Does Affirmative Action Work? Evaluating India's Quota System

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Abstract

This paper examines four common critiques of affirmative action policies in government hiring and education: (1) That they do not benefit the target group, (2) that any benefits are highly concentrated within the target group, (3) that they provide no spillovers to non-beneficiaries, and (4) that they raise the salience of group divisions. It examines the effects of educational and hiring quotas for OBC castes in India, using difference-in-difference and triple difference designs that take advantage of the gradual introduction of these quotas. The results provide little support for these critiques: Affirmative action is associated with small increases in educational attainment and middle class employment among eligible age cohorts, with no large differences in effect size between rich and poor OBCs in the sample as a whole. Quotas also increase the probability that OBCs know government officials, and do not increase caste association membership among OBCs.

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1 Introduction

Many countries feature severe economic inequalities between ethnic groups, often based on deep-seated social discrimination or legacies of previous discrimination (Cederman et al., 2010). One of the most common proposed solutions to such problems is the introduction of ethnic quotas or preferences in government hiring and educational admissions. In the United States, African American and Latino applicants are granted preferential treatment in admissions to most universities and in hiring for many jobs, while in India a proportion of places at public universities and jobs in public sector institutions are "reserved" for members of specific lower caste groups. The efficacy and justice of these policies have been, and continue to be, fiercely debated.

In this debate, critics of affirmative action frequently make empirical claims about the effects of these polices. Firstly, some have claimed affirmative action does not fulfill its primary goal of raising the socioeconomic status of the targeted group due to limited scope or poor "matching" of recipients to opportunities, leading to high rates of failure and no lasting gain (Sander, 2004). Secondly, some have claimed that any benefits affirmative action are disproportionately concentrated among the socio-economic elite of the targeted category (Massey et al., 2006; Galanter, 1984; Shah, 1985; Sowell, 2005). Thirdly, while all agree that the number of actual beneficiaries of affirmative action is usually small relative to the size of the targeted category, it is unclear whether preferential policies in government have any individual spillover effects on non-beneficiaries within the targeted category, such as those sometimes found for political quotas (Dunning and Nilekani, 2013; Jensenius, 2017; Chauchard, 2014). Finally, the imposition of quotas may make ethnic distinctions more important in structuring social and political interaction than they might otherwise have been, since citizens must profess group membership in order to claim the benefit (Glazer, 1975; Sowell, 2005; Jaffrelot, 2003).

Despite the importance of the question, the purely empirical literature on educational and hiring preferences is modest in size, particularly relative to the flourishing literature on the effects of electoral quotas. In fact, only the first of these critiques has undergone any sustained empirical investigation, most of it producing results critical of the "matching" hypothesis (Howard and Prakash, 2012; Khanna, 2018; Arcidiacono, 2005; Hinrichs, 2012; Frisancho and Krishna, 2016; Bagde et al., 2016). A related literature has accessed the effect of preferences on social or institutional efficiency (Bhavnani and Lee, 2018; Bertrand et al., 2010). However, there is relatively little empirical little work on the other three critiques.

This project focuses on a particularly controversial instance of affirmative action: the gradual implementation of hiring quotas for members of the Other Backward Classes (OBC) social category in India. Some Indian caste groups (jatis) are much poorer than others. Reservations for OBCs (members of jatis not sufficiently disadvantaged as "Scheduled Castes" or "Scheduled Tribes") were instituted in some states during the early and mid-20th century, and at the national level and in all states in 1994. The wisdom and scope of OBC reservations are still intensely debated in India.

One reason for the small size of the literature on affirmative action relative to the enormous political importance of the policy is the difficultly of causally identifying the effects of preferential policies at the group level. These policies are not imposed randomly: Groups that benefit from preferences are (almost by definition) different socioeconomically before treatment from those that do not. Similarly, these policies are often imposed at times of political and social change, which might have changed the social position of disadvantaged groups even without quotas. In the Indian context, quotas were targeted towards poor groups, and implemented in the 1990s at the same time as several other important economic and political reforms .

To assess the efficacy of OBC reservations, the paper uses a research design designed to mitigate these selection effects. The main models use a difference-in-difference design that compares OBC and non-OBC Indians who came of age before and after 1994 in the states where local policy changed in this year. A second set of models use a difference-in-difference-in-difference design that assesses the effect of state policies, accounting not only for national trends but region and category-specific onez. The "simple" DD and DDD models are supplemented by very conservative models that include a full range of fixed effects for state-birth years, state-caste categories, and caste category-birth years. Other models add controls, though many plausible controls are either post-treatment or collinear with the fixed effects. Additional tests use alternative measures of reservation that account for individual movement between caste categories and show that there were no pretreatment differences in trends between OBCs and non-OBCs. Note that due to limited appendix space, many additional results are available only on request.

An analysis of national survey data using the DD and DDD designs indicates that reservations increased the education level and occupational status of OBCs without decreasing the achievement levels of other groups, though these effects appear to have been modest in substantive size—an increase of between a quarter and three quarters of a year of education, and between one and four percentage points in the probability of holding a middle class job. The largest effects of the policy are seen among those from moderately educated OBC families, thought this pattern is not especially strong. The lack of concentrated benefits among the highly educated may stem from the fact that the tiny number of OBCs from educated families was too small or poor to monopolize the impact of reservations; in the wealthiest states, there is some evidence for concentrated benefits among highly educated families.

The results also indicate that reservations are associated with changes in social network structure. The introduction of reservation is associated with increases of between one and five percentage points in proportion of individuals with a doctor, teacher, or gazetted government officer from their caste within their social network, a potentially significant result given the importance of connections in Indian life and Indians' relationships with the state. The introduction of reservations is also not associated with increases in the importance of caste in structuring social activity, as measured by membership in caste associations: If anything, membership seems to be relatively low among new quota beneficiaries. The results indicate that some critiques of affirmative action policies are not supported empirically, at least in the Indian context.

2 Predicting the Effects of Affirmative Action

2.1 Socio-Economic Effects

The term "affirmative action" (hereafter AA) describes a policy of preferences for members of a disadvantaged category in opportunity allocation, either in the form of a formal quota or (as in the United States) a less formal set of preferences. These preferences may be implemented in any process in which opportunities are distributed among individuals, though by far the most common are in admissions to higher education and government hiring, usually implemented together.

Arguably the most important goal of affirmative action policies is to raise the socio-economic status of the targeted group and increase its representation within the social and economic elite. The narrowest test of affirmative action would thus be whether it provides economic and social benefits to the beneficiaries—the students who are admitted or the bureaucrats who are hired. While it may seem may seem obvious that affirmative action would benefit the targeted group, an influential account, using US law school data, has argued for null or negative AA effects on beneficiaries due to poor matching (Sander, 2004). For Sander, AA leads to the allocation of opportunities to those who are not prepared to handle them, leading to high rates of failure. This gives us a critique of affirmative action:

> ***Critique One:*** *Affirmative action programs will not improve the socioeconomic status of beneficiaries and targeted groups in relative terms.*

This critique is, by a sizable margin, the one with the largest empirical literature accessing it. Sander's claim has been strongly challenged by others, using a broad range of data and more sophisticated causal inference strategies, who find positive effects of AA on the beneficiaries (Arcidiacono, 2005; Bertrand et al., 2010; Frisancho and Krishna, 2016; Bagde et al., 2016), even if they are skeptical of its broader social effects. Indeed, the avidity with which AA policies are sought by the beneficiaries would lend credence to the view that they confer some sort of benefit. These studies are supplemented by others that focus on beneficiary groups as a whole, and have found AA to have positive aggregate effects on education and occupational status (Howard and Prakash, 2012; Cassan, 2019; Khanna, 2018). Khanna (2018) argues that this effect stems from strategic investment by potential beneficiaries, rather than the direct effect of admissions.

2.2 Concentrated Benefits

Even if affirmative action does improve the socio-economic status of underprivileged groups, it not clear that these benefits flow to the most underprivileged members of these groups. Consider the common situation where AA policies establish a quota or preference for members of the underprivileged category, but within the category distribute opportunities based on perceived merit. Frequently, merit (or ability to excel in the procedures designed to measure it) is correlated with socio-economic status: Indeed, this correlation is one reason why quotas are implemented in the first place. If this is the case, open competition on "meritocratic" criteria within the disadvantaged category will lead to a situation where the beneficiaries of affirmative action are disproportionately made up of socio-economically advantaged individuals within the disadvantaged group, or members of relatively advantaged subgroups within the disadvantaged group. This is usually considered undesirable, because if only the children of middle class individuals benefit from programs that help individuals join the middle class, the size of the underprivileged group middle class will increase little over time.

There have been numerous claims that a pattern of concentrated benefits occurs in real world affirmative action programs. Sowell (2005, 167-8) states that "Those individuals most likely to be compensated are often those with the least disadvantages, even when the groups they come from may suffer misfortunes." India's programs, which give benefits to large categories of castes, has been dogged by allegations that they disproportionally benefit richer groups within the categories (Shah, 1985; Deshpande and Yadav, 2006). These claims have led to the adoption of rules (discussed below) to subdivide caste large categories and exclude the rich as beneficiaries. In the United States, critics of reservations for African Americans have claimed that they tend to benefit relatively educated children of African immigrants, or the children of educated African Americans in general (Massey et al., 2006). Cassan (2019) tests a gendered version of the concentration hypothesis, and finds that quota benefits are concentrated among men.[1]This claim gives us a second critique of affirmative action programs:

> ***Critique Two:*** *Affirmative action programs will only improve the socio-economic status of the pretreatment elite of targeted groups.*

2.3 Spillovers and Contacts

Even if all members of the targeted group have an equal chance of receiving the benefit, only a small number will actually do so, given that the number of university seats or desirable government jobs redistributed by AA is usually small relative to the size of the category as a whole. This flaw has been acknowledged by many AA proponents, and is one argument for replacement of AA by more extensive programs of reparations (Coates, 2016). This problem gives us a third critique of affirmative action programs:

> ***Critique Three:*** *Affirmative Action Programs will only have effects on the immediate beneficiaries of the policy.*

One possible defense of AA's narrow scope is that it might have spillover effects on non-beneficiary members of the targeted category. In recruitment to political office and some bureaucratic positions, the spillovers might be institutional: The new recruits will change policy or practice to benefit coethnics (Dunning and Nilekani, 2013; Jensenius, 2017; Bhavnani and Lee, 2018; Chauchard, 2014). This will occur because coetnic favoritism may lead to more representative bureaucracies to transfer state resources more

[1]Frisancho and Krishna (2016) and Bertrand et al. (2010) find that AA admits in India are poorer than other admits, but do not address their relative position within the targeted category.

equitably (Ejdemyr et al., 2017; Kramon and Posner, 2016). In addition, AA may create "role models" of success to members of the targeted category, who might not previously have been familiar with members of their own group who achieved this level of educational and occupational achievement, and were correspondingly unwilling to pursue opportunities they were unfamiliar with or viewed as impossible (e.g. Chung, 2000). We are not aware of any studies of the effects of AA on the social networks of the population as a whole, though Vanneman et al. (2006) suggests that the fact that Indian urban low-caste individuals have a higher level of contacts than Muslims might reflect reservation policies.

The question of whether AA creates these useful social relationships is intimately related to Critique One: If affirmative action does not increase the number of professionals in the target group, it will obviously not increase the role model pool. However, the network effects of affirmative action are more than a mechanical consequence of the socio-economic ones, since they capture subtle patterns of ties within the target group, in particular the extent and social composition of the networks of beneficiaries. In groups with thick social ties, a single beneficiary may know many poor people, while in more segmented groups she might know only her own family or to individuals who already had many official contacts available.

2.4 Salience and Associations

Many opponents of AA argue that, whatever positive socio-economic effects it may have, it represents an undesirable phenomenon because it reinforces group divisions (Glazer, 1975; Sowell, 2005). According to these authors, the division of society into ascriptive groups is an artificial and deplorable phenomenon. Left to themselves, these identities will either fade away or remain at current levels of salience. However, if the state creates material incentives for individuals to identify with particular identities, they will tend to become more salient, as citizens organize and shift their own identity repertoire to gain the benefit. Sowell (2005, 179) states that "those who imagine themselves promoting intergroup harmony by attempting to reduce economic disparities between groups seldom consider whether their politicizing of those differences may have the opposite effect."

