Discrimination in an Elite Labour Market? Job Placements at IIM-Ahmedabad

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Using data on the IIM -Ahmedabad's 2006 batch of MBA graduates, we find that graduates belonging to scheduled castes or scheduled tribes get significantly lower wages (19 per cent lower in domestic jobs and 35 per cent lower when foreign jobs are included) than those in the general category. This difference disappears once their lower Grade Point Averages are taken into account, suggesting that the large wage difference is due to the weaker (on average) academic performance of sc/st candidates. The study suggests that in the absence of any serious attempt to equalise school-level opportunities, the current policy of reservations at elite educational institutions will be insufficient to equalise career outcomes even for the minority of sc/st candidates who can benefit from them.

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he existence of economic and educational disparities between different castes and genders in India has been extensively documented by social scientists.

1 Introduction

The proportion of people below the poverty line among scheduled castes and tribes (sc/sts) is about 50 per cent higher than those among the general population. Access to a reasonable quality of education is far from universal and differs by caste. The fraction of the population that belongs to a sc/st shrinks as one moves up educational attainment classes. For example, in urban India in 1999-2000, persons belonging to the sc/sts constituted 18.3 per cent of those in the 17-25 age group, but only 11.3 per cent of them had passed high school. Their proportion among college graduates was only 7.4 per cent [Sundaram 2006]. Similarly, the urban female-to-male wage ratio was found to be 82 per cent for literates and 59 per cent for illiterates [Deshpande and Deshpande 1992] and 78 per cent of this was attributed to differential schooling [Kingdon 1999].

It is only recently, however, that social scientists have systematically studied discrimination against lower castes in the labour market. Madheswaran and Attewell (2007), using National Sample Survey (NSS) data, found that employees from SC/STS in urban salaried jobs in 1999-2000 received wages that were about 30 per cent lower on average than those of other castes. Further, 15 per cent of this differential could not be explained by the measures of education and work experience available in the NSS data. Thorat and Attewell (2007) conducted a field experiment and found that companies discriminate by caste and religion in the frequency with which they contact (fictitious) job applicants with identical resumes. Banerjee et al (2007) conducted similar experiments and found less discrimination in the call-centre industry and none in the software industry.¹

It is useful to consider these results in the light of the two major economic theories of discrimination. In Arrow's (1972) theory of statistical discrimination, employers have imperfect information about the productivity of employees, and use group identity to proxy for productivity. This leads them to offer different wages to apparently identical employees from different groups. In contrast, in Becker's (1967) description of "taste based discrimination", employers discriminate even if it means realising a lower level of profit. Prejudice is built into their preferences and the agents performing the discrimination obtain some utility from adversely affecting the economic condition of certain groups even if it means lowering their own earnings.

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While employers represented in the NSS data presumably have fairly good information about the productivity of their employees, those in the callback studies have far less information regarding the productivity of prospective employees. So it seems that statistical discrimination is a possible explanation for why employers discriminate in callback experiments and in entry-level labour markets. But it is much less likely to explain discrimination against employees who have been on the job for a while, which will mostly be the case in the NSS.

It is nevertheless possible, that the wage differential observed in the NSS data is due to unobserved productivity differentials because there data include only crude measures of educational attainment. On the other hand, in the callback experiments, employers do not see the candidates, only their resumés. One advantage of the study reported here is that data on job candidates' grades is available, offering a fine degree of control. At the same time, the labour market is real, not experimental, and candidates typically go through several rounds of interviews with prospective employers, so that employers get a fair amount of information about them.

Using data from the Indian Institute of Management, Ahmedabad's (IIM-A) 2006 batch of Post Graduate Diploma in Management (PGDM, equivalent to an MBA) graduates, we find no evidence of discrimination against minorities by employers in placements. Controlling for work experience and GPA, there is no wage penalty to being female, or of belonging to a sc/st. This study is also of interest because IIM-A graduates often come to occupy positions of prestige and power. When historically disadvantaged groups gain access to such positions, this may serve to create role models and break down stereotypes.

