Labor Market Discrimination in Delhi: Evidence from a Field Experiment

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Abstract

We study the role of caste and religion in India's new economy sectors – software and call-centers – by sending 3160 fictitious resumes in response to 371 job openings in and around Delhi (India) that were advertised in major city papers and online job sites. We randomly allocate caste-linked surnames across resumes in order to isolate the effect of caste on applicants' job-search outcomes. We find no evidence of discrimination against non-upper-caste (i.e. Scheduled Caste, Scheduled Tribe, and Other Backward Caste) applicants for software jobs. We do find larger and significant differences between callback rates for upper-castes and Other Backward Castes (and to a lesser extent Scheduled Castes) in the case of call-center jobs. There is no evidence of discrimination against Muslims for either of the two kinds of jobs we apply for. Overall, the evidence suggests that applicants' caste identities do not significantly affect the callback decisions of firms in these rapidly-growing sectors of the Indian economy.

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1 Introduction

In India, caste is closely correlated with socio-economic status. Upper-caste Hindus have better economic outcomes than both non-upper-caste Hindus (Scheduled Castes, Scheduled Tribes, and Other Backward Classes), and Muslims, who constitute India's largest religious minority group. Detailed breakdowns of employment status and occupation by caste are hard to come by; however, the 2001 Census reports that while 3.5 per cent of Indians are classified as 'marginal workers', who were employed less than 6 months of the preceding year, this figure is 10.9 per cent for Scheduled Castes and 6.5 per cent for Muslims. The Sachar Committee, a government committee set up to probe the economic and educational status of Muslims in India claimed that Muslims had the highest unemployment rate of any socio-religious group in India (Sachar 2006). No systematic data about the representation of different caste and religious groups in different occupations is readily available, but anecdotal evidence on specific occupations suggests that non-upper-castes are under-represented relative to their population proportions. For example, surveys of workers in the IT industry in Chennai and Bangalore, respectively, found that between 75 and 86 per cent belonged to 'upper castes' and there were no Scheduled Caste workers in their samples. Nationally, non-upper-castes constitute around 51 per cent of the population (Upadhya and Vasavi 2006, Krishna and Brihmadesam 2006).

To what extent is the hypothesized under-representation of non-upper-caste groups in skilled occupations and sectors the result of discrimination by employers? Some commentators argue that it is the relative lack of suitably-qualified people from these groups that is responsible for their under-representation. In contrast to this, politicians representing Backward and Scheduled Castes argue that even when people from traditionally under-represented groups gain the adequate qualifications, they are shut out of good jobs due to discriminatory hiring practices. Answering this question is difficult, given that researchers possess much less information about potential employees than employers do, so that workers who appear identical to researchers may look very different to employers.

In this paper, we adopt a resume audit methodology similar to that used in Bertrand and Mullainathan (2004), to analyze whether firms in India's fast-growing 'new economy' sectors - namely software and 'call-centers' – discriminate against equally-skilled members of historically disadvantaged caste groups (Scheduled Castes, or SCs and Other Backward Castes, or OBCs) and Muslims. We send resumes in response to job advertisements seeking people to work in software or call-centers in and around Delhi from major Delhi newspapers and the largest job websites in India and measure whether our fictitious applicants were called back or not. We vary the caste or religion of the applicant by randomly assigning caste/religion-identified last names (such as Sharma, Bhatia or Aggarwal, all upper-caste last names, or Paswan, Manjhi or Pasi, all SC last names) to our fictitious candidates, typically sending two resumes in each caste cell. In the case of software jobs, we also vary the perceived 'quality' of the applicant by randomly using one high-quality and one low-quality resume in each caste cell. In all, we responded to 371 job ads, of which 106 jobs were call-center jobs and the rest software jobs.

Our results are more nuanced than the strong race-based callback differentials found in Bertrand and Mullainathan (2004). We find no evidence that non-upper-castes are called back less often than equally qualified upper-caste applicants for software jobs, nor do we find any callback differences between upper-caste Hindus and Muslims for either of the two kinds of jobs we apply for. We do, however, find larger and significant differences between callback rates for upper-castes and OBCs (and to a lesser extent SCs) in the case of call-center jobs. These are less demanding in terms of formal qualifications and technical skills than software jobs. But they require employees with better English-speaking abilities and other 'soft skills', such as familiarity with telephone etiquette and American culture, plausibly the sorts of qualities potential employers may be tempted to guess from what information or clues a resume provides about an applicant's social background. Among applicants to software jobs, SC applicants have the highest return to having a high- rather than low-quality resume. However, we find that OBCs both have the biggest callback gaps with upper-castes for the relatively less-skilled call-center jobs but also get no return to having higher-quality resumes for technical software jobs.

We also find some differences by gender in the case of call-center jobs, with the results for SCs being driven entirely by callback differentials for male applicants, while the callback deficit is much higher for OBC women than OBC men. However, the smaller number of call-center jobs we were able to respond to leads to a small sample size when we break our applicants into caste-gender cells, preventing us from exploring this in detail.

The rest of this paper is organized as follows. Section 2 provides some background on caste and religious divisions in India and existing affirmative action policies. Section 3 provides a brief summary of previous empirical work on discrimination at the hiring stage. Section 4 explains the experimental design, including the rationale for choosing the sectors/jobs we focus on, the generation of identities for our fictitious applicants, and how resumes were created, assigned and sent, and callbacks tracked. Section 5 presents the main results of our work. Section 6 concludes.

2 Background: Caste and Religion in India

Hindu society in India was historically divided into endogamous sub-groups that were ranked hierarchically in a complex system of social stratification. This system had its roots in the ancient Hindu system of 'varna', which divided people into four categories based on their occupations. While historians are divided on when caste became strictly hereditary and how stable the rankings within the hierarchy were, by the early modern period, each region of India had a social structure that involved a complex web of castes and sub-castes related to each other by economic and patronage links that had both horizontal and vertical divisions. The caste system is complex, as a huge literature in social anthropology attests to (Dumont 1970, Ghurye 1961, Srinivas 1957, and Beteille 1969 are classic social-anthropological works on the caste system in India, while Beteille 1992 is a major recent works on the topic). However, several fundamental features of the caste system as it exists today are important in motivating the questions studied in this paper and understanding the choices made at the experimental design stage, and these are discussed briefly in the rest of this section.

First, while there is a great deal of variation between different regions of India in which groups occupy different parts of the caste hierarchy, it would be accurate to say that while the top and bottom of the caste hierarchy are well-defined and understood by people in most parts of India, there is considerable fuzziness about the precise position of groups between these extremes. Thus, Brahmin castes sit at the top of the caste hierarchy everywhere in India, followed by several non-Brahmin upper caste groups, who were traditionally powerful either by virtue of land ownership (Rajputs in Rajasthan, Jats in Punjab, Bhumihars in Uttar Pradesh and Bihar, for example), or education and access to professional/literate occupations (Baidyas in Bengal, Baniyas in most of North India, Kayasthas in Uttar Pradesh, Bihar and Bengal, and Khatris in Punjab, for example). Together, these are what we refer to as 'upper castes'. For example, Brahmins constitute about 5 per cent of India's population but 40 per cent of India's Associate Supreme Court Justices since 1950 have been Brahmins, and 37 per cent of the top tier of the Civil Service, the Indian Administrative Service, were Brahmins as of 2007 (Outlook 2007).