While the actual effect of AA on the salience of ascriptive division has never been tested. However, an extensive literature has found that shifts in identity are closely associated with shifts in state policy (Rao and Ban, 2007). In the political sphere, the adoption of affirmative action in India was closely associated temporally with the increase in the salience of caste in political rhetoric and voting (Jaffrelot, 2003). More directly, Francis et al. (2012) found that the adoption of AA in Brazil increased the propensity of respondents to self-identify as black, though this does not of course test its effect on individuals who already self-identified as black. This claim gives us a fourth critique of affirmative action programs:

> ***Critique Four:*** *Affirmative action programs increase the associational salience of ascriptive identities among targeted groups.*

3 Affirmative Action in India

3.1 Historical Background

India contains thousands of endogamous caste groups or *jatis*, most specific to a given region and associated with a traditional occupation. In traditional conceptions of the caste system, castes are sorted in a religiously legitimated hierarchical ordering from high to low, with lower groups considered naturally fitted to a subordinate social and economic role.

For the purposes of the Indian government, jatis and communities are grouped into four categories: Scheduled Castes (SCs), Scheduled Tribes (STs), Other Backward Classes (OBCs) and General. The SC groups, sometimes known as untouchables or dalits ,have traditionally faced high levels of social discrimination. The ST groups, who inhabit highland regions of India, have suffered from similar problems of social marginality. The OBC category is less homogenous, comprising a grab bag of groups who have faced some level of social discrimination, but where the discrimination is thought to be less severe than that faced by SCs and STs.

Despite the artificial nature of these caste categories, they are strongly correlated with socioeconomic status. According to the 2011-12 Indian Human Development Survey, among adults born before independence literacy was 21% among SCs, 17% among STs, 37% among OBCs, and 53% in the general category. Crucially, in the mid-20th century the three lower caste categories were underrepresented in both government employment and higher education (Mathur, 2004; Jaffrelot, 2003).

3.2 The Adaptation of OBC Reservations

India's post-independence leaders, while overwhelmingly upper caste, were keenly conscious of both these inequalities and the discrimination that gave rise to them. They also faced competition from lower caste elites who had succeeded in implementing quotas for official hiring and university admissions in several western and southern provinces during the late colonial period (Mathur, 2004). These early reservations programs were primarily targeted against the social and educational predominance of the Brahmin caste, and thus all non-Brahmins were eligible for benefits.

In the Indian constitution, SCs and STs were granted quotas proportional to their share of the population in university admissions, government hiring, and political representation at both the local and state levels, which have remained in place since then. The drafters could not find a consensus, however, on whether reservation should be extended to other groups. The compromise solution was to include a non-binding "directive principal" that the government should promote the welfare of an undefined set of "Other Backward Classes." In practice, this meant that states could decide for themselves whether to impose quotas.

The story of the spread of caste quotas is told in Table B.2. The period immediately after independence was one of flux in reservation policy, as changing state borders and law suits from aggrieved upper caste plaintiffs made the alteration of colonial era policies inevitable. There was, however, a sharp regional trend. By 1964, every state in the south of the country had implemented some form of OBC reservation. In the north, where caste discrimination remained more entrenched, help for OBCs took the form of modest scholarship schemes, or nothing at all. The other major trend was the narrowing in the set of targeted groups, as the supreme court in *MR Balaji v Mysore* (1962) had held that no more that 50% of places could be allocated by quota (Galanter, 1984).

After the electoral defeat of the Congress Party in 1977 several other states passed reservation laws, and the new Janata Party government also established a commission, chaired by BP Mandal, which recommended OBC reservations at the national level. The Mandal report was finally implemented in 1990 by the next non-Congress government led by VP Singh, though court challenges and administrative difficulties delayed its implementation until 1994. At this time, all states that had not done so implemented reservations for OBCs in education and hiring, and several other states took the opportunity to reform their existing quota systems. The central government also implemented OBC reservation in its own hiring, though reservation in the small number of central educational institutions had to wait until 2006. The implementation was bitterly contested by upper caste activists, some of who immolated themselves in public places in protest. The controversy led to a realignment of political loyalties in India, in particular the rise of "pro-Mandal" politicians dedicated to defending reservation policies (Jaffrelot, 2003).

3.3 Reservations in Practice

In India today, admissions to government universities and hiring to government jobs or jobs in state-owned corporations are subject to hiring quotas. Reservations in private sector hiring and public sector promotion have been proposed but not widely implemented. However, the areas where reservation is used are significant: public universities make up the majority of university seats and are considered the most prestigious, and public sector employment is considered both more secure and desirable than comparable private employment.

Both university admissions and government recruitment in India are determined based on competitive written exams. The highest scoring individuals (up to a number equivalent to 50% of the final goal) are admitted or hired as the "general" quota. Officials then continue down the list, admitting the highest scoring SCs, STs and OBCs until the quotas for these groups are filled or until there are no applicants who meet a minimal quality threshold. Note that the percentage of members of underprivileged groups among the beneficiaries can be above 50% (if many applicants from these groups score above the general cutoff) or less than 50% (if most applicants from these groups score below the qualification cutoff). Sensitive to the criticism that this system provides an advantage to wealthier OBC jatis, some states (mostly in the south) have subdivided the OBC category into various subcategories, each with their own list and quota.

To qualify for the OBC quota, applicants must provide caste certificates showing that they belong to a group on the central or state lists of OBCs. These certificates are issued by the subdistrict administration, and are based on inquires by government officials in the individual's neighborhood. Individuals must also provide certificates that they do not belong to the so-called "creamy layer" of individuals that are too rich to qualify for reservations. In 2012, the creamy layer included individuals with a family income above 450,000 rupees a year, as well as the children of politicians and senior civil servants. There have been reports of corruption in the provision of both caste and income certificates, the empirical consequences of which are discussed in Section A.

Not surprisingly, there is considerable controversy about which groups belong in the OBC category, and a large number of claimants to OBC status. The initial list of OBC groups at the national level was made by the Mandal Commission, while at the state level they were also initially taken from the Mandal Commission list in the castes that added reservation in 1994, the focus of the main analysis. Since 1994, both the state and national governments have established commissions to consider group applications for OBC status, and in some cases ministers have granted such status on their own authority. While most "late additions" are small groups neglected in the early process, a few are large groups with political pull. These late additions will be excluded from the analysis below.

4 Data and Models

4.1 Measuring Social and Political Outcomes

The primary data for this study is the 2011-2012 Indian Human Development Survey, a clustered random survey of social conditions and social attitudes (Desai and Vanneman, 2015). This survey was chosen over the more commonly used NFHS and NSS surveys because of its wide range of questions (particularly related to salience and social networks) and the public availability of a survey more than two decades after 1994. All models are weighted to account for variation in sampling probability. After excluding individuals who turned 18 before 1964 or were not 18 at the time of the survey, and residents of a few small states with few OBCs and no OBC reservation,[2] the sample includes 120,062 individuals in 35,879 households. All reported standard errors are clustered at the household level. Substantively identical results with standard errors clustered at the caste level are available on request from the authors.

C1. Socio-economic Status: The most immediate effects of affirmative action in government hiring and education would be to increase the educational attainment and occupational status of the recipients. The primary measure of educational attainment is the *number of years of education* possessed by each individual, excluding individuals aged less than 23 at the time of the survey. This is similar to the main dependent variable in Khanna (2018) and Cassan (2019). To measure occupational status, it uses a binary measure of whether an employed individual is *employed in a middle class job*.[3] Note that, due to lack of data, we are unable to measure another factor potentially influenced

[2] Tripura, Meghalaya, Mizoram and Arunachal Pradesh. Jammu and Kashmir has class-based reservations.

[3] Middle class workers were those coded with their primary activity as "organized business," "salaried" or "professional."

by AA, the relative prestige of different subtypes of jobs and educational institutions.

C2. Concentrated Effects: If the concentrated benefit hypothesis claim is correct, the benefits of AA should be only apparent among those individuals with a high socio-economic status before the implementation of the policies. This raises a problem, since the cross-sectional nature of the data means that we do not observe pretreatment SES—and in fact, the beneficiaries in the sample were children at the time of the implementation of AA policies. The only variable that captures pretreatment SES is the *father's level of education* which is available for all household heads and individuals living with their parents.[4] We use two different education cutoffs to capture differences between high, medium and low levels of paternal education. The first is a binary measure of whether one's father attended secondary school, a qualification held by only 30% of fathers, and the second is a binary measure of whether one's father attended university, a qualification held by only 4% of fathers. Father's education is correlated with caste category: 7.9% of general category respondents' fathers attended university, versus 3% of OBC respondents' fathers.

C3. Contacts: The necessary condition for any type of role-model or contact-driven spillover of AA benefits is that the implementation of AA will increase the proportion of members of the underprivileged group who know an individual from their own group in a position recruited through quotas. To test this claim, the paper examines the self-reported *social contacts* of IHDS respondents. Respondents were asked if anyone in their household was acquainted with individuals holding a wide variety of jobs. We have focused on four occupations which all require higher education of some sort: doctors, teachers, police officers of inspector rank or above or gazetted (middle to senior ranking)

[4]Note that since the IHDS took place 17 years after the implementation of AA, virtually none of their fathers would have benefited from AA.

civil service officers. The main measure is a binary variable coding whether someone in an individual's household knew someone from their caste with any one of these four jobs, something that was true of 42% of respondents.

C4. Salience: Measuring the salience of caste identity is another difficult problem, since it represents an abstract concept that varies from context to context and that individuals may have an incentive to misrepresent. This paper focuses a simple behavioral measures of whether caste influences social behavior: Individual *membership in caste associations* among Hindus. Caste associations are common feature of Indian life, both conducting welfare activities within their community and advocating community interests within the wider political system. In India as a whole, 9% of respondents were members of caste associations in 2012.

4.2 Measuring Reservation

To study the effects of India's quota policies, it is first necessary to know who the beneficiaries were. Table B.2 notes the year reservations were implemented and the amount of the quota(s). This is the only comprehensive listing of past quotas that we are aware of, and was compiled through a combination of official websites and Mathur (2004). Periods of reservation of less than two years that were subsequently overturned by the courts are ignored. As Section Three mentioned, about half the states adopted reservation in 1994, while the other half implemented them earlier in the 20th century. The main tests use a binary indicator for reservation status: Section A.2 shows that the results are similar when a continuous DV is used.

Beneficiary status was defined by birth year. One must be 18 (the age of high school graduation and legal adulthood) in order to benefit from reservation policies in both education and hiring in India. Since individuals older than 18 would have already be admitted to college before the advent of reservations, they cannot benefit from any change in the quota system after this date, and will find it difficult to benefit from employment reservations (since they will have already made many decisions effects their level of human capital and choice of career). While individuals may choose to reenter education as adults, but this is extremely rare: In 2012, only .19% of individuals over the age of 20 were enrolled in non-tertiary education, and only .43% of individuals over 25 were engaged in any kind of education.

In fact, there is a good case to be made that people who are teenagers at the time of a policy change will not get the full benefit from a change in AA policy: Since taking up these opportunities involves graduating from secondary school, individuals who are already on a trajectory not to graduate from secondary school will be unable to do so. Put simply, policy changes might have small immediate effects because the pipeline of eligible students from disadvantaged groups is small, and it will take time for this pipeline to adjust to the new policy. This will be particularly true if secondary education and exam preparation are costly investments, as they are in modern India. To account for this "pipeline" possibility, a second set of tests defines beneficiaries as those who turned 14 (the age of secondary school entry) in the year of a policy change, rather than 18.

The final problem is determining who is a member of the targeted group. In the Indian context, the simplest way of doing this, used in the main models, is to ask individuals which caste category they belong to. To correct for those added to the OBC category since 1994, individuals whose self-reported jati matched one of these "late addition" groups on the state OBC lists were only coded as OBC if they turned 18 after their caste was reclassified.

Using self-reported caste categories raises several problems. Firstly, members of the general category may reclassify themselves, possibly using forged certificuates, if doing so will bring them benefits. Secondly, since we do not have data have data on parental income, we cannot accurately determine if these members were part of the "creamy layer." These problems are discussed in Section A.