In addition to examining the possibility of discrimination by gender and caste, we study another form of discrimination that to our knowledge has not been studied in the Indian context. This may take the form of a beauty premium arising from betterlooking individuals obtaining a higher reward from economic activity. This has been documented for the us labour market by Hamermesh and Biddle (1994, 1998) and Hamermesh and Parker (2006), and in the uk by Harper (2000). We find weak evidence of this form of discrimination by employers.

The next section describes the placement process at IIM-A, while Section 3 describes the data. Section 4 describes the estimation procedure and results, and Section 5 points to the study's conclusions.

2 The Placements Process at the IIM

The business school placements process is the way most business graduates and MBA students obtain employment. Students wishing to participate in placement submit their resumés to the placement office. After perusing the resumés, companies decide which candidates to interview on campus.²

Interviews take place over several days. Higher paying companies like investment banks and international consulting firms get slots on earlier days, giving them the first chance to make lucrative offers to the best students. The interviewers initially screen candidates and progressively shortlist to interview candidates until they make a final offer, so that a company may interview a particular candidate several times.

About 5 per cent of the students chose not to go through placement because they dropped out of the programme, received other offers, or started their own companies. None of these were sc/sr students.

3 Data and Variables

Our data set comprises 242 final-year students of IIM-A from 2006, who were part of the 250 students who enrolled in the programme in 2004. Of these, we have salary data on 226.³ The salaries of 221 were reported to the IIM by the companies that employed them and five self-reported salaries of those with preplacement offers or with independently negotiated offers that we obtained through a survey.

We have data on gender, SC/ST status, GPA on a 4-point scale, Class 10 and Class 12 public examination marks, college graduation percentage, and years of work experience. The IIM did not, however, provide data on student scores in the Common Admission Test (CAT) and subsequent interviews (in 2004), which together form the basis for selecting students for admission to the IIM'S PGDM programme.

A student may get several job offers but only the final offer accepted by a graduating student is reported to the placement

office. This is what we use in our analyses. One complication is that about 30 per cent of students receive offers from abroad (Table 1). This necessitates a choice of exchange rate to make rupee and foreign currency salaries comparable.

Table 1: Student Placement by Location in 2006

| Region | Percentage |
|---------------------|-------------|
| India | 70 |
| Rest of Asia | 11 |
| US | 7 |
| Europe | 12 |
| Source: Placement O | ffice IIM-A |

Foreign acceptances (all reported in us dollars) were converted into rupees as described below. The market exchange rate was Rs 44 per dollar at the time of the survey and the World Bank's purchasing power parity (PPP) rate was approximately eight according to the Penn World Tables [Heston et al 2006]. The PPP rate probably adjusts too much for cost-of-living differences because executives may consume a larger share of tradable goods than the share of tradables included in GDP. We used the data from an e-mail survey of students who received multiple offers to arrive at the appropriate rate. The idea was to use data from prospective employees who received offers in both currencies, and assume that the individual accepted the highest offer using an exchange appropriate for him/her.4 Eleven students who accepted an Indian offer also received foreign offers, and Rs 13.79 per dollar was the mean of the weakest value of the rupee consistent with accepting an Indian offer, with these values ranging from Rs 6.35 to Rs 19.33 per dollar. However, looking at the five students who received at least one Indian offer but accepted a foreign offer, we find that the mean of the strongest value of the rupee consistent with this behaviour was Rs 20.53 per dollar, with values ranging from Rs 9.71 to Rs 32.86 per dollar.

Owing to this inconsistency, we present the results of our analysis of the determinants of pay using both the mean exchange rates reported above. We also report results using only the subsample that accepted Indian offers.

Variable definitions and descriptive statistics on the main variables used are given in Tables 2a and 2b (p 47).

