compare to values assigned by chance. Full regression results are available on request.

E.14 Counterfactual Job Cutoffs (Cash-Equivalent Subsidy)

Table E.26: Select Counterfactual Job Cutoffs by Pay Category, Job Sector and Job Title

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

Notes: Table E.26 includes counterfactual job cutoffs by pay category, job sector and job title under a policy in which employers are subsidized the cash-equivalent amount to remain indifferent between an observably identical advantaged or disadvantaged caste.

E.15 Counterfactual Job Cutoffs (Pre-College Intervention)

Table E.27: Select Counterfactual Job Cutoffs by Pay Category, Job Sector and Job Title

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

Notes: Table E.27 includes counterfactual job cutoffs by pay category, job sector and job title under the "pre-college intervention" policy. The "pre-college intervention" policy equalizes the distribution of pre-college skills (entrance exam scores) across caste.

Table E.28: Job Offers by Sector in Baseline and Counterfactuals

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

Notes: Table E.28 shows the fraction of job offers by each pay category under both baseline and counterfactuals.

Table E.29: Job Choices by Sector in Baseline and Counterfactuals

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

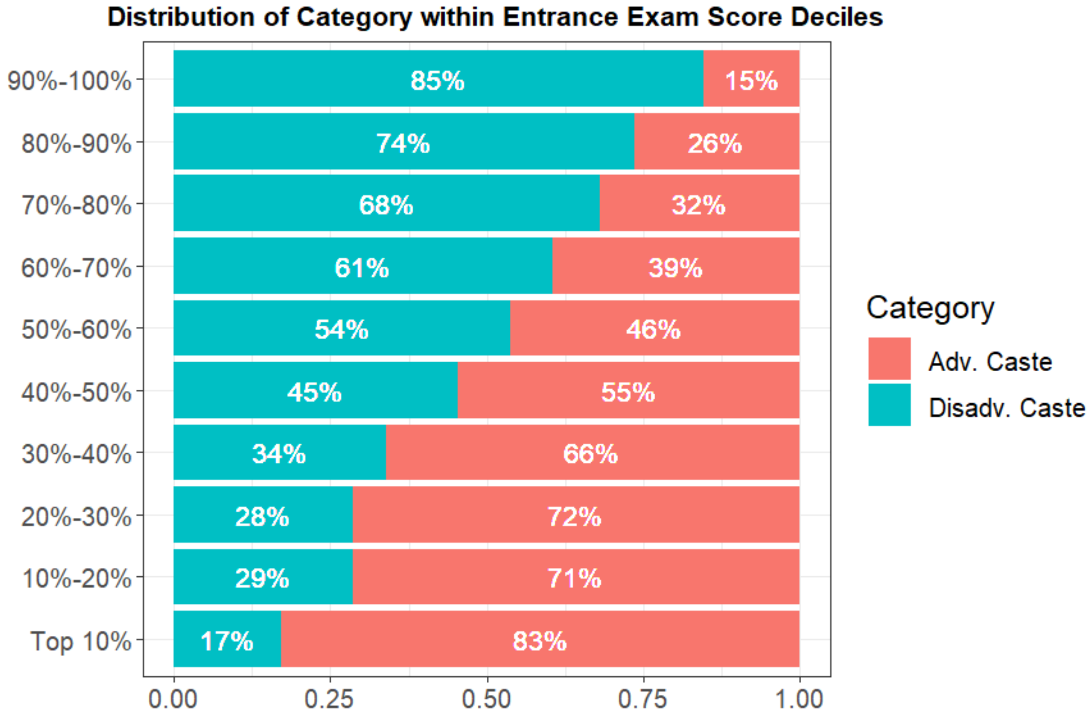
Notes: Table E.29 shows the fraction of job choices by each pay category under both baseline and counterfactuals.

E.16 Counterfactual Job Cutoffs (Hiring Quotas)

Table E.30: Select Counterfactual Job Cutoffs by Pay Category, Job Sector and Job Title

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

Notes: Table E.30 includes counterfactual job cutoffs by pay category, job sector and job title under hiring quotas. Notice that firms solve for two hiring cutoffs under quotas, one for the disadvantaged caste and the other for the advantaged caste.



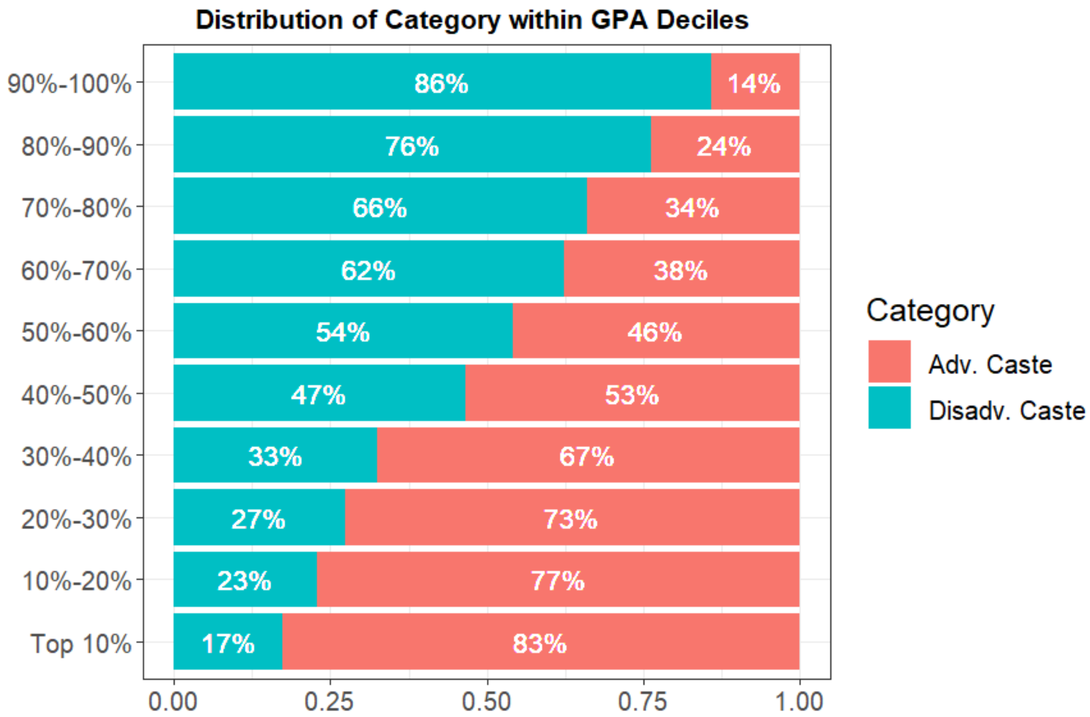


Figure A.1

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