At the other end of the hierarchy, a heterogeneous group of castes were historically treated as 'untouchable' by the upper castes, and some such caste groups existed everywhere in India, constituting about 16.2 per cent of the population as of the last available estimates (Census of India 2001). These groups were historically considered 'unclean' and not permitted to use public facilities such as wells, schools, temples, etc., and forced to live in specific parts of the village or town in order to minimize contact between them and the upper castes. Occupational segregation and denial of access to education were key features of the discrimination faced by these groups, who were consigned to perform those jobs that upper caste Hindus considered 'unclean', such as working with dead animals or human bodies, garbage disposal, and the manual disposal of human excrement. Discrimination against members of these groups, commonly referred to by the term 'Scheduled Castes' (SCs), was officially made illegal by the Constitution of independent India in 1950[1]. Indeed, reservations of places in higher education institutions, jobs in the public sector, and seats in regional and national legislatures, which are constitutionally mandated as a corrective for historical discrimination, have led to a sizeable and growing educated middle class among these caste groups. Still, both educational and economic indices for SCs remain below the national average, and little is known about occupational patterns by caste in the private sector. SCs are thus one of the groups we focus on in this experiment as an obvious social group whose members might be expected to face systematic disadvantages in the job market even if they are able to acquire the necessary skills. Similar considerations and legal provisions apply to India's indigenous tribal groups, known as the Scheduled Tribes, who are a much smaller share of the population but also have access to the proportional reservation like the Scheduled Castes. STs continue to have the lowest educational and social indicators of all of India's social groups, and it has been argued that geographical isolation and lack of political success are in some measure responsible for this.

In the early 1990s, the Indian government implemented a further set of positive discrimination policies in public sector jobs, 27 per cent of which were reserved for members of what were referred to as 'Other Backward Classes', or OBCs. While the basis for identifying groups for possible inclusion in the OBC category was 'caste', the aim was to remedy perceived educational and social inequality in Indian society. In essence, the OBC category is a collection of caste groups who ranked just above the untouchables in the ritual hierarchy but were educationally and socially 'backward', as measured by their low literacy, early age at marriage, low female literacy, etc. The OBCs are therefore another broad caste group whose job search experiences we try to understand.

[1] The term 'Scheduled Castes' comes from the Ninth Schedule of the Indian Constitution, which lists for each state in India the specific caste groups who are eligible to benefit from the affirmative action provisions outlined in the Constitution.

In addition to the caste groups mentioned above, India also has a substantial Muslim population which constitutes its largest religious minority at about 12 per cent of the population. We therefore try to measure whether Muslims face disadvantages in their job search process relative to upper-caste Hindus.

The relationship between caste and last name is crucial to our experimental strategy. Hindu last names are, in the vast majority of cases, indicative of the person's position in the caste hierarchy, although the enormous regional variations mean that the precise coding of a particular last name is unlikely to be familiar to people from a different linguistic region of India. Muslims have distinctive first and last names that are immediately informative about their religion.We therefore use last names as our signal of caste background (except for Muslims who have Muslim first and last names), as will be explained in more detail when we discuss how we generated our applicants' identities. It is important to point out that there may be differences in frequency of particular first names by caste (and class), but we do not attempt to exploit this. We do try to avoid any possible conflation of caste and class by rotating the same set of generic Hindu first names among all categories of applicants.

3 Previous Research

Altonji and Blank (1999) define labor market discrimination as 'a situation in which persons who provide labor market services and who are equally productive in a physical or material sense are treated unequally in a way that is related to an observable characteristic such as race, ethnicity, or gender'. While persistent wage gaps by race have long been documented for countries like the US, it has been pointed out that gaps in labor market outcomes, such as wages, are not clear evidence of discrimination on the part of employers. This is because standard labor force surveys do not contain all employee characteristics that employers use to make hiring, pay and promotion decisions. So it is difficult to be certain that two workers who look identical in terms of the characteristics contained in survey data are truly identical from employers' point of view.

The difficulties of inferring unequal treatment from aggregate data have led researchers to use a variety of quasi-experimental and experimental approaches to measuring workplace discrimination at the hiring/pre-hiring stage. An influential quasi-experiment is Goldin and Rouse (1997) which looks at the impact of the introduction of blind auditions into the process of hiring in orchestras, and infer gender discrimination from changes in the treatment of women candidates. Experimental approaches have included labor market audit studies, where comparable minority and non-minority (or male and female) actors are sent to actual interviews to measure differential treatment (see Altonji and Blank 1999 for a survey of such studies). However, as Heckman and Siegelmann (1992) and Bertrand and Mullainathan (2004) point out, the fact that the actors are aware of the purpose of the experiment as well as the difficulty of ensuring that the mock candidates in a pair are truly 'observationally identical' are serious problems with these approaches.

Finally, resume audit studies such as this one, where researchers vary the perceived race (or other group membership characteristic, such as ethnicity) of applicants by randomly assigning names that signal a particular social group, provide the cleanest evidence on differential treatment by race at the earliest stage of the hiring process, i.e. whether or not applicants are called for an in-person interview or not. The best-known of these is Bertrand and Mullainathan (2004), on which the research here is based, which finds large gaps in callback rates by race. However, these studies suffer from the crudeness of the outcome they measure: whether or not race (or another group identity characteristic, such as gender, ethnicity, etc.) affects the probability of a candidate being *called back for interview,* rather than the actual probability of being hired, although 'to the extent that the search process has even moderate frictions, one would expect that reduced interview rates would translate into reduced job offers' (Bertrand and Mullainathan 2004: 11).

In addition to the literature on discrimination, this paper also relates to the broader literature on labor regulation and its effects on firms performance and behavior, both across countries and in the Indian context, which is one of particularly stringent restrictions on the labor market practices of firms in the formal sector. For example, Botero et. al. (2004) find that countries with stronger labor-market regulations have lower rates of labor-market participation and higher levels of unemployment. This is echoed in a number of within-country studies, a subset of which have studied the Indian case in depth. Papers that examine the effects of Indian labor law, which severely limits firms' abilities to fire incumbent workers, find detrimental effects of labor regulations on employment and firm efficiency (e.g. Besley and Burgess 2004). For example, Ahman and Pages (2008) find that laws that increase employment protection or the cost of resolving labor disputes substantially reduce registered-sector employment and output. Likewise, Amin (2008) finds that employment in India's retail sector is strongly negatively affected by the strength of labor regulation, with one important effect being that excessive regulation drives a large proportion of firms into the informal sector, where labor laws are hardly implemented. With these in mind, it is helpful to think about the results here as informative of firms' hiring behavior in the absence of governmental attempts to explicitly control the caste composition of their hires, but operating in a setting where firms' abilities to fire workers is severely constrained by existing economy-wide labor regulation.

4 Experimental Design

4.1 Identifying Jobs/Sectors for the Experiment

In order to implement a resume audit in the context of the Indian job market, it was necessary to identify sectors and jobs to which fictitious resumes would be sent. Scanning the job supplements of the two highest-readership English-language dailies in Delhi (the Times of India and the Hindustan Times) as well as the two largest online job sites (Naukri.com and Monsterindia.com) revealed that the key constraint for the purposes of this experiment was the method of recruitment used to fill positions advertised.

Unlike in the US, recruitment to several kinds of jobs and sectors in India could not be studied using a resume audit, since the method of recruitment followed by employers in filling these positions made them unsuitable for our purposes. Most lower-level positions in the private sector (for example, secretarial jobs, administrative positions, lower-level sales positions) are filled not by soliciting resumes but by asking potential applicants to 'walk in' with their resumes at a time and place mentioned in the advertisement. Jobs in the public sector, banks, educational institutions, etc. were also unsuitable because they recruited either through examinations or required supporting material such as exam score-sheets to be mailed as part of the application process.