4.3 The Difference-in-Difference Estimator

Though OBC reservations have gradually been implemented through the 20th century, for reasons of analytical simplicity the analysis focuses on the largest and most recent of these changes: the extension of OBC reservations at both the state and national levels that occurred in 1994. For this reason, the main models exclude individuals who turned 18 before the last major round of reservation expansion in 1978.

The main models include SC and ST respondents in the "Non-OBC" category, creating a counterfactual group with social traits more similar to the OBCs than the general category alone. These groups could be excluded from the analysis without substantively altering the main results (results available on request).

Any test of the effects of quota implementation in India faces obvious problems of selection. Even at the margin, OBCs are different from members of other groups, since they were either poor, had enough political muscle to be included on the OBC list, or both. Similarly, individuals who came of age between 1979 and 1994 are systematically different from those who came of age between 1994 and 2012, when (among other things) the Indian economy was more prosperous and the political position of OBC groups much stronger, and the variety of social welfare programs available was much larger. Finally, while the final implementation of OBC reservation at the state level in 1994 was exogenous to the states involved, the states that were forced to implement quotas at that time differed both spatially and socially from those that implemented them voluntarily earlier.

The standard way of estimating this type of gradually implemented policy shift would be a difference-in-difference (DD) design focusing on the states where the policy changed in 1994 (the "Mandal states"), estimating a treatment effect conditional on time and unit effect. The simplest way to estimate this treatment for individual i of caste category c in year y in state s would be:

$$\text{Outcome}_i = \beta_0 + \beta_1 \text{OBC Caste}_c + \beta_2 \text{Post 1994}_y + \beta_3 \text{Post 1994 OBC Caste}_{cy} + \varepsilon_i \quad (1)$$

A more conservative version of this model, which accounts for variation at the level of the state-caste category and state year, would be:

$$\text{Outcome}_i = \beta_0 + \gamma_{cs} + \delta_{ys} + \beta \text{Post 1994 OBC Caste}_{cy} + \varepsilon_i \quad (2)$$

Where γ_{cs} is a vector of fixed effects for each state-caste category and δ_{ys} is a vector of fixed effects for each state-year. In Model 1, members of castes are being compared to each other across different states and years, whereas in Model 2 the comparisons are within castes and years. Note that this model desegregates the three non-OBC caste categories.

The simple DD model thus accounts for the two types of selection that we are most concerned about in this case: Pre-treatment differences between OBCs and others (e.g. the general category having better outcomes than other groups) and differences between the pre or post-treatment periods based on age or birth year (e.g. those who turned 18 before 1994 having lower educational attainment or elder people having better jobs). Equation two estimates a treatment effect conditional on an even larger set of factors: Pre-treatment differences between categories, birth cohort effect, pre-treatment regional differences in caste traits (e.g. OBC groups being richer relative to the general category in Rajasthan than in Uttar Pradesh) and time trends at the state level (e.g. Bihar becoming poor relative to Rajasthan during the late 20th century).

4.4 The Difference-in-Difference-in-Difference Estimator

There is an obvious weakness to the DD design in this context, even with the full set of fixed effects: It does not account for time trends at the caste category level. For instance, many scholars have argued that the social conditions of OBCs have been improving relative to other caste categories during the 20th century, (Jaffrelot, 2003). If this is the case, it is possible that any improvement in their social conditions is a result of these trends rather than reservation; in fact, reservation might be a consequence rather than a cause of social change within the OBC category. Similarly, any national effect or policy that helped OBCs more than other groups would lead to an overestimate of the treatment effect.

While, as we will see below, the actual level of category-specific pretrends is modest, the theoretical problem is very real. Since the DD model focuses on states where AA policy did not change, it assumes that any post treatment divergence in outcomes is due to the policy: We do not observe trends among OBCs not affected by the policy change. To address this problem, we also estimate a set of difference-in-difference-in-difference (DDD) models. Intuitively, these models use time trends among OBCs in states where

AA policy did not change to separate the effects of the policy change from group-specific trends. The model estimated is:

$$\begin{aligned}\text{Outcome}_i = \beta_0 + \beta_1 \text{OBC Caste}_c + \beta_2 \text{Post 1994}_y + \beta_3 \text{Mandal State}_s + \\ \beta_4 \text{Post 1994 OBC Caste}_{cy} + \beta_5 \text{OBC Caste in Mandal State}_{cs} + \\ \beta_6 \text{Mandal State Post 1994}_{ys} + \beta_7 \text{OBC Caste in Mandal State Post 1994}_{cys} + \varepsilon_i \quad (3)\end{aligned}$$

Where "Mandal States" are the set of states where OBC quotas were introduced in 1994.[5] Note that β_7 corresponds to the estimated conditional effect of state-level changes to the quota system, while the estimated effect of the national changes is subsumed within other category-specific trends in β_4. Equation 4 includes a more comprehensive set of fixed effects.

$$\text{Outcome}_i = \beta_0 + \gamma_{cs} + \delta_{ys} + \phi_{cy} + \beta \text{OBC Caste in Mandal State Post 1994}_{\ cys} + \varepsilon_i \quad (4)$$

Where ϕ_{cy} is a set of caste category-year fixed effects.

It is worth emphasizing the extreme conservatism of this model, which accounts caste category specific cohort effects (e.g. for STs turning 18 1997, or OBCs turning 18 in 2009) in addition to those accounted for in the DD models. In fact, the only possible confounding factors are trends that are specific to a set of castes in a specific set of

[5]Rajasthan, Uttar Pradesh, Madhya Pradesh, Himachal Pradesh, Assam, Orissa, West Bengal, Sikkim, Manipur, and the union territories. Haryana, where quotas were introduced in 1991, is also included in this category, and observations from Haryana in 1991-3 are dropped. This procedure has no effect on the final results. States where the quota was expanded in the early 1990s (Maharashtra, Bihar, Punjab) could also be recategorized without affecting the results (results available on request).

states, after accounting for overall group and regional trends. Below, we will show that such trends do not appear to exist.

One additional limitation of applying the DDD model in this context should be noted. In the classic DD or DDD models, outcomes in units where a new policy is adopted are compared to areas where the policy did not change. In the DDD model, we are comparing outcomes in units (caste categories or caste category-states) where a new policy is adopted to units where the policy had *already* been adopted. If the benefits of the policy do not increase over time in these already treated units (or the increases in benefit have diminished to zero), then the DDD term is an accurate estimate of the treatment effect. However, if the already treated units see an increasing effect of the policy between t_0 and t_1, then this term will be an underestimate of the treatment effect, since some part of the treatment effect will be subsumed into the time trend.

4.5 The Parallel Trends Assumption

For their estimates to be valid, DD and DDD models require that group-specific time trends not exist: the *parallel trends assumption*. For the DD model, the assumption implies that, in the absence of reservation, any change in outcomes among OBCs after 1994 would have been equal to the change among other groups, leaving intergroup differences the same. There is nothing inherently implausible in this assumption, since the policy change began at the national level, and there was little sign that the remaining states would have imposed reservation endogenously without a national shift.[6]

The simplest way to show that this assumption holds is to visually display time trends in important outcomes. Figure C.5 shows pretreatment time trends in the out-

[6] See Jaffrelot (2003) for a discussion of the stalemate of reservation policy in the 1980s.

come variables for OBCs and non-OBCs separately for “Mandal” states, using smoothed local polynomial functions.[7] The most obvious features are the strong upward trend in education over time, and the flat trends in the other variables. As we would expect, the gap between OBCs and non-OBCs is also perceptible for all the variables except caste association membership, reflecting the lower social status of OBCs in the Mandal states. However, before 1994 the gap between OBCs and non-OBCs for the various variables remains fairly constant: there is no evidence of pretreatment convergence in any outcome in the full sample.

A more formal test of the parallel trend assumption is to used leads of the treatment as a placebo: Since the distribution of OBC reservations did not change for those who turned 18 in 1996 or 1990, we should not expect a positive treatment effects in those years. Tables G.1 to G.4 show the results for four and eight year leads of all the outcomes, using both the DD and DDD models. None of these models show positive and statistically significant “treatment” effects, supporting the idea that there were no noticeable differences in trends between OBCs and non-OBCs before 1994.

5 Results

Section Four discussed four models of varying levels of complexity and conservatism to examine the effect of the imposition of reservation on OBCs in the Mandal states. However, since full exposition of these models would be both time consuming and repetitive, this section will only report the marginal effects of the simple difference-in-difference model in the Mandal state sample (Equation One). The full results are reported in Sections D and E of the online appendix.

[7] Figures C.1 through C.4 show pretends in the raw data (averaged by year).

5.1 Critique One: Socio-Economic Effects

Does the introduction of quotas for OBCs in education increase their educational attainment? Table 1a shows the marginal estimates for a linear regression models with individual years of education as the dependent variable. In the simple DD model, individuals who turned 18 after 1994 in the Mandal states are considerably better educated than their elders (by 2.15 years), while OBCs are less educated than the average of General, SC, and ST respondents (by .82 years). Conditional on these two effects, the estimated effect of being an OBC who turned 18 after 1994 is positive and statistically significant, though small in substantive size: .52 years of education. In Table D.1, the coefficient remains similar in size and statistically significant once caste-state and state year fixed effects are added. Similarly, the estimated effect increases slightly when the alternative treatment threshold age (those who were starting secondary school in 1994) is used. These increases in educational attainment do not occur at the university level, but rather in secondary school, echoing Khanna's (2018) conclusion that the effects of reservations are driven by an increase in the expected value of education rather than a direct admission effect. Results that measure different types of educational attainment, are available on request from the authors.

Table 1b shows the results of a series a linear regression models with occupational status as the dependent variable. The results are substantively similar to those in Table 1a. In the DD model, the imposition of OBC reservations is associated with increase in the probability that OBCs are employed in a middle class job. The increase in the conditional probability of a middle class job in the treatment group is 3.6 percentage points in the DD model, a moderate substantive effect compared to the full sample average of 23.8%. As with the education effects, the result is stronger when a later

Table 1: Quotas and Socio-Economic Status

(a) Years of Education

	Pre 1994	*Post 1994*	***Difference***
Non OBC	5.26 (.07)	7.41 (.06)	2.15*** (.09)
OBC	4.44 (.09)	7.12 (.09)	2.67*** (.11)
Difference	-.81*** (.11)	-.29*** (.1)	.52*** (.14)

(b) Middle Class Job

	Pre 1994	*Post 1994*	***Difference***
Non OBC	.25 (.01)	.24 (.01)	-.01 (.01)
OBC	.19 (.01)	.21 (.01)	.02** (.01)
Difference	-06*** (.01)	-.02** (.01)	.04** (.02)

Notes: The tables show the estimated levels and marginal differences and differences in differences of linear regression models with individual years of education and an indicator for middle class employment as the dependent variables. "Post 94" refers to the year respondents turned 18. Compare to Model One of Table D.1. See Model Two of Table D.1 for FE estimates. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

treatment date is used to account for pipeline effects (Table D.1). The results echo the conclusions from a visual inspection of Figure 1. While there has been a trend towards convergence of OBC and non-OBC outcomes in the Mandal states, this trend only became marked for those who came of age some years after 1994. While the post treatment convergence is small and barely perceptible visually for education, the trend is fairly strong and dramatic for middle class employment. The DDD models, though more complex to interpret, produce similar results.