Of the graduating students, 21.3 per cent were sc/st, indicating compliance with the legal requirement that at least 22.5 per cent of all students admitted be sc/st (their share of the

| lable | 2a: L | ist of \ | Variab | iles |
|-------|-------|----------|--------|------|

| Variable | Definition |
|-----------------------|---|
| Log pay | Natural log of the final salary offer to the MBA graduate (foreign offers are converted at one of two exchange rates). |
| GPA | First-year grade point average on a 4-point scale in IIM. |
| Work experience | Employment experience in years before enrolling at IIM |
| Attractiveness rating | Average rating of attractiveness of passport-size photos performed by 20 graders and standardised to remove individual biases. |
| Female | Female = 1 if female, 0 if male. |
| College marks | Percentage marks received in college. |
| College score | College marks divided by 25 to conform to a 0-4 scale. |
| SC/ST | Whether the person belongs to a SC/ST. |
| Communication GPA | Cumulative GPA on three communication courses taught in the first year (including written, oral and managerial communication). 4-point scale. |
| Elite | Elite = 1 for IIT or BITS Pilani graduates. |

general population). Women constituted 16 per cent of the sample. There is no positive discrimination in favour of women and we observe that the share of women has stagnated for at least the last two decades.⁵

4 Results

Since there is no positive discrimination in favour of female students, the incoming distributions of college marks of women and men are essentially the same.

sc/st students have considerably lower incoming undergraduate college marks, on average. This is a consequence of the fact that sc/sTs have access to inferior educational opportunities than the rest of the population, together with the legal requirement that 22.5 per cent of all seats be reserved for sc/st students (their share in the general population). The mean college mark for sc/st candidates is 10 percentage points lower than that of the general category. In fact, the distribution of college marks for sc/sT students is first-order stochastically dominated by that of the general category (Figure 1). The difference in the two distributions is clear. For example, 62 per cent of sc/sT students have college marks below 70 while only 20 per cent of students in the general category have college marks below 70.

The difference in sc/st and other students' college marks is replicated in first-year GPAs in the IIM (Figure 2). However, by the end of the second year, sc/st grades do appear to converge to those of the general category, as reflected in the distributions of second-year GPA in Figure 3. It would, however, be overly optimistic to attribute this wholly to catching up by

sc/sr students. Unlike first-year courses, many second-year courses are optional and some may have easier grading policies compared to the more rigid and standardised core courses taken

| Tab | le 2b: | Descr | iptive | Stati | istics | |
|-------|--------|-------|--------|-------|--------|--|
| Varia | hle | | | | | |

| Variable | N | Mean | SD |
|--------------------------------|-----|-------|------|
| Pay in Rs lakh (20 Rs/\$) | 226 | 12.53 | 5.91 |
| Pay in Rs lakh (14 Rs/\$) | 226 | 10.72 | 3.70 |
| Pay in Rs lakh (Domestic jobs) | 160 | 9.93 | 3.15 |
| SC/ST | 242 | 0.21 | 0.41 |
| Female | 242 | 0.16 | 0.36 |
| Work experience (years) | 242 | 1.1 | 1.92 |
| 1st-year GPA | 242 | 2.32 | 0.31 |
| Communication GPA | 242 | 1.8 | 0.2 |
| 2nd-year GPA | 241 | 2.68 | 0.4 |
| College marks (%) | 242 | 76.77 | 9.82 |
| College score (scale 0-4) | 242 | 3.07 | 0.39 |
| Elite college graduate | 242 | 0.33 | 0.47 |
| Age in years | 242 | 22.99 | 2.29 |
| Attractiveness rating | 242 | 0 | 0.98 |

in the first year. Moreover, our regressions below suggest that second-year gpas do not appear to be used by companies. This may be because of the variability in grading strictness, and because not all second-year grades are available by the time students are interviewed. In this situation, it is entirely plausible that weaker students will avoid the harder courses, while betterprepared students will not. This will tend to reduce the gap in grades between them.

The determinants of GPA are given in Table 3 (p 48). As expected, the strongest determinant of academic performance in the IIM is prior academic performance, here measured by college marks, normalised to a 4-point scale. Regression analysis confirms the finding mentioned above that sc/sts get lower first-year gpas than general category students, even controlling for college marks. This suggests that, unsurprisingly, college marks do not fully measure academic ability. sc/st students were, on average, academically weaker than those in the general category with the same college scores. Attractiveness positively affects GPA, possibly through greater selfconfidence. Table 3 does not report specifications with an interaction term between attractiveness and being female, since this was not statistically significant.