On this basis, we restricted ourselves to applying to two categories of jobs for which the first stage of recruitment involved the screening of resumes, and of which there was a steady flow of new openings advertised through newspapers or online job sites. These were what we refer to as 'software jobs' and 'call-center jobs', shorthand for openings for software engineers (primarily but not exclusively in firms whose main business was producing software), and openings for Customer Service Agents in the BPO (Business Process Outsourcing, or Call-Center) industry, respectively. Broadly speaking, the former were technical jobs, requiring either formal engineering qualifications or a specified set of software skills, or both, whereas the latter were open to a college graduate in any field.

Both the IT sector, to which most of our software resumes were sent, and the ITES (IT-enabled-services) sector, which includes the call-centers we applied to, are rapidly growing sectors in India, which explains the steady flow of new job openings: NASSCOM, the trade association for the IT and ITES industries in India, estimates that employment in software firms grew from 215,000 in 2004-05 to an estimated 398,000 in 2006-07. In the same period, employment in call-centers, which includes the non-technical call-center jobs we applied for, grew from 216,000 to 409,000 (NASSCOM 2007). These are, of course, figures for India as a whole, whereas we sent resumes only to jobs recruiting in Delhi, one of the several major centers of these industries.

The difference in the requirements for the two kinds of jobs is clear from a comparison of the columns in Table 1, which summarizes the information the job listings provided about the qualifications, skills, and experience of the people they sought to hire. Almost all software jobs have an experience requirement, while one-third of call-center positions are entry-level, and those that do require prior work experience ask, on average, for 1.5 fewer years of experience than software jobs. About 41 per cent of software jobs explicitly mention an Engineering degree requirement and 29 percent also mention a Master of Computer Applications degree, whereas none of the call-center jobs do (these are not jobs for call-center positions involving technical assistance). In contrast, none of the software jobs are open to someone with just a Bachelor of Arts degree, whereas the 68 per cent of call-center jobs which mention a formal qualification all accept (non-engineering) college graduates with no other formal qualifications. Call-center employers are much more concerned about potential employees' 'presentability' - measured by such criteria as unaccented, fluent English, Americanization, familiarity with phone etiquette, etc., than software employers are. For our purposes, this meant that we expected a far greater reliance on subtle markers of social background on the part of employers in the call-center industry and a greater emphasis on formal technical qualifications in the software industry. Throughout this paper, we will therefore present results separately for software and call-center jobs, since the difference in the nature of the jobs suggested caste, with its potential to signal social background, might play a more crucial role in the call-center industry than in software, where formal technical qualifications are paramount.

4.2 Creating A Pool of Resumes

The next stage of the experimental design involved generating templates for the resumes to be sent in response to advertisements for the two kinds of jobs discussed in Section 4.1. The goal was for resumes to be realistic and representative of the kinds of resumes that jobseekers sent out, without using real people's resumes. As a starting point, we began with real resumes which job-seekers who were seeking jobs like the ones we would apply to had posted on the job site www.naukri.com. We then removed names, addresses, etc. from these resumes, and modified them by changing the names of the educational institutions from where degrees were listed, and the firms in which the person had worked, if any. However, we maintained the structure of the resumes so as to mimic real job-seekers' resumes as closely as possible without using real resumes.

In the case of resumes of software professionals, we also classified the resumes into two groups, high and low quality. We used several features of the resume to differentiate between 'high-quality' and 'low-quality' resumes: the bachelor's degree listed (whether or not it was an engineering qualification and whether or not it was from a top-10-ranked engineering college), whether the resume listed additional computer-related qualifications such as an MCA (Master of Computer Applications), an IBM Ace Certification, or a Cisco Professional Certification (which were qualifications we found to be commonly listed on resumes of people seeking employment as software professionals), and the number of on-the-job projects (a crucial part of the resume for software professionals, who use it to demonstrate the range of their technical capabilities) . We also added extra computer-related qualifications or skills to some of the high-quality resumes, and manipulated the institution that granted their undergraduate degree, and whether they mentioned a high score at the Bachelors' level. Resumes that we classified as high-quality were much more likely to have a BTech/BE degree, and to mention high undergraduate college grades/marks. They were also more likely to have a computer-related skill certification of the type mentioned above, to have an MCA, to know UNIX and Oracle, and to have worked on more projects in previous jobs. High-quality and low-quality resumes did not differ in terms of whether or not they had an undergraduate degree of some kind (all of them did), and whether they provided a list of software skills (another standard feature of actual software professionals' resumes) or years of experience in the industry, since we did not want resumes that were either over-qualified or under-qualified for the pool of jobs we would apply for.

This process left us with a a set of realistic resume templates for each job category, software or call-centers, with the software resume templates being further classified into high and low-quality resumes.

4.3 Identities of Fictitous Applicants

Generating the identities of the fictitious applicants was a key part of the experimental design. As explained above in the discussion of the link between last names and caste, while last names are usually but not always linked to caste in India, there are many regional variations in the caste connotation of different names. For this experiment, we wanted a list of last names which are linked to castes in different parts of the caste hierarchy (upper-caste, scheduled caste, scheduled tribe, and other backward caste), but also which would be likely to be recognized as such by people scanning resumes at firms to which we would apply.

We began by preparing a list of last names of people belonging to the broad caste categories we were interested in. While it was straightforward to find upper-caste-identified names, we got our SC/ST last names from two main sources. The first was Election Records available on the website of the Election Commission of India, from where we acquired a list of Scheduled Caste and Scheduled Tribe last names by state, by exploiting the fact that constitutionally-mandated positive discrimination policies in India earmark some seats in the national Parliament as reserved for members of the Scheduled Castes or Scheduled Tribes, which means that only members of the specified groups can compete. By scanning the list of candidates from reserved seats in the 1991 General Elections, we were able to draw up a list of Scheduled Caste/Tribe last names by state for the the north Indian states of Uttar Pradesh and Bihar, as well as for Gujarat, Maharashtra, West Bengal, and Tamil Nadu. We supplemented this list with information from a list of names of people who had applied for admission under the quotas for Scheduled Castes and Scheduled Tribes in one of the undergraduate colleges of Delhi University. For OBC names, we consulted the official list of OBCs for states in North India.

Next, we carried out a small survey among unversity students and faculty to check what associations, if any, people made between names and caste/religion. In particular, we were concerned to see whether people who lived and worked in New Delhi would make associations between caste and names from other parts of the country. We presented survey respondents, who were all either students or faculty at a number of Delhi undergraduate colleges, with a list of names, followed by a series of descriptive phrases that could potentially pertain to the profession, wealth, or the class, linguistic, caste, or religious background of the person named. Respondents were instructed to circle all the phrases that they thought described the person named.

While our survey was small and not intended to be analyzed rigorously, it did clarify several things that aided the choice of names for the experiment. The first was that our respondents, who all lived and worked in Delhi and the majority of whom self-identified as being from one of the North Indian states of Uttar Pradesh, Bihar, Delhi, Punjab, were not familiar at all with the link between caste and last name for names from the states of Gujarat and Maharashtra. The second was that Muslim names were universally recognised as such, as were upper-caste names from North India. Finally, at least some Scheduled Caste and Scheduled Tribe names from North India and Bengal, while not eliciting universal recognition, were recognized by large fractions of those we surveyed as being associated with the correct caste category: over three-quarters of our respondents recognized Paswan, Manjhi, Kori, Mandal, Jatav and Pasi as being Scheduled Caste last names.