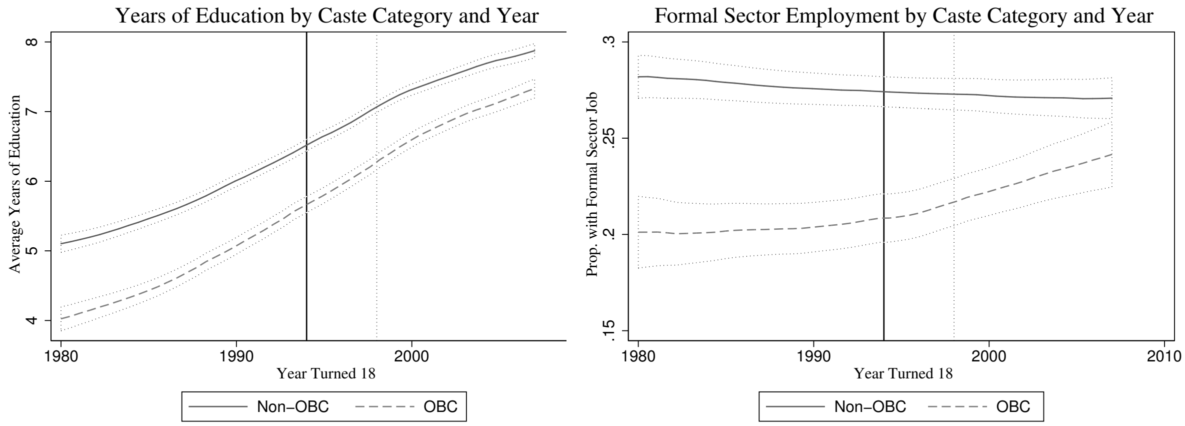
One final interesting aspect of these models is that there is no evidence for the effects of AA being zero sum, with gains for OBCs being counterbalanced by losses for other groups. Non-OBC achievement either stays static (occupation) or increases (education) indicating that any losses by non-OBCs are relative rather than absolute.

5.2 Critique Two: Concentrated Benefits

Are these benefits concentrated in any one segment of the population? Table 2 reruns the models in Table 1a, but interacts the key independent variables with an additional binary variable for whether or not the respondent's father attended Secondary school

Figure 1: Caste SES by State and Caste Category in India 1979-2012

(a) Years of Education (b) Middle Class Job



Note: The Y axis shows the proportion of employed individuals in a caste category who turned 18 in that year with a middle class job, and their average years of education. The lines represent caste category specific linear polynomial estimates. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998 (the year when those who were 14 in 1994 turned 18).

(Panel A) or University (Panel B).

The results differ considerably depending on which definition of an "educated father" is used. In the DDD models, there is some evidence that OBCs with fathers who received some secondary education see their education increase faster in the post 1994 period than one would expect based on the experiences of non-OBCs with educated fathers or OBCs with uneducated fathers: Education levels increased by more than three times as much in the post 1994 period among OBCs with educated fathers as they did among other OBCs, though this result is only inconsistently close to conventional levels of statistical significance.

By contrast, there is no evidence for concentration in Panel B, which defined educated fathers as those with some university education. In all models, the post-1994 gains in education are larger among those whose fathers did not attend university than those

Table 2: Quotas, Education and Paternal Education

(a) Fathers with Secondary Education

	Non-Secondary Educated Fathers			Secondary Educated Fathers			
	Pre 1994	*Post 1994*	***Difference***	*Pre 1994*	*Post 1994*	***Difference***	**DDD**
Non OBC	3.73 (.07)	5.26 (.07)	1.52*** (.1)	9.44 (.14)	10.39 (.08)	.95*** (.16)	
OBC	3.61 (.09)	5.33 (.1)	1.72*** (.13)	7.99 (.27)	9.63 (.12)	1.64*** (.29)	
Difference	-.12 (.12)	.08 (.12)	.2 (.17)	-1.45*** (.30)	-.76*** (.15)	.69** (.32)	**.50** **(.37)**

(b) Fathers with University Education

	Non-University Educated Fathers			University Educated Fathers			
	Pre 1994	*Post 1994*	***Difference***	*Pre 1994*	*Post 1994*	***Difference***	**DDD**
Non OBC	4.63 (.07)	6.75 (.-7)	2.11*** (.09)	12.72 (.27)	12.95 (.15)	.24 (.3)	
OBC	4.12 (.09)	6.64 (.08)	2.52*** (.12)	12.35 (.49)	12.16 (.25)	-.19 (.54)	
Difference	-.5*** (.12)	-.11*** (.11)	.4*** (.15)	-.37 (.56)	-.79*** (.3)	-.42 (.32)	**-.82** **(.64)**

Notes: The tables show the estimated effects and marginal differences and differences in differences of linear regression models with individual years of education as the dependent variable. Compare to Model One in Table F.1. See Model Two of Table F.1 for FE estimates. See the notes to Table 1 for further information. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

whose fathers did, though this difference is not usually statistically significant. While individuals from moderate or highly educated families appears to gain more access to education after the implementation of reservation than those from poorly educated families, those from highly educated families appear to benefit less than others, though it is possible that educated OBCs attend more prestigious institutions than they would otherwise (Bertrand et al., 2010), a hypothesis that cannot be tested here. Note that levels of educational attainment are still very high among the children of college educated OBCs, much higher than among other OBCs.

Note that given the historical poverty of most of the Mandal states, the proportion of OBCs with university educated fathers in 1994 was very small: 2.2%, and many of these probably held degrees that brought little prestige in a national context. Given this fact, it is possible that there were simply not enough "elite" OBCs in the Mandal states to monopolize the benefits of reservation. If this is correct, concentrated effects should only be apparent in states with high levels of wealth. This mechanism can be tested, since India's wealthiest territories as well as its poorest ones implemented reservation in 1994. Table F.3 reports the results of a set of DD models that focus only on India's five richest states and territories,[8] with most of the cases coming from the Delhi metro area. In this small, relatively privileged sample, there is strong, statistically significant evidence that the effects of reservation were heavily concentrated among those with university-educated fathers. Between the pre-and post 94 periods, the gap in educational attainment between educated family OBCs and educated family non-OBCs diminished by 3.3 years, while the gap between non-educated family OBCs and non-educated family non-OBCs diminished by only .35 years. While these results should be interpreted with caution (the sample is small and the rich states are quite unrepresentative of India as a whole), they provide suggestive evidence that concentration effects might be observed in wealthier societies than contemporary North India.

5.3 Critique Three: Spillovers and Contacts

The small substantive size reservations on OBC education and employment are in many ways not surprising: Even if quotas have a large effect on the socio-economic status of the beneficiaries, this effect must be averaged across the much larger number of non-beneficiaries within the targeted group. Do non-beneficiaries at least gain social contact with some of the beneficiaries? Table 3 reports the marginal effects of a model with a measure of contact with educated professionals. The results fit with the idea that at least

[8] Delhi, Sikkim, Goa, Chandigarh, Pondicherry

social networks are being enriched in relative terms, if not absolute ones: The estimated conditional effect of reservation on social contacts is positive and usually statistically significant. Overall, the gap in the percent having government contacts OBC and non-OBCs was reduced from 6.9 percentage points to 3.2 percentage points between the two periods: These results are somewhat stronger using the alternative (age 14) treatment cutoff (Table D.2), and are also positive (though not always statistically significant) in the DDD models (Table E.2).

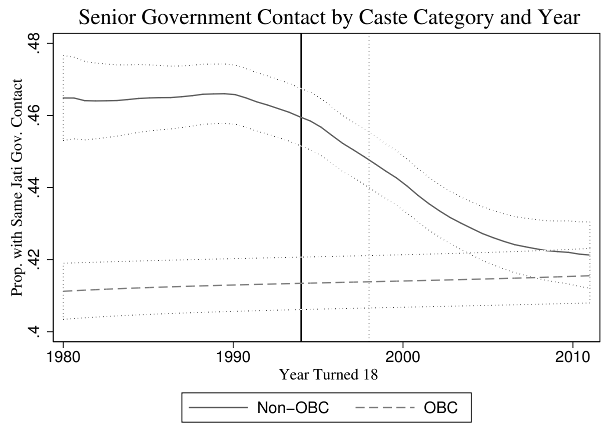
Table 3: Quotas and Social Contacts

	Pre 1994	*Post 1994*	***Difference***
Non OBC	.47 (.01)	.44 (.01)	-.03*** (.01)
OBC	.4 (.01)	.41 (.01)	.01 (.01)
Difference	-.07*** (.01)	-.03*** (.01)	.04** (.014)

Notes: The tables show the estimated effects and marginal differences and differences in differences of linear regression models with a binary measure for whether someone in the household knows a doctor, teacher, police inspector or gazetted government officer as the dependent variable. Compare to Model One in Table D.2. See Model Two of Table D.2 for FE estimates. See the notes to Table 1 for further information. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

These trends are confirmed by visual inspection. Figure 2 shows that while post-treatment convergence in contacts between caste categories is a very marked trend, it is centered in the Mandal states and only becomes noticeable a few years after 1994, after reservation had become well established. Interestingly, however, the decrease among non-OBCs appears much more marked than the increase among OBCs. While the overall level of contacts among non-OBCs in Mandal states is lower among the young (probably a reflection of their age, given the similar patterns in Figures C.3a and C.3b), the proportion is constant across age groups among OBCs.

Figure 2: Social Contacts by State and Caste Category in India 1979-2012



Note: The Y axis shows the proportion of individuals in a caste category who turned 18 in that year who live in a household where a member knows a doctor, teacher police inspector or gazetted government officer . The lines represent caste category specific linear polynomial estimates. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998.

5.4 Critique Four: Associations

If caste-based quotas have some positive impact on OBCs, does it lead them to be more conscious of their caste identity, or make it more central to their social and political interactions? Table 4a shows the marginal effects of a set of linear models with caste association membership at the same time. In the Mandal States, caste association membership is very slightly more common among younger Indians that older ones, but is no more common among younger OBCs than younger members of other groups. In fact, the tiny upward trend in caste association membership was almost entirely concentrated among non-OBCs. In the Mandal states, caste association membership increased from 3.5% for those who turned 18 between 1979 and 1994 to 3.7% among non-OBCs who turned 18 between 1994 and 2012, while among non-OBCs the figure stayed constant at 3%.

Both the general decline in caste association membership and the lack of a surge

Table 4: Quotas and Caste Associations

(a) Caste Association Membership

	Pre 1994	*Post 1994*	***Difference***
Non OBC	.035 (.003)	.037 (.004)	.002 (.004)
OBC	.029 (.003)	.03 (.003)	-.001 (.004)
Difference	-.006 (.004)	-.007 (.005)	.002 (.005)

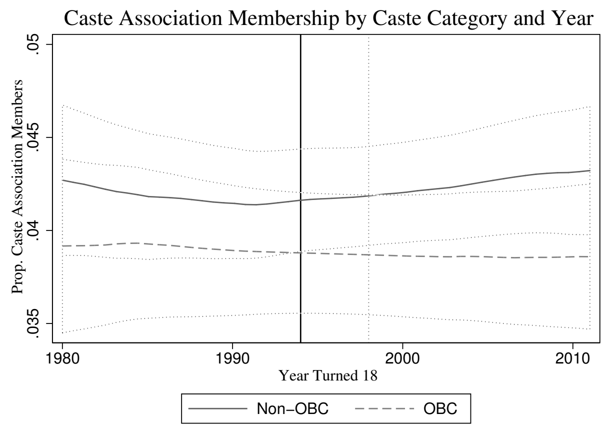
Notes: The table shows the estimated effects and marginal differences and differences in differences of linear regression models with a binary measure for whether someone in the household is a caste association member. Compare to Model One of Table D.3.See Model Two of Table D.3 for FE estimates. See the notes to Table 1 for further information. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

among OBCs after reservations may seem strange in light of the rise of caste-based parties in late 20th century India. However, they make sense in light of the exact nature of the counterfactual considered by the DD estimators: We are not simply comparing individuals affected by reservation to those not affected, but those who lived in a political climate where reservation had already been enshrined in statue to one where it was hotly debated. The decline of interest in OBCs in caste association may simply reflect the fact that they have already won the major policy goal of OBC politicians and activists in the 1970s and 1980s, and do not need to collective action to enjoy its benefits. As the DDD models show (Table E.3), caste association membership was actually declining in this period in the non-Mandal states, where the benefits were well established.

It is also worth noting the slight increases in both caste association membership among non-OBCs. These findings could be interpreted as evidence for a "backlash effect": that AA is leading to an increase in ethnic salience among *non-beneficiaries*, possibly because of their exclusion from AA benefits. However, given the tiny sizes of the coefficients in substantive terms, the existence of multiple potential explanations, and the lack of robustness of this finding in alternative models, it is difficult to make

Figure 3: Caste Salience by State and Caste Category in India 1979-2012

(a) Caste Association Membership



Note: The Y axis shows the proportion of individuals in a caste category who turned 18 in that year who live in a household where a member was a member of a caste association. The lines represent caste category specific linear polynomial estimates. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998.

authoritative statements on the basis of this evidence alone.