Finally, we turn to the determinants of pay on graduation from the IIM. In Tables 4A & 4B (p 48), we report regressions of the natural log of pay on a number of variables, the former using a 20-rupee exchange rate for the dollar, and the latter a 14-rupee exchange rate. The estimated standard errors of the coefficients allow for correlation of the errors within companies and for heteroscedasticity.

College Marks for General and SC/ST Students (in %)

1

SCST

General

2

0

50

60

70

80

90

100

Figure 1: Empirical Cumulative Distribution Functions of

Figure 2: Empirical Cumulative Distribution Functions of GPA for General and SC/ST Students in the First Year at IIM

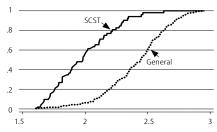
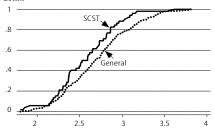


Figure 3: Empirical Cumulative Distribution Functions of GPA for General and SC/ST Students in the Second Year at IIM



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The main determinants of the starting salary of an IIM graduate are the first-year gpa, gpa in communications courses, and work experience. An increase of one grade point (on a o-4 scale) in the first-year gpa is estimated to raise the wage by more than 40 per cent (Column (3) of Table 4A and Column (2) of Table 4B).

Table 3: Determinants of Grade Point Averages

Coefficient

SC/ST

Female

Constant

Observations

R-squared

Work experience (years)

Attractiveness rating

Elite college graduate

College score (scale 0-4)

First-Year GPA

(1)

(0.038)

0.00326

(0.0072)

0.0316**

(0.015)

-0.0746*

(0.039)

(0.031)

(0.040)

(0.13)

242

0.53

Standard errors in parentheses

p<0.01, ** p<0.05, * p<0.1

0.117***

0.319***

1.372***

-0.284***

Communication

GPA

(2)

(0.031)

0.00888

(0.0057)

(0.012)

(0.031)

(0.024)

(0.032)

(0.10)

242

0.30

0.0562**

0.119***

1.434***

-0.00132

-0.135***

0.0437***

4.1 Wage Penalty for SC/STs

The estimated wage penalty associated with being sc/st is between 24 (at Rs 14/\$ exchange rate) and 35 per cent (at Rs 20/\$) compared to their counterparts in the general category (Column (1) in Tables 4A and 4B). This estimated penalty is slightly smaller at 19 per cent if only domestic jobs are considered (Table 4A, column (2)). However, once we control for work experience and GPA, the wage penalty to being sc/st becomes much smaller and not significant (Columns (3) and (2) in Tables 4A and 4B respectively). Since sc/st job candidates have, on average, much lower first-year gpas, and slightly lower work experience than general category candidates, the wage penalty seems to

be operating through these factors. Thus, once we control for the influence of grades, there is no evidence here of discrimination against sc/st candidates by employers.

The last two columns of Tables 4A and 4B introduce additional controls. GPA in communications courses also has a positive effect on the wage, raising it by 30 or 18 per cent (at Rs 20/\$ and Rs 14/\$ exchange rates, respectively). An interaction between the sc/sr dummy and first-year GPA is also negative and statistically significant. An F-test reveals that the predicted value of the wage

| Table 4A: Determinants of Pa | v (Exchange Rate: Rs 20/\$) |
|------------------------------|-----------------------------|
| | |