Based on the results of our survey, we restricted ourselves to using last names from North India. Last names were paired with common North Indian first names[2] so as to generate a set of full names. We rotated the assignment of first names to last names so that, for example, in one month our SC male applicant might be called Anil Mandal and our upper-caste male applicant Suresh Arora, whereas the next month our SC male applicant might be called Suresh Paswan and our upper-caste male applicant Anil Gupta. Muslim applicants, of course, had Muslim first names.

Once the set of full names which were being used in each round of the experiment were finalized, we opened an email account for each fictitious applicant on www.rediffmail.com or www.hotmail.com, both popular web-based email providers. As we discuss in Section 4.4 below, these email addresses were used to mail out resumes in response to job advertisements, and in some cases callbacks were received by email. Finally, each caste/religion-gender cell (for example, Upper Caste Male, Scheduled Caste Female, Muslim Female, etc.) had a unique, functional cellphone number at which firms could contact him or her.

Applicants were also randomly allocated either of two types of residential addresses, 'high' or 'low'. Neighborhoods in Delhi, as in most cities, vary a great deal in terms of the socio-economic profile of their residents. This is reflected in the system of property tax assessments that is used by the Municipal Corporation of Delhi, which categorizes all neighborhoods (known as 'colonies') into one of 8 categories, with a unit area in a Category A neighborhood being valued at roughly 6.3 times the corresponding area in a Category H neighborhood[3]. Using this, we chose addresses in Category A or B neighborhoods[4] as our 'high' type addresses, and addresses in F or G category neighborhoods[5] as our 'low' type addresses.

[2] The first names used were: Amit, Anil, Ashok, Dinesh, Deepak, Kamal, Rajiv, Sunil, and Suresh for Hindu males, and Anita, Manju, Sangeeta, Seema, and Sunita for Hindu females.

[3] The tax differential is, of course, a multiple of this multiple because category A houses are much larger than Category F, G or H houses.

[4] The 'high' type addresses were in the following neighborhoods: Greater Kailash-I, Greater Kailash-II, Jor Bagh, Safdarjung Enclave and Vasant Vihar, all of which are in South/Central Delhi and are Category A or B neighborhoods.

[5] The 'low' type neighborhoods were Mangolpuri, Seelampur, Rehgarpura, Nand Nagri, Welcome Colony and Balmiki Colony, Mandir Marg.

We would expect the differences in the socio-economic status of typical residents of these neighborhoods to be obvious to any person reading one of our resumes who was familiar with the city.

4.4 Responding to Job Advertisements

Each week, we used online and print job listings to generate a list of software and call-center positions which we could apply to. Once all jobs had been listed, we randomly assigned the names we were using in that round of the experiment to resume templates. The mix of caste and religion for the applicants varied through the course of the experiment, which had two phases. In the first phase, which covered the first four months of the experiment, we applied for 154 jobs, sending 8 resumes[6], two in each caste/religion cell. While we always sent two resumes using Upper Caste names and two using Scheduled Caste names, for the first 116 jobs, we sent two Scheduled Tribe resumes, and two Muslim resumes, while for jobs 117-54, we sent two Other Backward Caste resumes and two Hindu Neutral resumes. In November 2004, we expanded the experiment by increasing the number of resumes sent in response to each job opening to 12, so that we could always send two resumes (one male and one female) in each caste/religion cell. In all we sent resumes in response to 361 jobs, of which 106 were call-center jobs and the rest software jobs.

We then merged the resume template with an appropriate 'contact details' section header, which had the applicant's name, fictitious address, and functional cellphone number and email address. They then opened the email account of the fictitious applicant, pasted a standard, short cover letter into the body of an email, attached the appropriately-renamed resume to the email, and sent it to the email address specified in the job listing with the appropriate subject line. The aim of this rather mechanical system of sending out applications was to ensure that our 'applicants' looked different from each other only in ways that we intended.

4.5 Measuring Responses

Answering machines are relatively little-used in India, and voicemail is not standard on most cellphone contracts, so that we could not rely on people leaving messages that would allow us to record callbacks. However, since we had one cellphone for each fictitious applicant, it was straightforward to track callbacks. Research assistants were instructed to record all the 'missed calls' on each cellphone, and to then call each number back and find out where the call was from, and record a callback as well as the date of the call in the spreadsheet against the job and 'person' in question. (In a small number of cases, applicants

[6] Because of the rapid growth in these industries, we were confident that sending this many resumes would only insignificantly alter the overall pool of resumes received for each job ad, which typically run into the thousands. In the case of call-center jobs, ads often mentioned that they were looking to hire several hundred new workers.

received 'callbacks' only over email; it was somewhat more common for the recruiter to both call the person and send an email). In practice, if the same number was recorded as having called several of our cellphones, it was only necessary for RAs to call it once and figure out which firm had called; once that was done, checking which phones the firm had called provided the information about which candidates the firm had called back. If it proved necessary to engage in further discussion, RAs were instructed to politely decline the offer of an interview citing another job offer that they had just accepted.

We could not track any responses that may have arrived by mail for our fictitious applicants, though Human Resources professionals informed us that because most firms in these sectors have a tight recruitment schedule, they prefer to use the telephone rather than rely on the postal system (though they may sometimes use email) since a phone call allows them to confirm the candidate's availability for interview and schedule a time in a single step.

5 Results and Interpretation

5.1 Mean Callback Rates by Caste/Religion and Job Type

Tables 2a, 2b and 2c compare the mean callback rates for Upper Castes to those for SCs, OBCs and Muslims respectively. The upper panel in each table shows the callback rates for software jobs, while the lower panel shows the corresponding rates for call-center jobs. As discussed earlier, the structure of the experiment was such that the composition of the non-upper-caste category of applicants varied over the course of the experiment, because while UC and SC resumes were sent to every job, not all jobs received applications from OBCs, STs, and Muslims. Each panel thus includes only jobs for which resumes were sent in both caste/religion cells being compared, so that the number of observations and callback rates for upper castes vary between panels. (We try to control for differences between firms to which resumes were sent more systematically in the regression estimates that follow.)

The difference between callback rates for software versus call-center jobs is striking, with software jobs having much lower callback rates: the average callback rate over the entire experiment was 5.23 per cent for software jobs and 16.7 per cent for call-center jobs. However, whereas we see large differences between callback rates for upper-caste and OBC applicants to call-center jobs (and smaller differences between UC and SC applicants), we see no such difference for software jobs, where we are unable to reject the hypothesis that upper-castes get callbacks at identical rates to OBC and SC applicants, although the mean callback rates are actually lower for upper-castes. It is also striking that Muslim applicants are almost exactly as likely to be called back as upper-caste Hindu applicants in both kinds of jobs. Finally, there are intriguing differences between callback rates for SC and OBC women and men relative to their upper-caste counterparts in the call-center industry. The difference we observe between SC applicants' callback rates and those for upper-caste applicants to call-center jobs is entirely because SC men are much less likely to be called back than upper-caste men, whereas SC women are exactly as likely to be called back as upper-caste women. The opposite is true of OBCs, for whom women appear to suffer a greater disadvantage in callbacks for call-center jobs than men. Given the very small gender-caste cell sizes, we do not explore these differences by gender further at this point.