5.5 Robustness

See Section A for a discussion of some major robustness checks, including models that account for individuals movement and the creamy layer and models that include individual and state-year-caste controls. Additional results that control for the presence of OBCs in positions of political power are available on request.

6 Conclusion

The imposition of hiring and educational quotas in India appears to have neither ignited a social revolution nor been an abject failure. While the effects of the programs took some time to be fully realized, they have been associated with modest increases in individual education, middle class employment, and levels of social contacts with educated professionals. Moreover, there is no sign that these changes have increased caste association membership among the treated groups: If anything, the opposite is the case. These effects do not appear to be concentrated among the children of the very highly educated, though this many be a product of the specific design of Indian affirmative action policies and the relative poverty of Indian OBCs: Certainly, there appears to be evidence for concentrated effects in the very wealthiest states, a promising topic for future research.

These results paint a more nuanced, and somewhat more positive, portrayal of affirmative actions' effects than those common in many accounts of the issue. It shows that affirmative action tends neither to redistribute opportunities to those who are too poor a "match" to make use of them, or are so wealthy that they would always take advantage them. More research is necessary on whether these results can be extended to other regions or regions with differently designed policies—i.e. "soft" quotas or no exclusion for the wealthy. Similarly, more research is needed on the interaction between the social effects of policies on targeted groups (discussed here) and their effects on social and institutional efficiency. Given the importance of these types of policies in many countries, this is research well worth pursuing.

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Online Appendix for: Does Affirmative Action Work? Evaluating India's Quota System

Online Appendix Table of Contents

A Robustness Checks

A.1 Movement between Categories and the Creamy Layer

The main analysis defined the treatment group (OBCs) as those who self-defined as OBCs in 2012, less those who self-identified as members of jatis that were added to the OBC category after the respondent turned 18. However, individuals may move between categories, particularly if they have an incentive to do so (Rao and Ban, 2007), and affirmative action can provide just such an incentive (Francis et al., 2012). This might be particularly true because caste categories, unlike jatis, are not primary social identities. Individuals might either be unaware that their jati is classified as an OBC, or may decide to classify themselves as members of a category that they feel will bring benefits. This may be one reason why the proportion of self-reported OBCs has risen gradually in the younger age cohorts of the IHDS, from 38.1% among those who came of age before 1994 to 41% among those who came of age afterwards. Both Figures are higher than the Mandal commission's estimates of OBC population.

To test whether the results are a product of this type of self-reclassification, Tables I.2 through I.5 show the results of a set of models in which caste category is imputed based on self-reported jati. Individuals are coded as being members of a caste category if they are members of a caste category, if they are members of a caste category with more than two individuals in the sample and were members of a jati in which more than 90% of individuals identified with a given caste category. This thus includes "stray" individuals who grouped themselves with caste categories different from their coethnics with their larger jati, while excluding entirely jatis whose caste category position appears to be ambiguous or disputed. By this measure, the proportion of OBCs India has remained constant in the pre and post 1994 periods, increasing only to 37.3% from 36.9%.

The results in these Tables broadly echo those in Section Five. The estimated effect of quotas on education is slightly higher in these tables, while the estimated effect of quotas on social contacts is slightly lower. Similarly, at least in the DDD models, there are no signs that the treatment effect is confined within a specific social subgroup.

An additional form of movement is at the group level, as castes successfully petition for OBC status. As noted, the main results include individuals in the category their jati was in when they turned eighteen. Additional Tables showing that the results are robust to entirely excluding all reclassified castes are available on request.

An additional "categorization problem" is the presence of the creamy layer policy, which means that some OBCs did not benefit from reservation because their families had too high an income. It is unfortunately not possible to cleanly exclude these individuals, since the IHDS does not include questions on the respondent's household income at age 18 (the relevant variable), and even if it were available the widespread faking of income certificates would make such a measure an unreliable guide to who actually took advantage of the policy. As a rough proxy, Tables M.1 through M.5 report results that exclude all OBCs whose fathers had both a professional occupation[9] and had completed secondary school. These Tables produce results that are similar in substantive size and significance to those in the main tables.

A.2 Continuous Treatment

The main analysis assumed that quotas a binary treatment: One can benefit from them or not. However, in the Indian context OBC quotas vary somewhat in their level of

[9] "Managerial," scientists, government officials, doctors, lawyers and accountants.

generosity. In some states, the proportion of OBCs in the population is smaller than the proportion of OBCs in the population, while in others it is larger. These differences mainly come from the interaction between the national 50% limit on reservation and the varying policies of state OBC commissions as to which castes should be coded as backward. Reservation as a percent of the OBC population varies from 29% in Chhattisgarh to 104% in Tamil Nadu.[10] Table J.1 shows results using a continuous measure of treatment: the state OBC quota as a proportion of percent of OBCs in the state (from the IHDS). Overall, the results are quite similar to those in Section Five. Education has a robust positive association with quotas, contacts have a positive but statistically significant association, and there is no association between quotas and caste association membership.

A.3 Additional Controls

There are any number of potential factors that might influence individual education, social contacts, and associational membership. Most however, fall into two categories: They are either perfectly collinear with the state, birth year and caste category fixed effects included in the main models, or are potentially causally associated with quotas, and thus post treatment. However, Tables H.1 through H.5 include five additional individual control variables that are arguably assigned independently of quotas: Gender, Household size and gender composition, urban residence and marriage. Including these controls in the models has minimal effects relative to the models in Section Five.

Four unreported tables examine two additional hypotheses that might explain changes in the relative social status of OBCs. The mid-1990s were a period when OBC politicians

[10]Three outlier border states that have class based reservations or large immigrant populations are excluded: Assam, Manipur, Himachal Pradesh.

rose to political prominence in much of northern India, and also a period of increasing migration to urban centers, but in an out of regions. Either trend might explain advances among OBCs in this period, at least if we believe that OBC politicians favor their coethnics over others and that migration might favor the traditionally marginalized. These tables include controls for OBC chief ministers and the presence of migrants in the household, and their interaction with OBC. These tables produce results quite similar to the 18 year cutoff models in the main text.

B Data Description and Summary Statistics

Table B.1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**N**
Education: Completed Years, never,< 1=0	7.116	5.046	95636
Middle Class	0.238	0.426	44455
Log. Wages	9.738	1.14	27924
Member Caste Association	0.088	0.284	95611
Prof. Contact of Own Caste	0.418	0.493	95765
Educated Father	0.158	0.365	76051
Urban residence from census 2011	0.364	0.481	95765
# 21+ men in Household	1.758	1.037	95765
# 21+ women in Household	1.73	0.935	95765
Age	32.188	9.552	95765
Married	0.731	0.443	95765
OBC Caste (Defined By Jati)	0.372	0.483	65982
OBC Caste	0.4	0.49	95765
Post 1994	0.65	0.477	95765
Mandal State	0.539	0.498	95765

Table B.2: OBC Reservations in India: A Summary

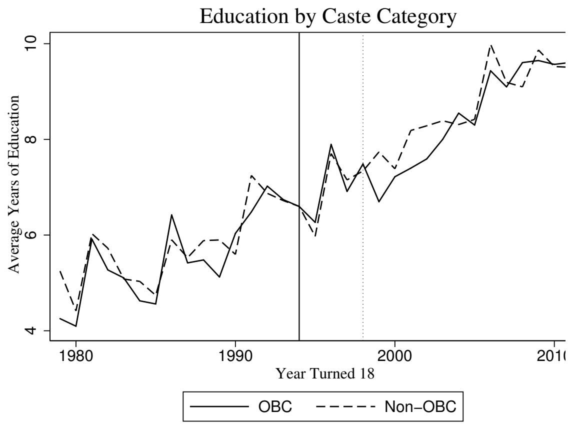
State	*Some Colonial Res.*	*Post 1947 Res. Began*	*2011 OBC Quota*	*Subquota Year*	*Notes*
Andhra Pradesh	Yes	1947	23%	1970	System reformed on state reorganization 1964
Tamil Nadu	Yes	1947	68%	1989	Quota expanded from 25% before 1971 and 31% before 1980
Maharashtra	Yes	1947	32%	1964	System reformed on state reorganization 1964
Kerala	Yes	1964	40%		
Punjab	No	1964	12%		Quota 5% before 1993
Karnataka	Yes	1977	32%	1977	50% quota pre-1956, changed to class-based 1961, 35% 1977, 55'% quota 1986, 32% quota 1994
Bihar	No	1978	33%	1978	Quota increased from 20% in 1992
Gujarat	Yes	1978	27%		Some quotas pre-1964, before states reorganization
Jharkhand	No	1978	14%	1978	Quota shrunk from 33% in 2000 on state reorganization
Haryana	No	1991	27%	1995	Class-based res. from 1969
Assam	No	1994	27%		
Chhattisgarh	No	1994	14%		
Delhi	No	1994	27%		
Goa	No	1994	19.5%		
Himachal Pradesh	No	1994	20%		Class-based res. from 1970
Madhya Pradesh	No	1994	14%		
Manipur	No	1994	17%		
Orissa	No	1994	12%		
Rajasthan	No	1994	21%		
Sikkim	No	1994	23%		
Uttar Pradesh	No	1994	27%		
Uttarakhand	No	1994	14%		Quota shrunk from 27% in 2000 on state reorganization
West Bengal	No	1994	7%		

Tripura, Meghalaya, Mizoram and Arunachal Pradesh do not have OBC reservations, Jammu and Kashmir has class-based reservations. Union territories are not included for reasons of space. Sources: See Mathur (2004).

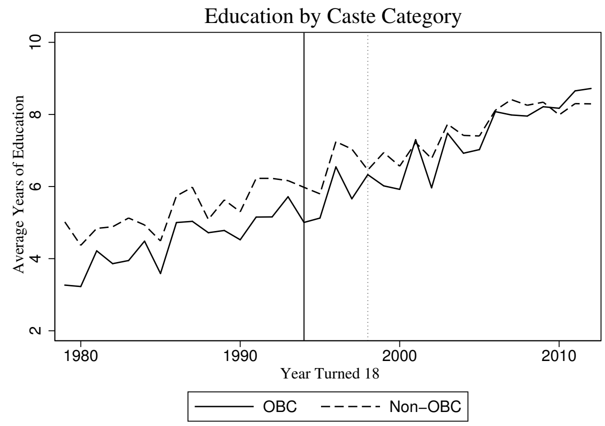
C Additional Figures

Figure C.1: Education by State and Caste Category in India 1979-2012

(a) Non-Mandal State



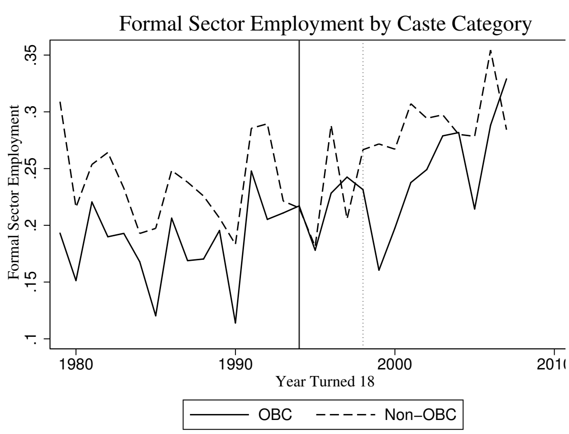
(b) Mandal State



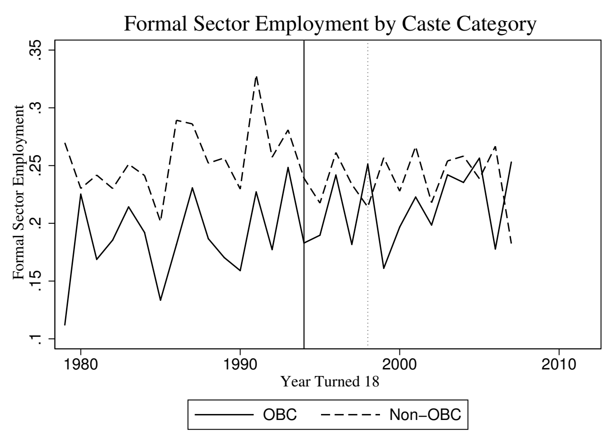
Note: The Y axis shows the average years of education for those over 23 for individuals in a caste category born in that year. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998 (the year when those who were 14 in 1994 turned 18).