| Coefficient | Log (pay) | Log (pay) Domestic Jobs | Log (pay) | Log (pay) | Log (pay) |
|------------------------|-----------|----------------------------|----------------|------------|-------------|
| | (1) | (2) | (3) | (4) | (5) |
| SC/ST | -0.351*** | -0.194*** | -0.0855 | 1.411*** | 1.406*** |
| | (0.072) | (0.043) | (0.057) | (0.30) | (0.31) |
| Work experience (years | 0.0392*** | 0.0509*** | 0.0409*** | 0.0422*** | 0.0391*** |
| | (0.011) | (0.0073) | (0.0082) | (0.0074) | (0.0077) |
| Attractiveness rating | 0.0857** | 0.0205 | 0.0774* | 0.0718* | 0.0623* |
| | (0.040) | (0.017) | (0.039) | (0.037) | (0.035) |
| First-year GPA | | | 0.606*** | 0.738*** | 0.596*** |
| | | | (0.092) | (0.10) | (0.12) |
| SC/ST*GPA | | | | -0.730*** | -0.724*** |
| | | | | (0.15) | (0.15) |
| Female | | | | 0.0507 | 0.0341 |
| | | | | (0.061) | (0.062) |
| CommunicationGPA | | | | | 0.303*** |
| | | | | | (0.11) |
| Second-year GPA | | | | | 0.0575 |
| | | | | | (0.052) |
| Constant | 13.98*** | 13.77*** | 12.51*** | 12.18*** | 11.82*** |
| | (0.081) | (0.043) | (0.19) | (0.22) | (0.24) |
| Observations | 226 | 160 | 226 | 226 | 226 |
| R-squared | 0.24 | 0.37 | 0.38 | 0.41 | 0.42 |
| Ordinarul | Causeac | Dobust stan | dard arrare in | naronthoco | c clustored |

Ordinary Least Squares, Robust standard errors in parentheses, clustered by company

*** p<0.01, ** p<0.05, * p<0.1

for sc/st candidates is not significantly different (p = 0.42) from that of general candidates at a first-year GPA of 2, the mean level of GPA for sc/st candidates. This is seen clearly in Figure 4 (p 49).

However, in the same F-test done at a first-year gpa of 2.4, the upper end of the range of sc/st gpas reveals that the predicted

Quantitative

GPA

(3)

-0.404***

(0.060)

-0.00240

(0.011)

0.0448*

(0.023)

(0.062)

(0.048)

(0.063)

(0.20)

242

0.51

-0.166***

0.215***

0.463***

1.155***

wage for sc/sts is 33 per cent lower than that of the general candidates (p = 0.000). This suggests that sc/sT candidates are not able to get the same reward as general category students for higher GPAs. We checked whether this is only because sc/st students have low gpas (with a maximum of 2.4), by regressing pay against GPA and other variables for general category students within the same range of GPAs. We find a positive and significant slope coefficient of o.68. Thus, it is not just the low gpas of SC/ST students that accounts for their wages not responding to their GPA.

It is worth remarking that the standard deviation in wages between companies is about 2.5 times the standard deviation within companies.

Not surprisingly, then, the strong effect of first-year GPA on the wage is mostly due to students with higher GPAs finding employment at higher-paying companies, and not due to their being paid more in the same company. This can be seen from regressions of log pay on the same set of variables, done with company means on the one hand, and with company fixed effects on the other. In the former case, the effect of GPA is strong (and, as expected, being sc/st has a strong negative effect if GPA is omitted from the set of controls). But the latter, within-company, regressions give

Table 4B: Determinants of Pay (Exchange rate: Rs 14/\$)