5.2 Regression Results, Software Jobs

In order to explicitly control for firm-level heterogeneity, results from regressions with firm fixed effects are presented in Table 3, which compare the differences in callbacks between UC applicants and the other, non-upper-caste categories, namely SC, OBC, Muslim and ST applicants. The sample of resumes is all resumes with a 'non-neutral' surname sent in response to software jobs, and the coefficients of interest are those on the various caste dummies (SC, ST, OBC, and Muslim) which measure how callbacks from that caste/religion category fared in comparison to upper-caste candidates. Column I reports results from a regression with no attempt to control for the quality of resume sent, while Column II controls for differences in resume template quality by adding a dummy for high-quality resumes (we do not expect this or the address quality variable, which is included in all regressions, to make a difference to our estimated coefficients of interest, since addresses and resumes were randomly allocated to caste cells). The coefficients of interest are small and insignificantly different from zero, reinforcing the conclusion from the simple test of proportions in Table 2.2: for software jobs, upper-caste candidates are no more or less likely to be called back than candidate of any comparison group. However, the low means for the callback rates for software jobs suggest that the 95 per cent confidence interval around the estimated coefficient even on the SC and Muslim dummies contains negative values. In other words, the results here would not cause a person who believed that there was economically significant discrimination against SCs to update their prior by much, even though the point estimates are positive.

One further concern that arises because of the low mean of the dependent variable is that the effect of caste would be expected to increase with resume quality, because low-quality software resumes almost never get called back. To account for this concern, Column III of Table 3 presents results from a probit regression, which allows the incremental effect of caste to be larger when the resume is better.

Finally, the estimated coefficient on the high-quality resume dummy (see Column II) is, however, positive and highly statistically significant, suggesting that the resume quality manipulation worked on average. This will be explored further below.

5.3 Regression Results, Call-Center Jobs

Table 4 repeats these regressions for call-center jobs. The point estimates on the non-upper-caste dummies are all negative, though they vary greatly in magnitude, with the greatest disadvantage seen for STs, followed in descending order by OBCs and SCs, with the estimated coefficient on Muslim being the smallest. Upper-castes are thus more likely to be called back than both STs, SCs and OBCs, though the effect is statistically significant at conventional levels of significance only for OBCs and SCs. The 7.79 per cent callback rate difference between upper castes and OBCs means, given the mean rates, that an upper caste candidate is approximately 60 per cent more likely to be called back than an OBC candidate who has the same resume (see column III of Table 2b). Given the slow rate of arrival of new jobs of this kind, which was the main constraining factor for the purposes of our study, and a potentially low (even if identical) conversion rate of callbacks into actual job offers, this could represent non-trivial differences in job search costs by caste. A candidate with an OBC or SC last name therefore has a significantly more difficult time getting an interview that an identically-qualified upper-caste candidate who applies for the same job.

5.4 Callback Rates at the Firm Level

Rather than studying the distribution at the applicant level as in Tables 2-4, we can tabulate differences in callback rates at the firm level by calculating the fraction of firms who treat two categories of applicants equally (that is, who call back either none, one, or two applicants in each caste category), or those who favor either upper castes (calling back both uppercastes and 1 or 0 SC/OBC candidates, or 1 upper-caste and 0 OBC/SC candidates) or SCs/OBCs (calling back both SC/OBC candidates and 1 or 0 upper caste candidates, or 1 SC/OBC and 0 upper-caste candidates). Table 5a presents the results of this exercise for call-center jobs, comparing the treatment of upper castes to SCs in Panel A, and to OBCs in Panel B. 78.3 per cent of firms treat Upper castes and SCs equally and 77.1 per cent treat upper castes and OBCs equally. As expected, the major part of the equal treatment comes from firms from whom no callbacks to either group are recorded. 12.26 per cent of employers favor upper castes relative to SCs and9.43 per cent favor SCs relative to upper-castes, a difference in proportions that is not statistically significant. However, while 18.07 per cent of employers favor upper-castes over OBCs, only 6.02 per cent of employers discriminate in the reverse direction, a difference in proportions that is statistically very significant (p=0.02), in spite of the small sample. At the firm level too, therefore, it seems that significantly more firms discriminate against OBC candidates than favor them.

The same exercise is carried out for software jobs in Table 5b. Here too equal treatment dominates by virtue of the large fraction of firms who did not call any of our candidates back. However, although a greater fraction of firms actually favor SCs over upper castes than vice versa, the difference in proportions is insignificantly different from zero. A greater fraction of firms favor upper castes over OBCs than favor OBCs over upper castes, but this difference is also statistically insignificant.

5.5 Returns to Resume Quality: Software Jobs

The resume template design stage included an attempt to manipulate the perceived quality of some resume templates which were used to apply for software jobs. This was done by adding formal computer qualifications, more programming skills, more impressive academic credentials, and a longer list of on-the-job projects completed in the software industry. Table 6 summarizes resume characteristics by caste/religion (Columns I-VI) and by resume quality (Columns VII and VIII). Since caste was randomly allocated, we do not expect resume characteristics to vary by caste/religion, as Columns I-VI indicate. Columns VII and VIII show how high-quality resumes differed from low-quality resumes, that is, how the resume quality manipulation was implemented. The quality manipulation was quite subtle, since we did not wish to make our candidates either grossly under- or over-qualified for these software-engineering jobs: all our candidates therefore had bachelors' degrees (though those with high-quality resumes were more likely to have studied engineering and to mention high college grades); and high- and low-quality resumes did not differ substantially in whether or not they listed a set of software skills and claimed proficiency in some set of software tools and operating systems, though high-quality resumes were more likely to know UNIX in addition to Windows, to have a formal computer skills certification or an MCA than low-quality resumes.

The callback rates tabulated in Table 7 show that the resumes we classified as 'high-quality' were 60 per cent, or 2.41 percentage points, more likely to be called back than those we classified as 'low-quality; and that this difference is highly statistically significant. On average, therefore, the resume quality manipulation seems to have worked. Table 8 presents the results of regressions with firm fixed effects, which measure the effect of having a high-quality resume for the whole experiment as well as for each caste/religion cell separately. Reading across the columns of Table 8 suggests that the benefit in terms of getting more callback differed between caste/religion cells. In particular, having a 'better' resume increases the likelihood of being called back for the most for SCs, Muslims, upper castes, and STs (though the coefficient for STs is similar in magnitude to that for the entire sample, it is not statistically significant). It does *not* work at all, however, for OBCs, whose estimated 'return' from having a better resume is virtually zero. Thus, while upper castes, Muslims, SCs and STs get a large return to having a better set of skills, the same appears not to be true of OBCs.

5.6 Interpreting Callback Rate Differentials

For call-center jobs, our results indicate that an individual with an OBC or SC (and, to a lesser extent, an ST name) name is significantly less likely to get called back by a prospective employer than an identically-qualified person from an upper caste. Does the fact that we find differential treatment of OBCs relative to Upper castes within our experiment necessarily imply that employers are discriminating against OBCs? In other words, could it be the case that although OBC candidates in our experiment are less likely to be called back than our upper-caste candidates, on the whole employers do not discriminate against OBCs while shortlisting candidates to be called for interview when we take the entire pool of resumes they receive into account?