Figure C.2: Middle Class Employment by State and Caste Category in India 1979-2007

(a) Non-Mandal State



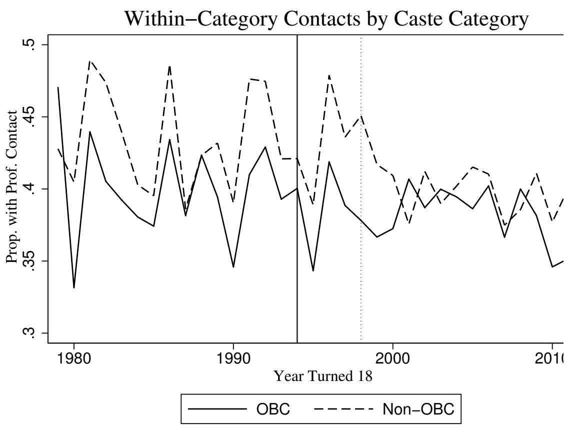
(b) Mandal State



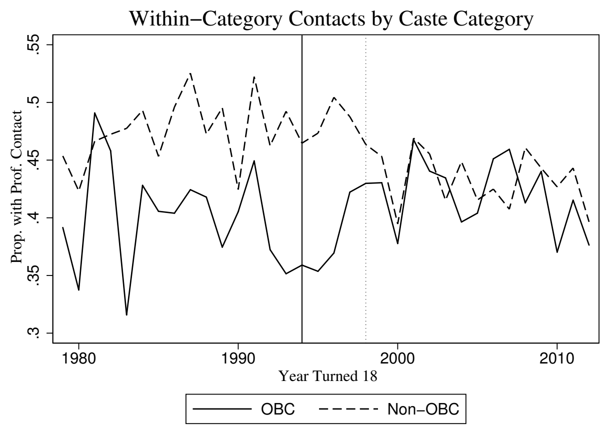
Note: The Y axis shows the proportion of employed individuals in a caste category who turned 18 in that year who have a middle class job. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998 (the year when those who were 14 in 1994 turned 18).

Figure C.3: Social Contacts by State and Caste Category in India 1979-2012

(a) Non-Mandal State



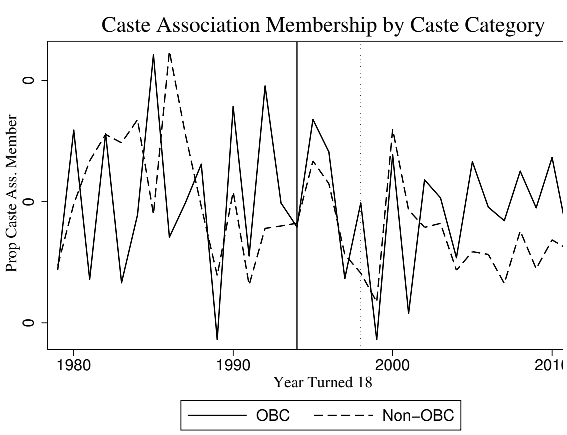
(b) Mandal State



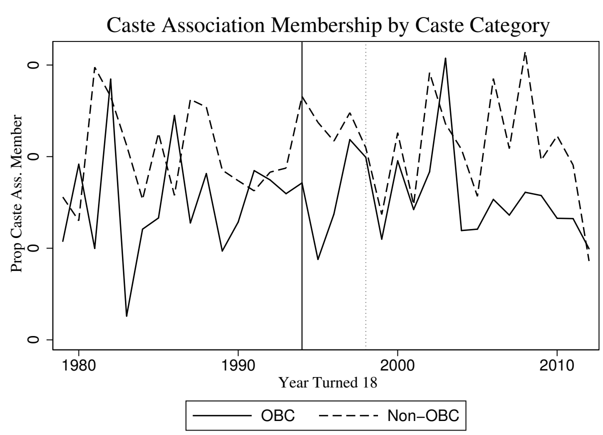
Note: The Y axis shows the proportion of individuals in a caste category who turned 18 in that year who live in a household where a member knows a doctor, teacher police inspector or gazetted government officer. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998 (the year when those who were 14 in 1994 turned 18).

Figure C.4: Caste Association Membership by State and Caste Category in India 1979-2012

(a) Non-Mandal State



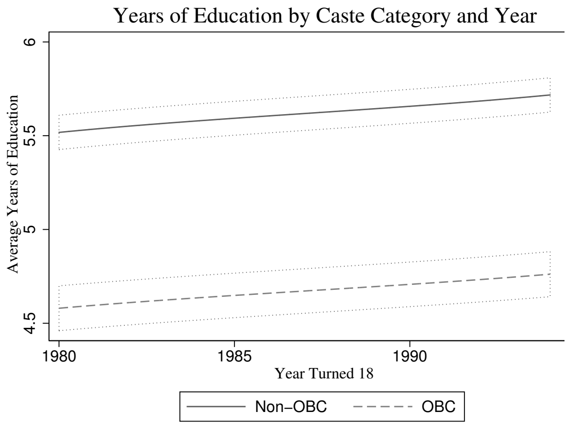
(b) Mandal State



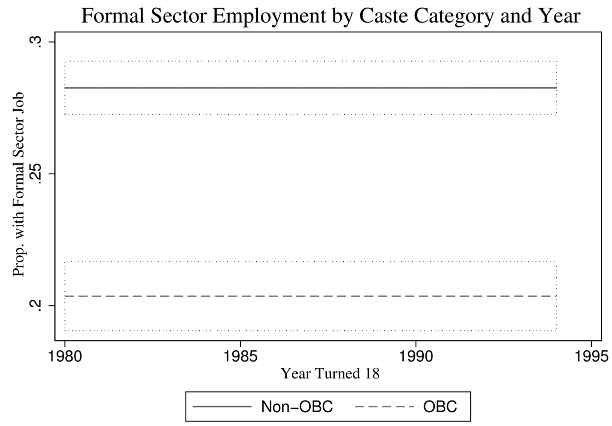
Note: The Y axis shows the proportion of individuals in a caste category who turned 18 in that year who live in a household where a member is a member of a caste association. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998 (the year when those who were 14 in 1994 turned 18).

Figure C.5: Outcome Pretrends In Mandal States 1979-1994

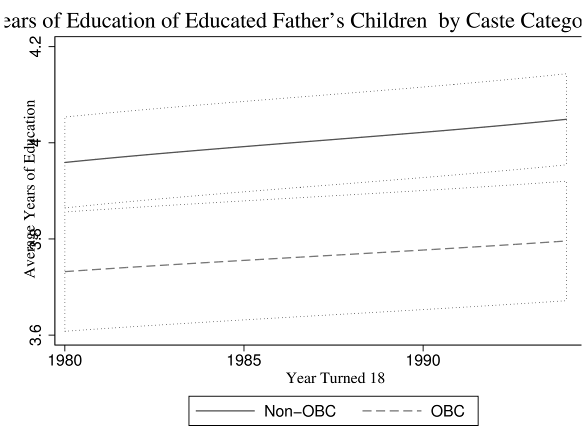
(a) Education



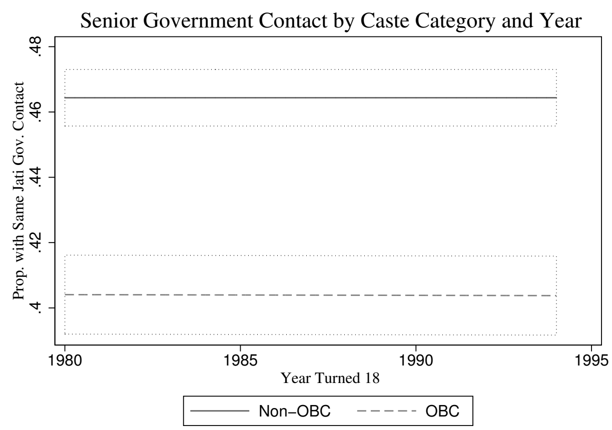
(b) Middle Class Jobs



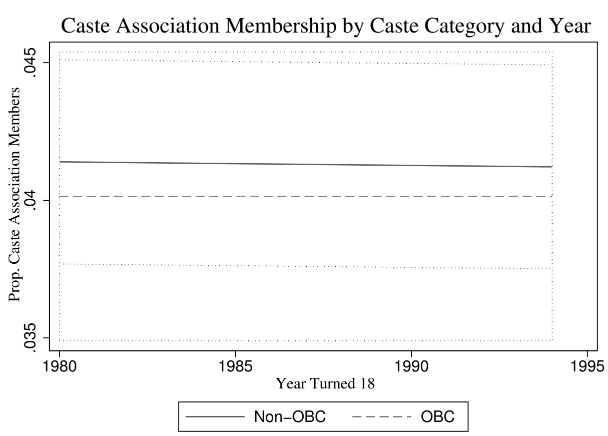
(c) Education: Educated Fathers



(d) Contacts



(e) Caste Association Membership



Note: The Y axis shows the smoothed local polynomial estimate of the dependent variable for individuals in a caste category born in that year. The solid vertical line corresponds to 1994, the dotted line corresponds to 1998 (the year when those who were 14 in 1994 turned 18).

D Difference-in-Difference Models

Table D.1: Quotas and Education

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: Years of Education				
OBC Caste	-0.819***		-0.791***	
	(0.117)		(0.114)	
Post 1994	2.150***		1.931***	
	(0.0856)		(0.0861)	
OBC*Post 94	0.525***	0.357**	0.591***	0.400***
	(0.140)	(0.139)	(0.141)	(0.139)
Observations	51,571	51,571	47,155	47,155
R-squared	0.049	0.194	0.045	0.180
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO
Panel B: Middle Class Job				
OBC Caste	-0.0599***		-0.0608***	
	(0.0111)		(0.0107)	
Post 1994	-0.0114		-0.00922	
	(0.00934)		(0.0104)	
OBC*Post 94	0.0361**	0.0307**	0.0427***	0.0372**
	(0.0151)	(0.0150)	(0.0166)	(0.0164)
Observations	22,334	22,334	19,737	19,737
R-squared	0.002	0.147	0.003	0.143
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education and an indicator for middle class employment as the dependent variables. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.2: Quotas and Within-Caste Professional Contacts

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
OBC Caste	-0.0693***		-0.0821***	
	(0.0142)		(0.0138)	
Post 1994	-0.0280***		-0.0421***	
	(0.00852)		(0.00920)	
OBC*Post 94	0.0374**	0.0249	0.0649***	0.0565***
	(0.0146)	(0.0153)	(0.0152)	(0.0161)
Observations	51,629	51,629	47,211	47,211
R-squared	0.002	0.075	0.003	0.074
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household knows a doctor, teacher police inspector or gazetted government officer as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.3: Quotas and Caste Association Membership

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Z				
OBC Caste	-0.00558		-0.00553	
	(0.00415)		(0.00438)	
Post 1994	0.00206		0.00322	
	(0.00386)		(0.00486)	
OBC*Post 94	-0.00163	-0.00385	-0.00192	-0.00242
	(0.00504)	(0.00557)	(0.00616)	(0.00693)
Observations	43,790	43,790	39,960	39,960
R-squared	0.000	0.059	0.000	0.058
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household is a caste association member and a binary measure for whether someone in the household reports practicing untouchability as the dependent variables. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