| (1) -0.243*** (0.051) 0.0483*** 0.0083) 0.0513* (0.027) | (2) -0.0542 (0.043) 0.0495*** (0.0064) 0.0454* (0.027) | (3) 0.948*** (0.24) 0.0498*** (0.0060) 0.0440* (0.025) | (4) 0.920*** (0.24) 0.0475*** (0.0064) 0.0380 (0.024) |
|---|--|--|---|
| (0.051) 0.0483*** 0.0083) 0.0513* | (0.043) 0.0495*** (0.0064) 0.0454* (0.027) | (0.24) 0.0498*** (0.0060) 0.0440* | (0.24) 0.0475*** (0.0064) 0.0380 |
| 0.0483*** 0.0083) 0.0513* | 0.0495*** (0.0064) 0.0454* (0.027) | 0.0498*** (0.0060) 0.0440* | 0.0475*** (0.0064) 0.0380 |
| 0.0083) 0.0513* | (0.0064) 0.0454* (0.027) | (0.0060) 0.0440* | 0.0380 |
| 0.0513* | 0.0454* (0.027) | 0.0440* | 0.0380 |
| | (0.027) | | |
| (0.027) | | (0.025) | (0.024) |
| | 0.422*** | | (|
| | 0.432*** | 0.515*** | 0.415*** |
| | (0.060) | (0.066) | (0.071) |
| | | -0.490*** | -0.475*** |
| | | (0.12) | (0.12) |
| | | 0.0101 | -0.00414 |
| | | (0.041) | (0.041) |
| | | | 0.183* |
| | | | (0.093) |
| | | | 0.0631 |
| | | | (0.047) |
| 13.83*** | 12.79*** | 12.58*** | 12.32*** |
| (0.056) | (0.13) | (0.15) | (0.19) |
| 226 | 226 | 226 | 226 |
| 0.26 | 0.38 | 0.40 | 0.41 |
| | (0.056) 226 0.26 | 13.83*** 12.79*** (0.056) (0.13) 226 226 0.26 0.38 | 13.83*** 12.79*** 12.58*** (0.056) (0.13) (0.15) 226 226 226 |

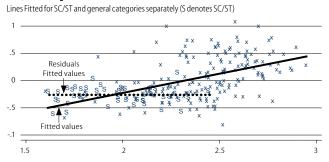
Ordinary Least Squares, robust standard errors, clustered by company, in parentheses

*** p < 0.01, ** p < 0.05, * p < 0.1

small and insignificant estimates for the coefficients of GPA and of the sc/st dummy even with GPA omitted. We do not explicitly report these results here to save space.

The importance of these results lies in that they show sc/st candidates are mostly placed in lower-paying companies. This suggests that the wage differential between them and general category students may persist even later in their careers because companies with high starting salaries probably continue to pay their employees better.

Figure 4: Residuals of Log Pay on Variables in Column (5) of Table 4A Except First-Year GPA, Plotted against First-Year GPA



It is interesting to compare our finding of an absence of wage discrimination by caste in this elite market for entry-level managers with the results of Madheswaran and Attewell (2007), the only other study of wage discrimination in India of which we are aware. They use NSS data and find that in 1999-2000, SC/ST employees in urban salaried jobs in India received wages that were 31 per cent lower on average than those of others, and that 15 per cent of this wage differential could not be explained by endowments of human capital and other factors. Thus, they find that discrimination results in a 5 per cent wage penalty for sc/st employees. It is worth noting that NSS data do not have information on grades, only on educational qualification, crudely measured. So their 5 per cent wage penalty should be compared with the 19 per cent wage penalty that we estimate for domestic jobs, without controlling for GPA. If measures of academic performance or other measures of productivity were available in the NSS data, it is possible that Madheswaran and Attewell's finding of discrimination in the Indian labour market would shrink in magnitude, and conceivably even disappear, like ours above.6

On the other hand, it may simply be the case that the IIM-A placement market is exceptional because it is an elite market. Moreover, in the IIM-A placement market, employers are less likely to know candidates' caste than the average employer in the NSS. Employers at the IIM will only be able to guess that someone is SC/ST in certain cases from their names and other cues. Most SC/ST students at IIM do not display a marked lack of the westernised brand of social skills that sometimes characterises this cohort in professional circles. This limits the scope for discrimination. It is, of course, possible that discrimination may make its appearance later in the career of employees after the employer learns their caste.

Two recent articles study callback differentials in field experiments for urban professional sector jobs in India. Banerjee et al (2007) who study the software and call-centre sectors in Delhi find that though there is some discrimination against scs in

call-centre jobs, for software jobs that require "harder" skills, there no are significant differences in callback rates between castes. They interpret their results as being consistent with statistical discrimination. Thorat and Attewell (2007), studying the urban professional sector, find larger differences in callback rates. Since their article does not report whether the resumes included grades, it is impossible to say whether the discrimination they observed is likely to have been statistical or taste-based.