If employers did not take caste into account while ranking resumes, they would rank all CVs according to quality, and call back those candidates whose resumes were above a threshold quality. Because names are randomly allocated to resumes, the resumes of candidates from different castes should rank similarly on average. So irrespective of what the composition of the rest of the applicant pool is, a selection process that did not take caste or religion into account should produce identical callback rates for upper castes and those of other castes/religions. Indeed, this is precisely what does happen in our experiment with respect to Muslims and upper-castes: on average, candidates from these two groups are exactly as likely to be called back. That this does not happen for SCs and OBCs therefore suggests that those screening resumes must be taking caste into account in making their callback decisions.

A caveat is, however, in order: to the extent that we cannot know what (apart from caste) those screening resumes are inferring from a job-seeker's name, it is important to be cautious as interpreting all of any difference in callbacks as being *entirely* due to caste, since we can control the applicant's name but not what is inferred from it by the person reading the resume. Nonetheless, our survey results suggested that the names we used did evoke a strong association with caste, so that at least some part of what a recruiter infers from seeing a lower-caste name as opposed to an upper-caste one is indeed likely to be the caste connotation.

A further weakness of the resume audit approach is that we are forced to rely on a crude and somewhat unsatisfactory outcome measure, that is, whether or not a person is called for an interview. Whether or not what we find about callback rates translates into actual differences in hiring and wage outcomes is not something we are able to study. Nonetheless, given the rate at which new jobs arrive, a large difference in the likelihood of callback is a serious issue in itself in that it makes the job search much more tedious and time- and effort-intensive for candidates from certain caste groups than others.

6 Conclusion

The results presented here present a nuanced picture of the status of caste in the workplace in new-economy companies in Delhi. Candidates from Other Backward Classes, Scheduled Tribe, or Scheduled Caste backgrounds are at a substantial disadvantage in applying for jobs where soft skills of the sort that may be relatively hard to signal using formal qualifications are a key part of what employers seek, but this disadvantage disappears when the jobs being applied for require harder skills, for which acquiring credible certifications may be easier and more straightforward. Candidates who are Muslim face no systematic disadvantages at the callback stage. Taken at face value, these results imply that training and credible skill certification may be crucial to reducing gaps in job opportunities between upper castes and historically disadvantaged groups such as SCs and OBCs in the private sector in India.

References

[1] Ahsan, Ahmed and Carmen Pages. 2008. 'Are All Labor Regulations Equal? Evidence from Indian Manufacturing'. Mimeo.

[2] Aigner, Dennis and Glenn Cain. 1977. 'Statistical Theories of Discrimination in Labor Markets'. Industrial and Labor Relations Review 30(2)

[3] Altonji, Joseph. G., and Rebecca Blank. 1999. 'Race and Gender in the Labor Market', in Orley Ashenfelter and David Card, eds. Handbook of Labor Economics, vol. 3. Elsevier Science B.V.

[4] Amin, Mohammad. forthcoming. 'Labor Regulation and Employment in India's Retail Stores'. Journal of Comparative Economics.

[5] Becker, Gary. 1971. 'The Economics of Discrimination'. Economic Research Series

[6] Bertrand, Marianne and Sendhil Mullainathan. 2004. 'Are Emily and Greg More Employable Than Lakisha and Jamal'. American Economic Review 94(4), pages 991-1013

[7] Besley, Timothy and Robin Burgess. 2004. 'Can Labor Regulation Hinder Economic Performance? Evidence From India'. Quarterly Journal of Economics 119(1).

[8] Beteille , Andre. 1969. Castes: Old and New: Essays in Social Structure and Social Stratification. Bombay: Asia Publishing House

[9] Beteille, Andre. 1992. 'The Backward Classes in Contemporary India'. New Delhi, OUP

[10] Borjas, GJ and S Bronars .1989. 'Consumer Discrimination and Self-Employment' NBER Working Paper 2627.

[11] Botero, Juan Carlos, Simeon Djankov, Rafael La Porta and Florencio López de Silanes. 2004. 'The Regulation of Labor'. Quarterly Journal of Economics 119(4).

[12] Black, D.A. 1995 'Discrimination in an Equilibrium Search Model'. Journal of Labor Economics, 13(2)

[13] Bowlus and Eckstein 1989 'Discrimination and Skill in an Equilibrium Search Model. International Economic Review 43(4):1309-45.

[14] Brass, Paul R, ed.1996. 'Riots and Pogroms'. NYU Press, New York.

[15] Census of India. 2001. Various Tables.

[16] Dumont, Louis. 1970. Homo Hierarchicus: The Caste System and Its Implications, Series: (Nature of Human Society)

[17] Election Commission of India. Various Issues. 'Statistical Report on the Lok Sabha Elections'. New Delhi, Election Commission of India

[18] Ghurye, G. S. 1961. Caste, Class and Occupation. Popular Book Depot, Bombay.

[19] Goldin, Claudia and Cecilia Rouse. 2000. 'Orchestrating Impartiality: the Impact of Blind Auditions on Female Musicians'. American Economic Review 90(4):715-41

[20] Heckman, James and P. Seligmann 1993. 'The Urban Institute Audit Studies: Their Methods and Findings' in M. Fix and R. Struyk, eds. 'Clear and Convincing Evidence: The Measurement of Discrimination in America'. Urban Instutute, Washington DC

[21] Krishna, Anirudh and Vijay Brihmadesam (2006): 'What Does It Take to Become a Software Professional?' Economic and Political Weekly, Vol 41 (30), pp 3307-14.

[22] NASSCOM. 2007. 'Strategic Review 2007'. National Association of Software Companies, New Delhi.

[23] Outlook. 2007. 'Brahmins in India'. Issue dated June 4, 2007.

[24] Sachar, Rajinder, ed. 2006. 'Report of the Prime Minister's High-level Committee on the Social, Economic and Educational Status of the Muslim Community of India'. New Delhi.

[25] Srinivas, M.N. 1957. 'Caste in Modern India' in The Journal of Asian Studies, Vol. 16, No. 4 (Aug., 1957), pp. 529-548

[26] Upadhya, Carol and A.R. Vasavi. 2006. 'Work, Culture and Sociality in the Indian IT Industry: A Sociological Study'. School of Social Sciences, Indian Institute of Science, Bangalore

[27] Varshney, Ashutosh. 2002. 'Ethnic Conflict and Civic Life: Hindus and Muslims in India. Yale University Press, New Haven.

Table 1: Job Requirements

	All	Software	CallCenter
Requires Previous Job Experience[1]	0.86	0.97	0.64
Mean Yrs Experience Requirement | Exp Required>0	3.88	3.99	2.54
Mean Minimum Experience Required| Exp Required>0[2]	2.44	2.59	0.56
Mean Maximum Experience Required | Exp Required>0[2]	5.20	5.38	2.81
Btech/BE Mentioned in Qualifications Required[3]	0.34	0.41	0.00
MCA Mentioned in Qualifications Required[4]	0.24	0.29	0.00
Mtech/ME Mentioned in Qualifications Required[5]	0.05	0.06	0.00
Mentions a formal Computer Qualification[6]	0.03	0.03	0.00
Requires Programming Skills			
Accepts non-Engineering graduates[7]	0.17	0.05	0.68
Mentions College Quality	0.02	0.02	0.00
Mentions College Grades	0.02	0.02	0.00
No Formal Educational Requirements mentioned	0.47	0.51	0.32
Located in Delhi/Around	0.83	0.80	0.98

Notes:

1.This is the fraction of jobs responded to that mention a non-zero number of years of work experience

2. If experience is mentioned as x-y years, then the minimum is x and the maximum y. If only one number is mentioned, both minimum and maximum are coded as that number.

3. BE refers to a Bachelors in Engineering; Btech is a Bachelors in Technology; both are 4-year engineering programs and are used interchangeably.