E Difference-in-Differencen-in-Difference Models

Table E.1: Quotas, Education and Employment

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: Years of Education				
OBC Caste	-0.147		-0.0396	
	(0.127)		(0.127)	
Post 1994	2.738***		2.701***	
	(0.101)		(0.106)	
Mandal State	-0.403***		-0.366***	
	(0.113)		(0.113)	
OBC*Post 94	0.0513		-0.108	
	(0.150)		(0.154)	
OBC Caste*Mandal State	-0.672***		-0.752***	
	(0.172)		(0.171)	
Post 94*Mandal State	-0.589***		-0.770***	
	(0.132)		(0.137)	
OBC*Post 94*Mandal State	0.473**	0.469**	0.699***	0.573***
	(0.205)	(0.188)	(0.209)	(0.190)
Observations	95,636	95,636	87,003	87,003
R-squared	0.065	0.238	0.063	0.226
Panel B: Middle Class Employment				
OBC Caste	-0.0536***		-0.0381***	
	(0.0100)		(0.0102)	
Post 1994	0.0386***		0.0683***	
	(0.0104)		(0.0117)	
Mandal State	0.0217**		0.0275***	
	(0.00992)		(0.00989)	
OBC*Post 94	0.0234		-0.00405	
	(0.0148)		(0.0167)	
OBC Caste*Mandal State	-0.00633		-0.0227	
	(0.0150)		(0.0148)	
Post 94*Mandal State	-0.0500***		-0.0775***	
	(0.0140)		(0.0156)	
OBC*Post 94*Mandal State	0.0127	0.0140	0.0468**	0.0430*
	(0.0212)	(0.0207)	(0.0235)	(0.0228)
Observations	44,455	44,455	39,106	39,106
R-squared	0.004	0.113	0.006	0.112
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table E.2: Quotas and Within-Caste Professional Contacts

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
OBC Caste	-0.0381***		-0.0331***	
	(0.0130)		(0.0128)	
Post 1994	-0.0214**		-0.0189**	
	(0.00867)		(0.00936)	
Mandal State	0.0416***		0.0536***	
	(0.0119)		(0.0120)	
OBC*Post 94	0.0119		0.0101	
	(0.0132)		(0.0139)	
OBC Caste*Mandal State	-0.0312		-0.0490***	
	(0.0193)		(0.0188)	
Post 94*Mandal State	-0.00665		-0.0232*	
	(0.0122)		(0.0131)	
OBC*Post 94*Mandal State	0.0255	0.0124	0.0548***	0.0435**
	(0.0197)	(0.0200)	(0.0206)	(0.0210)
Observations	95,765	95,765	87,127	87,127
R-squared	0.003	0.089	0.003	0.088
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household knows a doctor, teacher police inspector or gazetted government officer as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table E.3: Quotas and Caste Association Membership

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: DD				
OBC Caste	0.0212*		0.0239**	
	(0.0111)		(0.0106)	
Post 1994	-0.0142**		-0.0150**	
	(0.00684)		(0.00686)	
Mandal State	-0.109***		-0.107***	
	(0.00692)		(0.00744)	
OBC*Post 94	-0.00185		-0.00348	
	(0.0110)		(0.0106)	
OBC Caste*Mandal State	-0.0267**		-0.0294**	
	(0.0118)		(0.0114)	
Post 94*Mandal State	0.0163**		0.0182**	
	(0.00786)		(0.00841)	
OBC*Post 94*Mandal State	0.000219	0.00220	0.00157	0.00224
	(0.0121)	(0.0112)	(0.0123)	(0.0121)
Observations	78,627	78,627	71,400	71,400
R-squared	0.038	0.137	0.038	0.137
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household is a caste association member as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

F Concentrated Effects Models

Table F.1: Quotas, Father's Education, and Outcomes

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: Years of Education DDD, Secondary Educated Fathers				
Post 94	1.523***		1.637***	
	(0.103)		(0.0971)	
Educated Father	5.715***		5.665***	
	(0.158)		(0.138)	
OBC	-0.115		-0.145	
	(0.117)		(0.102)	
Post 94*Educated Father	-0.577***		-0.659***	
	(0.187)		(0.177)	
OBC*Post 94	0.199	0.112	0.333**	0.232
	(0.169)	(0.173)	(0.164)	(0.166)
Ed. Father*OBC	-1.340***		-1.305***	
	(0.324)		(0.266)	
OBC*Post 94*Ed. Father	0.497	0.488	0.406	0.396
	(0.372)	(0.362	(0.320)	(0.320)
Observations	41,312	41,312	41,312	41,312
R-squared	0.248	0.337	0.254	0.337
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO
Panel B: Years of Education DDD, University Educated Fathers				
Post 94	2.119***		2.219***	
	(0.0953)		(0.0909)	
Educated Father	8.088***		7.940***	
	(0.283)		(0.232)	
OBC	-0.507***		-0.548***	
	(0.117)		(0.103)	
Post 94*Educated Father	-1.883***		-2.001***	
	(0.318)		(0.280)	
OBC*Post 94	0.397***	0.282*	0.551***	0.450***
	(0.153)	(0.152)	(0.145)	(0.143)
Ed. Father*OBC	0.141		0.158	
	(0.576)		(0.491)	
OBC*Post 94*Ed. Father	-0.822	-0.342	-0.997*	-0.521
	(0.639)	(0.641)	(0.564)	(0.572)
Observations	41,312	41,312	41,312	41,312
R-squared	0.115	0.249	0.125	0.249
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Ed. Father*State-Caste Category FE	NO	YES	NO	YES
Ed. Father*State-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. "Post 94" refers to the year respondents turned 18 or turned 14, depending on the column heading. Educated fathers are those with five or more or 12 or more years of education, depending on the panel. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.2: Quotas, Father's Education, and Middle Class Employment

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: Middle Class Employment DDD, Secondary Educated Fathers				
Post 94	-0.0313***		-0.0351***	
	(0.00960)		(0.01000)	
Educated Father	0.349***		0.302***	
	(0.0191)		(0.0183)	
OBC	-0.0250**		-0.0249***	
	(0.0106)		(0.00927)	
Post 94*Educated Father	-0.0792***		-0.00563	
	(0.0282)		(0.0302)	
OBC*Post 94	0.0281*	0.0140	0.0395**	0.0333**
	(0.0153)	(0.0156)	(0.0160)	(0.0164)
Ed. Father*OBC	-0.0661*		-0.0573*	
	(0.0380)		(0.0321)	
OBC*Post 94*Ed. Father	-0.00819	0.0208	-0.0380	-0.0184
	(0.0477)	(0.0460)	(0.0459)	(0.0442)
Observations	18,145	18,145	18,145	18,145
R-squared	0.087	0.233	0.084	0.233
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Ed. Father*State-Caste Category FE	NO	YES	NO	YES
Ed. Father*State-Birth Year FE	NO	YES	NO	YES
Panel B: Middle Class Employment DDD, University Educated Fathers				
Post 94	-0.0194*		-0.0126	
	(0.0102)		(0.0113)	
Educated Father	0.511***		0.444***	
	(0.0405)		(0.0361)	
OBC	-0.0431***		-0.0435***	
	(0.0111)		(0.00957)	
Post 94*Educated Father	-0.0768		0.0334	0.0368**
	(0.0530)		(0.0515)	(0.0170)
OBC*Post 94	0.0286*	0.0207	0.0400**	
	(0.0158)	(0.0160)	(0.0167)	
Ed. Father*OBC	-0.0429		0.0658	
	(0.0895)		(0.0728)	
OBC*Post 94*Ed. Father	0.0482	0.0192	-0.153	-0.219*
	(0.112)	(0.127)	(0.107)	(0.132)
Observations	18,145	18,145	18,145	18,145
R-squared	0.042	0.199	0.042	0.199
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Ed. Father*State-Caste Category FE	NO	YES	NO	YES
Ed. Father*State-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with middle class employment as the dependent variable. "Post 94" refers to the year respondents turned 18 or turned 14, depending on the column heading. Educated fathers are those with ten or more years of education. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.3: Quotas, Father's Education, and Outcomes in Rich States

	(1)	(2)	(3)	(4)
Panel A: Years of Education DDD, 18 year cutoff				
VARIABLES	Sec.	Sec.	Univ	Univ
Post 94	2.064***		2.726***	
	(0.397)		(0.277)	
Ed. Father	4.553***		7.423***	
	(0.415)		(0.402)	
OBC	0.345		-0.0610	
	(0.448)		(0.409)	
Post 94*Ed. Father	-0.805		-3.819***	
	(0.547)		(0.484)	
Post 94*OBC	-0.864	-0.292	-0.361	0.209
	(0.656)	(0.639)	(0.512)	(0.460)
Ed. Father*OBC	-1.088		-2.757**	
	(0.809)		(1.078)	
Post 94*Ed. Father * OBC	1.329	1.318	3.092**	3.848***
	(0.968)	(0.986)	(1.209)	(1.473)
Observations	2,930	2,930	2,930	2,930
R-squared	0.234	0.385	0.146	0.306
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO
Panel B: Years of Education DDD, 14 year cutoff				
VARIABLES	14	14	14	14
Post 94	2.389***		2.858***	
	(0.406)		(0.267)	
Ed. Father	4.573***		6.548***	
	(0.371)		(0.558)	
OBC	0.252		-0.156	
	(0.411)		(0.368)	
Post 94*Ed. Father	-1.137**		-3.115***	
	(0.534)		(0.652)	
Post 94*OBC	-0.841	-0.232	-0.227	0.267
	(0.651)	(0.650)	(0.487)	(0.454)
Ed. Father*OBC	-0.833		-1.209	
	(0.720)		(1.144)	
Post 94*Ed. Father * OBC	1.106	1.144	1.004	3.790**
	(0.924)	(0.945)	(1.341)	(1.473)
Observations	2,930	2,930	2,930	2,930
R-squared	0.240	0.385	0.157	0.306
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. "Post 94" refers to the year respondents turned 18. Educated fathers are those with five or more or 12 or more years of education, depending on the column heading. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

F Treatment Leads

Table G.1: Education: Leads

VARIABLES	(1) Years of Educ.	(2) Years of Educ.	(3) Years of Educ.	(4) Years of Educ.
Panel A: Four Year Lead				
OBC Caste	-0.885***		-0.274**	
	(0.122)		(0.129)	
Post 1994	0.895***		1.110***	
	(0.136)		(0.165)	
Mandal State			-0.351***	
			(0.116)	
OBC*Post 94	0.0303	0.124	0.348	
	(0.217)	(0.228)	(0.243)	
OBC Caste*Mandal State			-0.611***	
			(0.178)	
Post 94*Mandal State			-0.215	
			(0.214)	
OBC*Post 94*Mandal State			-0.318	-0.0451
			(0.325)	(0.319)
Observations	20,619	20,619	39,506	39,506
R-squared	0.013	0.168	0.017	0.187
Panel B: Eight Year Lead				
OBC Caste	-1.020***		-0.192	
	(0.119)		(0.128)	
Post 1994	1.057***		1.266***	
	(0.117)		(0.135)	
Mandal State			-0.244**	
			(0.120)	
OBC*Post 94	0.254	0.188	0.114	
	(0.191)	(0.201)	(0.196)	
OBC Caste*Mandal State			-0.828***	
			(0.175)	
Post 94*Mandal State			-0.209	
			(0.178)	
OBC*Post 94*Mandal State			0.140	0.0991
			(0.273)	(0.267)
Observations	24,225	24,225	46,528	46,528
R-squared	0.020	0.175	0.022	0.194
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. "Post 94" refers to the year respondents turned 22 or 26. Only individuals with fathers who graduated from secondary school are included. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.2: Middle Class Employment: Treatment Leads

VARIABLES	(1) Middle Class	(2) Middle Class	(3) Middle Class	(4) Middle Class
Panel A: Four Year Lead				
OBC Caste	-0.0608***		-0.0518***	
	(0.0119)		(0.0110)	
Post 1994	0.0141		0.00263	
	(0.0141)		(0.0150)	
Mandal State			0.0161	
			(0.0105)	
OBC*Post 94	-0.00989	-0.0118	-0.00385	
	(0.0216)	(0.0220)	(0.0203)	
OBC Caste*Mandal State			-0.00898	
			(0.0162)	
Post 94*Mandal State			0.0115	
			(0.0206)	
OBC*Post 94*Mandal State			-0.00604	0.00139
			(0.0296)	(0.0294)
Observations	12,124	12,124	24,574	24,574
R-squared	0.005	0.162	0.005	0.119
Panel B: Eight Year Lead				
OBC Caste	-0.0590***		-0.0496***	
	(0.0120)		(0.0113)	
Post 1994	0.0255**		0.00524	
	(0.0115)		(0.0123)	
Mandal State			0.0122	
			(0.0108)	
OBC*Post 94	-0.0135	-0.0116	-0.00167	
	(0.0186)	(0.0186)	(0.0170)	
OBC Caste*Mandal State			-0.00945	
			(0.0165)	
Post 94*Mandal State			0.0203	
			(0.0169)	
OBC*Post 94*Mandal State			-0.0119	-0.00392
			(0.0252)	(0.0250)
Observations	14,178	14,178	28,695	28,695
R-squared	0.006	0.162	0.005	0.120
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with an indicator for middle class employment as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.3: Association Membership: Treatment Leads