4.2 Beauty Premium?

From Tables 4A and 4B, we see that the facial attractiveness rating variable does not have a statistically significant effect on pay in the domestic market or in the overall market, when the exchange rate used is Rs 14/dollar. However, at an exchange rate of Rs 20/dollar, a one-standard-deviation increase in facial attractiveness is estimated to increase pay by 6 per cent, although this is significant only at the 10 per cent level, when controlling for communication GPA.8 Hamermesh and Biddle (1994), not controlling for grades, report a wage premium for attractiveness ranging from 1 per cent to 13 per cent in various us and Canadian labour markets. Hamermesh and Biddle (1998) control for class rank in a study of graduates from an American law school and find a statistically insignificant 3 per cent beauty premium in the first year after graduation. Harper (2000) finds a substantial penalty to unattractiveness in the UK labour market, but again, lacks a control for grades.

The effect of attractiveness, to the extent that it exists, may be a taste-based discrimination effect, or arise from the greater self-confidence and better social skills of the more attractive, possibly combined with a belief among employers that more attractive people will be more productive. The literature in social psychology finds that attractiveness is correlated with popularity and social skills, but not with mental ability [Feingold 1992].

4.3 No Gender Discrimination

There is no evidence of discrimination based on sex, with there being no wage penalty (or premium) to being female. But, as

noted earlier, the percentage of female IIM graduates has stagnated at 15 per cent for at least the last 18 years.

4.4 Foreign Offers

Finally, it is interesting to note that the probability of receiving and accepting a foreign offer is significantly raised by better grades in communications courses (Table 5). Overall first-year GPA is significant at the 10 per cent level. These findings suggest that foreign jobs were

Table 5: Determinants of Foreign Placement

| Coefficient | Prob | Prob |
|-------------------------|-----------------|-----------------|
| | (Foreign Offer) | (Foreign Offer) |
| | (1) | (2) |
| SC/ST | -0.163 | -0.152 |
| | (0.10) | (0.10) |
| First-year GPA | 0.297* | 0.350* |
| | (0.18) | (0.20) |
| Communication GPA | 0.499** | 0.453** |
| | (0.22) | (0.21) |
| Elite college graduate | 0.0462 | |
| | (0.065) | |
| Work experience (years) | -0.0229 | |
| | (0.015) | |
| Attractiveness rating | 0.0562 | 0.0568 |
| | (0.035) | (0.036) |
| Female | 0.128 | 0.139 |
| | (0.080) | (0.085) |
| Observations | 233 | 233 |
| Pseudo R-squared | 0.20 | 0.19 |
| Robust standard e | rrors in pare | ntheses |
| | | |

*** p<0.01, ** p<0.05, * p<0.1

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perceived as more attractive, on average, since they attracted the candidates with desirable attributes.

5 Conclusions

We conclude that there is both good and bad news. The good news is that there is no evidence of discrimination by caste in this entry-level market for elite managers. This is quite different from results obtained by Madheswaran and Attewell (2007) and Thorat and Attewell (2007) and could be due to employers not knowing the caste of job candidates at the IIM. Even so, this is encouraging. Employers wanting to discriminate could probably learn candidates' caste if they tried hard enough. There is also no evidence of

discrimination against women and only weak evidence of discrimination against those rated as facially less attractive.

The bad news is that in the absence of a control for grades, sc/st candidates get wages that are between a fifth and a third lower than those in the general category. That sc/st students come in with, on average, weaker academic backgrounds and are heavily penalised for this in the job market, is a reminder (if one were needed) that the reservation for sc/st students in higher education cannot fully make up for the lack of equal opportunity in primary, secondary and high school education, even for the tiny fraction of them that make it to elite institutions of higher education.