4. An MCA is a Masters in Computer Applications

5. Mtech and ME are the Masters' level Engineering Qualifications

6. For example, CCNA/CCNE, Microsoft Certified Engineer, etc.

7. Non-engineering graduates are people with a standard three-year college degree in a non-engineering discipline

Table 2a: Mean Callback Rates by Caste: Upper Caste vs Scheduled Caste

	Upper Caste	Scheduled Caste	Ratio UC:SC	Difference (p-value)
Software Jobs				
Both Genders	4.79	6.02	0.80	-1.23
	[459]	[465]		[0.4085]
Male	4.35	6.61	0.66	-2.27
	[253]	[257]		[0.2625]
Female	5.34	5.29	1.01	0.05
	[206]	[208]		[0.9819]
CallCenter Jobs				
Both Genders	20.00	14.63	1.37	5.37
	[195]	[205]		[0.155]
Males	19.27	13.89	1.39	5.38
	[109]	[108]		[0.287]
Females	20.93	15.46	1.35	5.47
	[86]	[97]		[0.337]

Notes:
1. The table reports, for Software and Call Centre jobs, respectively, the callback rates for applicants with an Upper Caste surname (Column 1) and a Scheduled Caste surname (Column 2). Column 3 reports the ratio of these callback rates, and Column 4 the difference in callback rates

2.The number in brackets is the total number of resumes sent in that cell

3. Column 4 also reports p-values from a test of proportions with the Null of equal callback rates

4. The sample is all jobs to which both UC and SC applicants applied (all jobs)

Table 2b: Mean Callback Rates: Upper Caste vs Other Backward Caste

	Upper Caste	Other Backward Caste	Ratio UC:OBC	Difference (p-value)
Software Jobs				
Both Genders	4.64	4.28	1.08	0.36
	[323]	[327]		[0.8241]
Male	4.35	4.27	1.02	0.08
	[161]	[164]		[0.9717]
Female	4.94	4.29	1.15	0.64
	[162]	[163]		[0.78]
CallCenter Jobs				
Both Genders	20.81	13.02	1.6	**7.79**
	[149]	[169]		**[0.0629]**
Males	19.75	11.90	1.66	7.85
	[81]	[84]		[0.1664]
Females	22.06	14.12	1.56	7.94
	[68]	[85]		[0.2205]

Notes:
1. The table reports, for Software and Call Centre jobs, respectively, the callback rates for applicants with an Upper Caste surname (Column 1) and an OBC surname (Column 2). Column 3 reports the ratio of these callback rates, and Column 4 the difference in callback rates

2.The number in brackets in Columns 1 and 2 is the total number of resumes sent in that cell

3. Column 4 also reports (in parentheses) p-values from a test of proportions with the Null of equal callback rates
4. The sample is all jobs to which both UC and OBC applicants applied (thus, excludes the first round of sending, or 23 jobs, where no OBC resumes were sent)

Table 2c: Mean Callback Rates: Upper Caste vs Muslims

	Upper Caste	Muslim	Ratio UC:M	Difference (p-value)
<u>Software Jobs</u>				
Both Genders	5.26	5.78	0.91	-0.52
	[418]	[415]		[0.7424]
Male	4.72	6.09	0.78	-1.37
	[233]	[230]		[0.5143]
Female	5.95	5.41	1.10	0.54
	[185]	[185]		[0.8225]
<u>CallCenter Jobs</u>				
Both Genders	21.88	20.83	1.05	1.04
	[96]	[96]		[0.8591]
Males	22.64	22.64	1.00	0.00
	[53]	[53]		[1.000]
Females	20.93	18.60	1.13	2.33
	[43]	[43]		[0.7862]

Notes:
1. The table reports, for Software and Call Centre jobs, respectively, the callback rates for applicants with an Upper Caste surname (Column 1) and a Muslim surname (Column 2). Column 3 reports the ratio of these callback rates, and Column 4 the difference in callback rates

2.The number in brackets is the total number of resumes sent in that cell

3. Column 4 also reports p-values from a test of proportions with the Null of equal callback rates

4. The sample is all jobs to which both Upper-Caste and Muslim resumes were sent

Table 3: Regression Results, Software Jobs

Dependent Variable: Callback Dummy	I	II	III
Scheduled Caste	0.0087	0.0089	0.01213
[SE]	(0.0108)	(0.0107)	(0.0107)
t-ratio	0.81	0.83	1.2
OBC	-0.0045	-0.0047	-0.0049
[SE]	(0.0121)	(0.0121)	(0.01237)
t-ratio	-0.37	-0.39	-0.38
Scheduled Tribe	0.0026	0.0025	0.0032
[SE]	(0.0112)	(0.0112)	(0.01108)
t-ratio	0.23	0.23	0.3
Muslim	0.0064	0.0063	0.0099
[SE]	(0.0112)	(0.0112)	(0.01158)
t-ratio	0.57	0.57	0.91
High Quality CV	__	**0.0255*****	**0.0265*****
[SE]	__	(0.0072)	(0.0087)
t-ratio	__	3.50	2.95
Female Dummy	Yes	Yes	Yes
Address Type Dummy	Yes	Yes	Yes
No. of Observations	2083	2083	2083

Notes:
Sample: All resumes sent in response to Software ads, excluding caste-neutral category
RHS variables of interest are dummies for different categories of non-upper-caste surnames and the resume-quality dummy.
Columns I and II report the results of OLS regressions with job fixed effects
Column III reports results from a (marginal) probit regression clustered at the job level.
All regressions have dummies for gender and address type
Omitted category is Upper-Caste, all coefficients measure difference in callbacks with this category

Table 4: Regressions with Job Fixed Effects, Call-Center Jobs

	Dependent Variable: Callback Dummy	
	I	II
Scheduled Caste	**-0.513***	**-0.513***
[SE]	(0.0299)	(0.0313)
t-ratio	-1.71	-1.70
OBC	**-0.0575***	**-0.0559***
[SE]	(0.0313)	(0.0316)
t-ratio	-1.83	-1.77
Scheduled Tribe	-0.0588	-0.0619
[SE]	(0.0416)	(0.0418)
t-ratio	-1.41	-1.48
Muslim	-0.0074	-0.0059
[SE]	(0.0423)	(0.0423)
t-ratio	-0.17	-0.14
Resume Dummies	No	Yes
Female Dummy	Yes	Yes
Address Type Dummy	Yes	Yes
No. of Observations	761	761
No. of Jobs	106	106

Notes
Sample: Resumes sent in response to Call-Center ads, excluding 'Neutral' names
RHS variables of interest are dummies for different categories of non-upper-caste surnames
Column II adds dummies for the resume template used
All regressions are OLS with job fixed effects and have dummies for gender and address type

Omitted category is Upper-Caste, all coefficients measure difference in callbacks with this category

Table 5a: Distribution of Callbacks by Employment Ad, CallCenter Jobs
Panel A: Upper-Caste versus Scheduled Caste

Equal Treatment	***0 UC, 0 SC***	***1 UC, 1 SC***	***2UC, 2 SC***
78.3	67.92	6.60	3.77
[83]	[72]	[7]	[4]
Upper-Caste Favored	***1 UC, 0 SC***	***2 UC, 0 SC***	***2 UC, 1 SC***
12.26	5.66	4.72	1.89
[13]	[6]	[5]	[2]
Scheduled-Caste Favored	***1 SC, 0 UC***	***2 SC, 0 UC***	***2 SC, 1 UC***
9.43	7.54717	0.94	0.94
[10]	[8]	[1]	[1]

p-value from test of difference in proportion that favor UC versus fraction that favor SC: 0.5076