NOTES

- 1 This type of field experiment has come to be known as a "callback" study. In such a study, the experimenters send out resumes of fictitious individuals with different demographic characteristics (educational qualifications, religion, gender, etc) to different companies and then study the desirability of these different demographic groups in the job market.
- 2 If a candidate's grade point average (GPA) for the first year of the PGDM programme was not on his resumé, an employer could get it from the placement office.
- 3 Of the initial 250, three did not graduate in 2006 and six were self-employed so they could not be used in our analysis. A few did not obtain employment through the institute or did not accept the final offer generated by the placement process. Overall we have almost 94 per cent of the total population of graduates that year.
- 4 Offers in foreign currencies (the pound and the Singapore dollar) other than the US dollar were converted into US dollars at market exchange rates and a minor cost-of-living adjustment made in the case of Singapore.
- 5 Personal communication from Archana Garodia, 1988 IIM graduate
- 6 However, Weinberger and Joy (2003) report that in most studies using data from the US, controlling for the college attended and for grades does not significantly reduce the wage gap between white and black college graduates.
- 7 The experimenters send fictitious resumes to companies that have advertised job openings. They study the difference in rates at which resumes with names characteristic of different castes but identical in all other respects are called back by the companies.
- 8 These tables do not report specifications with an interaction term between attractiveness and the female dummy because this was never significant.

REFERENCES

- Arrow, K J (1972): Racial Discrimination in Economic Life, Heath, Lexington.
- Banerjee, A, M Bertrand, S Dutta and S Mullainathan (2007): 'Caste and Religion in India's 'New Economy': Evidence from a Field Experiment on Labour Market Discrimination in Delhi', Mimeo.
- Becker, G (1967): *The Economics of Discrimination*, The University of Chicago Press, Chicago.
- Deshpande, S and L K Deshpande (1992): 'New Economic Policy and Female Employment', *Economic & Political Weekly*, Vol 27, No 14.
- Feingold, Alan (1992): 'Good-looking People Are Not What We Think', Psychological Bulletin, 111(2): 304-41.
- Hamermesh, Daniel S and Jeff E Biddle (1994): 'Beauty and the Labour Market', *The American Economic Review*, 84:5, 1174-94.
- (1998): 'Beauty, Productivity and Discrimination: Lawyers' Looks and Lucre', Journal of Labour Economics, 16:1, 172-201.
- Hamermesh, D S and A Parker (2006): 'Beauty in the Classroom: Instructors' Pulchritude and Putative

- Pedagogical Productivity', *Economics of Education Review*, 24 (4): 369-76.
- Harper, Barry (2000): 'Beauty, Stature and the Labour Market: A British Cohort Study', Oxford Bulletin of Economics and Statistics 62 (81), 771-800.
- Heston, Alan, Robert Summers and Bettina Aten (2006): Penn World Table Version 6.2, Centre for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September.
- Kingdon, G (1999): 'Labour Force Participation and Returns to Education' in T Papola and A Sharma (eds), Gender and Employment in India, Vikas Publishing, New Delhi.
- Madheswaran, S and P Attewell (2007): 'Caste Discrimination in the Indian Urban Labour Market: Evidence from the National Sample Survey',

- Economic & Political Weekly, 42 (41): 4146-53, October 13-19.
- Mobius, Markus, M and Tanya S Rosenblat (2006): "Why Beauty Matters", The American Economic Review, March, 222-35.
- Sundaram, K (2006): 'On Backwardness and Fair Access to Higher Education: Results from NSS 55th Round Surveys, 1999-2000', Economic & Political Weekly, 41: 5173-82, December 16.
- Thorat, S and P Attewell (2007): 'The Legacy of Social Exclusion: A Correspondence Study of Job Discrimination in India', *Economic & Political Weekly*, Vol 42, No 41, October 13-19.
- Weinberger, CJ and LJoy (2003): 'The Relative Earnings of Black College Graduates 1980-2001' in Marlene Kim (ed), Race, Work and Economic Opportunity in the 21st Century, forthcoming, Routledge.

Appendix

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Table 3: Companies and the number of students recruited 2006 (Source: Placement Office, IIM-A)