Panel B: Upper-Caste versus OBC, updated

Equal Treatment	***0 UC, 0 OBC***	***1 UC, 1 OBC***	***2 UC, 2 OBC***
77.10	68.67	6.02	2.41
[64]	[57]	[5]	[2]
Upper-Caste Favored	***1 UC, 0 OBC***	***2 UC, 0 OBC***	***2 UC, 1 OBC***
18.07	9.64	0.00	8.43
[15]	[8]	[0]	[7]
OBC Favored	***1 OBC, 0 UC***	***2 OBC, 0 UC***	***2 OBC, 1 UC***
6.02			
[5]	3.61	2.41	0.00
	[3]	[2]	[0]

p-value from test of difference in proportions between fraction favoring UC vs favoring OBC: 0.0171

Note: The numbers are percentages of all jobs applied to; numbers in parentheses are the total numbers that fall into each cell. Each column heading refers to a pattern of responses. For example, 0 UC, 0 OBC that neither a UC candidate nor an OBC candidate received a callback.

Table 5b: Distribution of Callbacks by Employment Ad, Software Jobs

Panel A: Upper-Caste versus Scheduled Caste

Equal Treatment	***0 UC, 0 SC***	***1 UC, 1 SC***	***2UC, 2 SC***
91.32	88.68	1.51	1.13
[242]	[235]	[4]	[3]
Upper-Caste Favored	***1 UC, 0 SC***	***2 UC, 0 SC***	***2 UC, 1 SC***
3.40	3.02	0.00	0.38
[9]	[8]	[0]	[1]
Scheduled-Caste Favored	***1 SC, 0 UC***	***2 SC, 0 UC***	***2 SC, 1 UC***
5.28	4.15	0.00	1.13
[14]	[11]	[0]	[3]

p-value from test of difference in proportion that favor UC versus fraction that favor SC: 0.2882

Panel B: Upper-Caste versus Other Backward Caste

Equal Treatment	***0 UC, 0 OBC***	***1 UC, 1 OBC***	***2UC, 2 OBC***
95.85	93.96	0.75	1.13
[254]	[249]	[2]	[3]
Upper-Caste Favored	***1 UC, 0 OBC***	***2 UC, 0 OBC***	***2 UC, 1 OBC***
2.64	2.26	0.00	0.38
[7]	[6]	[0]	[1]
OBC Favored	***1 OBC, 0 UC***	***2 OBC, 0 UC***	***2 OBC, 1 UC***
1.51	1.13	0.38	0.00
[4]	[3]	[1]	[0]

p-value from test of difference in proportion that favor UC versus fraction that favor OBC: 0.3615

Note: The numbers are percentages of all jobs applied to; numbers in parentheses are the total numbers that fall into each cell. Each column heading refers to a pattern of responses. For example, 0 UC, 0 OBC that neither a UC candidate nor an OBC candidate received a callback.

Table 6: Summary of Characteristics of Software Resumes by Caste and Subjective Quality

	UC	**SC**	**OBC**	**M**	**ST**	**N**	**"H"**	**"L"**
Educational Background	**I**	**II**	**III**	**IC**	**V**	**VI**	**VII**	**VIII**
B.Tech	0.69	0.69	0.68	0.68	0.69	0.69	0.86	0.51
Grades Mentioned[1]	0.30	0.31	0.30	0.30	0.31	0.31	0.43	0.17
Top 10 Btech/Mtech[2]	0.45	0.46	0.45	0.46	0.46	0.46	0.56	0.34
Computer Skills/Training								
Formal Computer Certification	0.60	0.61	0.61	0.61	0.60	0.61	0.70	0.50
Software Skills[3]	0.84	0.85	0.85	0.85	0.84	0.85	0.86	0.83
MCA	0.23	0.22	0.22	0.24	0.22	0.23	0.28	0.17
Specific Technical Capabilities								
Lists Operating Systems	0.84	0.85	0.85	0.85	0.84	0.85	0.86	0.83
Proficient in UNIX	0.53	0.53	0.52	0.54	0.53	0.53	0.71	0.34
Lists Software 'Tools'	0.92	0.93	0.92	0.93	0.92	0.92	1.00	0.83
Lists Oracle	0.53	0.54	0.53	0.54	0.53	0.53	0.71	0.34
Yrs of Exp In Industry	5.0	5.1	5.1	5.1	5.0	5.1	4.47	4.65
Projects listed[4]	3.9	4.1	4.0	3.9	4.0	4.0	4.57	3.39
N	459	465	327	415	417	326		
U-Type Address	0.50	0.50	0.50	0.50	0.50	0.50	0.5	0.5

Notes:
1. Mentions a GPA, Class/Division, or a percentage score.
2. Has a degree from a school ranked in the top 10 nationally (based on annual India Today rankings).
3. Has a section of the resume that details software/programming skills.
4. Provides details of programming projects that the person has worked on.

Table 7: Mean Callback Rates by Caste and Resume Quality (H or L, subjective classification)
Software Jobs

	High	Low	Ratio	Difference (p-value)
All	6.38	3.98	1.60	**2.41**
	[1253]	[1156]		[0.0082]
UC	5.81	3.67	1.58	2.14
	[241]	[218]		[0.2838]
SC	8.20	3.62	2.26	**4.58**
	[244]	[221]		[0.0382]
OBC	4.14	4.43	0.93	-0.29
	[169]	[158]		[0.897]
M	7.34	4.06	1.81	3.28
	[218]	[197]		[0.1529]
ST	6.45	3.50	1.84	2.95
	[217]	[200]		[0.1687]
N	5.49	4.94	1.11	0.55
	[164]	[163]		[0.832]
Men	6.13	4.26	1.44	1.88
	[701]	[658]		[0.1216]
Women	7.09	3.61	1.96	3.47
	[522]	[498]		0.0139

Notes:

1. Column 1 reports callback rates for 'High-Quality' Software resumes
2. Column 2 reports callback rates for 'Low-Quality' Software resumes
3. Column 3 reports the ratio of Column 1:Column 2
4. Column 4 reports the difference, and the p-value from a test of proportions with the Null of equality between the callbacks in Cols 1&2
5. Numbers in brackets in Cols 1 and 2 are the total number of resumes sent in that cell

Table 8: Effect of Subjective Resume Quality on Likelihood of Callback, Software Jobs, Job Fixed Effects

Dependent Variable: Callback Dummy

Sample	All CVs	Upper Caste	SC	OBC	Muslim	ST	Neutral
High Quality	**0.0225*** **	**0.0289***	**0.0540*** **	0.0000	**0.0298***	0.0258	0.0075
(SE)	0.0067	0.0178	0.0207	0.0164	0.0170	0.0182	0.0195
z-ratio	3.37	1.62	2.61	0	1.76	1.42	0.39
High Addres	0.9940	-0.0905	-0.0363	0.0000	-0.0127	0.0155	dropped
(SE)	-0.0130	0.0736	0.1907	0.1145	0.1551	0.1036	dropped
z-ratio	0.013091	-1.23	-0.19	0	-0.08	0.15	dropped
N	2409	459	465	327	415	417	326

Notes: Each column gives the result of a regression with firm fixed effects where the Callback dummy is regressed on a dummy for a high-quality resume and a 'U'-type residential address.