VARIABLES	(1) Caste Association	(2) Caste Association	(3) Caste Association	(4) Caste Association
Panel A: Four Year Lead				
OBC Caste	-0.00527		0.00699	
	(0.00444)		(0.0118)	
Post 1994	-0.00444		-0.00813	
	(0.00479)		(0.0101)	
Mandal State			-0.109***	
			(0.00738)	
OBC*Post 94	0.00197	-0.00242	0.0338**	
	(0.00714)	(0.00764)	(0.0172)	
OBC Caste*Mandal State			-0.0123	
			(0.0126)	
Post 94*Mandal State			0.00369	
			(0.0112)	
OBC*Post 94*Mandal State			-0.0318*	-0.0217
			(0.0186)	(0.0175)
Observations	17,822	17,822	33,037	33,037
R-squared	0.000	0.063	0.041	0.147
Panel B: Eight Year Lead				
OBC Caste	-0.00399		0.00912	
	(0.00455)		(0.0118)	
Post 1994	-0.00152		-0.00502	
	(0.00409)		(0.00893)	
Mandal State			-0.110***	
			(0.00744)	
OBC*Post 94	-0.00102	-0.00443	0.0134	
	(0.00617)	(0.00644)	(0.0145)	
OBC Caste*Mandal State			-0.0131	
			(0.0126)	
Post 94*Mandal State			0.00350	
			(0.00982)	
OBC*Post 94*Mandal State			-0.0144	-0.0101
			(0.0158)	(0.0150)
Observations	20,939	20,939	38,915	38,915
R-squared	0.000	0.062	0.040	0.148
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household is a caste association member as the dependent variable. "Post 94" refers to the year respondents turned 22 or 26. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.4: Contacts: Treatment Leads

VARIABLES	(1) Caste Contact	(2) Caste Contact	(3) Caste Contact	(4) Caste Contact
Panel A: Four Year Lead				
OBC Caste	-0.0643***		-0.0292**	
	(0.0152)		(0.0139)	
Post 1994	-0.0120		-0.000290	
	(0.0134)		(0.0149)	
Mandal State			0.0431***	
			(0.0127)	
OBC*Post 94	-0.00471	-0.00629	-0.0155	
	(0.0226)	(0.0239)	(0.0223)	
OBC Caste*Mandal State			-0.0351*	
			(0.0206)	
Post 94*Mandal State			-0.0117	
			(0.0201)	
OBC*Post 94*Mandal State			0.0108	0.00548
			(0.0317)	(0.0323)
Observations	20,627	20,627	39,534	39,534
R-squared	0.004	0.089	0.004	0.096
Panel B: Eight Year Lead				
OBC Caste	-0.0501***		-0.0319**	
	(0.0155)		(0.0140)	
Post 1994	0.0107		0.00340	
	(0.0124)		(0.0127)	
Mandal State			0.0391***	
			(0.0133)	
OBC*Post 94	-0.0270	-0.0407*	-0.000620	
	(0.0209)	(0.0223)	(0.0187)	
OBC Caste*Mandal State			-0.0181	
			(0.0209)	
Post 94*Mandal State			0.00731	
			(0.0178)	
OBC*Post 94*Mandal State			-0.0264	-0.0443
			(0.0281)	(0.0287)
Observations	24,233	24,233	46,565	46,565
R-squared	0.004	0.090	0.004	0.099
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household knows a doctor, teacher police inspector or gazetted government officer as the dependent variable. "Post 94" refers to the year respondents turned 22 or 26. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

H Models with Controls

Table H.1: Education: Controls

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: DD				
OBC Caste	-0.465***		-0.451***	
	(0.108)		(0.105)	
Post 1994	2.022***		1.633***	
	(0.0738)		(0.0757)	
OBC*Post 94	0.411***	0.303**	0.471***	0.356***
	(0.129)	(0.128)	(0.131)	(0.130)
Observations	51,571	51,571	47,155	47,155
R-squared	0.238	0.350	0.233	0.338
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO
Panel B: DDD				
OBC Caste	-0.160		-0.105	
	(0.112)		(0.112)	
Post 1994	2.602***		2.292***	
	(0.0887)		(0.0942)	
Mandal State	0.0759		0.0463	
	(0.100)		(0.0993)	
OBC*Post 94	0.115		0.0485	
	(0.132)		(0.137)	
OBC Caste*Mandal State	-0.286*		-0.325**	
	(0.156)		(0.153)	
Post 94*Mandal State	-0.554***		-0.637***	
	(0.116)		(0.120)	
OBC*Post 94*Mandal State	0.301	0.305*	0.428**	0.367**
	(0.185)	(0.173)	(0.189)	(0.177)
Observations	95,636	95,636	87,003	87,003
R-squared	0.239	0.365	0.236	0.354
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. All models include controls for gender, urban residence, size of household, number on men and women in the household, and religion dummies. Models 1-4 correspond to Equations 1-4.

Table H.2: Differential Effects: Controls

VARIABLES	(1) Secondary	(2) Secondary	(3) Higher	(4) Higher
Post 94	1.686***		2.106***	
	(0.0952)		(0.0829)	
Ed. Fath.	4.739***		6.504***	
	(0.148)		(0.252)	
OBC	0.0191		-0.227**	
	(0.112)		(0.111)	
Post 94*Ed. Fath.	-0.674***		-2.183***	
	(0.174)		(0.287)	
Post 94*OBC	0.0962	0.0873	0.254*	0.220
	(0.160)	(0.162)	(0.142)	(0.139)
Ed. Fath.*OBC	-0.904***		-0.152	
	(0.288)		(0.486)	
Post 94*Ed. Fath.*OBC	0.402	0.346	-0.139	-0.185
	(0.333)	(0.330)	(0.559)	(0.571)
Observations	41,312	41,312	41,312	41,312
R-squared	0.361	0.440	0.276	0.387
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Ed. Father*State-Caste Category FE	NO	YES	NO	YES
Ed. Father*State-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. The definition of educated fathers is listed in the column headings. OBCs are defined as those belonging to a state-jati where over 90% of jati members identify as OBC. "Post 94" refers to the year respondents turned 18. All models include controls for gender, urban residence, size of household, number on men and women in the household, and religion dummies. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table H.3: Middle Class Employment: Controls

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: DD				
OBC Caste	-0.0334***		-0.0357***	
	(0.0101)		(0.00973)	
Post 1994	-0.0233***		-0.0314***	
	(0.00838)		(0.00944)	
OBC*Post 94	0.0215	0.0227	0.0266*	0.0297*
	(0.0139)	(0.0142)	(0.0153)	(0.0156)
Observations	22,334	22,334	19,737	19,737
R-squared	0.172	0.245	0.171	0.242
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO
Panel B: DDD				
OBC Caste	-0.0598***		-0.0494***	
	(0.00931)		(0.00949)	
Post 1994	0.0254***		0.0330***	
	(0.00936)		(0.0106)	
Mandal State	0.0489***		0.0496***	
	(0.00907)		(0.00913)	
OBC*Post 94	0.0234*		0.00362	
	(0.0137)		(0.0154)	
OBC Caste*Mandal State	0.0244*		0.0111	
	(0.0138)		(0.0136)	
Post 94*Mandal State	-0.0490***		-0.0652***	
	(0.0126)		(0.0141)	
OBC*Post 94*Mandal State	-0.00292	0.00733	0.0231	0.0328
	(0.0195)	(0.0196)	(0.0217)	(0.0217)
Observations	44,455	44,455	39,106	39,106
R-squared	0.161	0.220	0.161	0.219
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with an indicator for middle class employment as the dependent variable. "Post 94" refers to the year respondents turned 18 or turned 14, depending on the column heading. All models include controls for gender, urban residence, size of household, number on men and women in the household, and religion dummies. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table H.4: Association Membership: Controls

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: DD				
OBC Caste	-0.00550		-0.00562	
	(0.00424)		(0.00450)	
Post 1994	-0.00176		-0.00245	
	(0.00365)		(0.00440)	
OBC*Post 94	-0.00220	-0.00400	-0.00250	-0.00263
	(0.00505)	(0.00551)	(0.00613)	(0.00683)
Observations	43,790	43,790	39,960	39,960
R-squared	0.006	0.063	0.006	0.062
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO
Panel B: DDD				
OBC Caste	0.0211*		0.0237**	
	(0.0111)		(0.0106)	
Post 1994	-0.0167**		-0.0204***	
	(0.00688)		(0.00681)	
Mandal State	-0.106***		-0.105***	
	(0.00695)		(0.00750)	
OBC*Post 94	-0.00164		-0.00320	
	(0.0110)		(0.0106)	
OBC Caste*Mandal State	-0.0250**		-0.0274**	
	(0.0119)		(0.0115)	
Post 94*Mandal State	0.0161**		0.0185**	
	(0.00784)		(0.00836)	
OBC*Post 94*Mandal State	-0.000483	0.00233	0.000656	0.00224
	(0.0122)	(0.0113)	(0.0123)	(0.0121)
Observations	78,627	78,627	71,400	71,400
R-squared	0.040	0.138	0.040	0.138
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household is a caste association member as the dependent variable. All models include controls for gender, urban residence, size of household, number on men and women in the household, and religion dummies. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table H.5: Contacts: Controls

VARIABLES	(1) Age 18 Treat.	(2) Age 18 Treat.	(3) Age 14 Treat.	(4) Age 14 Treat.
Panel A: DD				
OBC Caste	-0.0646***		-0.0774***	
	(0.0139)		(0.0137)	
Post 1994	-0.0463***		-0.0682***	
	(0.00825)		(0.00889)	
OBC*Post 94	0.0317**	0.0231	0.0580***	0.0541***
	(0.0142)	(0.0151)	(0.0149)	(0.0159)
Observations	51,629	51,629	47,211	47,211
R-squared	0.032	0.099	0.033	0.099
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO
Panel B: DDD				
OBC Caste	-0.0335***		-0.0310**	
	(0.0128)		(0.0127)	
Post 1994	-0.0362***		-0.0431***	
	(0.00848)		(0.00913)	
Mandal State	0.0591***		0.0691***	
	(0.0117)		(0.0119)	
OBC*Post 94	0.00659		0.00790	
	(0.0130)		(0.0136)	
OBC Caste*Mandal State	-0.0315*		-0.0468**	
	(0.0189)		(0.0186)	
Post 94*Mandal State	-0.00812		-0.0221*	
	(0.0119)		(0.0129)	
OBC*Post 94*Mandal State	0.0247	0.0101	0.0501**	0.0400*
	(0.0193)	(0.0197)	(0.0202)	(0.0208)
Observations	95,765	95,765	87,127	87,127
R-squared	0.032	0.109	0.032	0.108
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household knows a doctor, teacher police inspector or gazetted government officer as the dependent variable. All models include controls for gender, urban residence, size of household, number on men and women in the household, and religion dummies. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

I Individual Movement between Caste Categories

Table I.1: Education: Caste Category Defined by Jati

VARIABLES	(1) Years of Educ.	(2) Years of Educ.	(3) Years of Educ.	(4) Years of Educ.
OBC Caste	-0.912***		0.0490	
	(0.133)		(0.160)	
Post 1994	2.148***		2.950***	
	(0.0954)		(0.122)	
Mandal State			-0.150	
			(0.134)	
OBC*Post 94	0.668***	0.501***	-0.125	
	(0.163)	(0.156)	(0.191)	
OBC Caste*Mandal State			-0.961***	
			(0.208)	
Post 94*Mandal State			-0.802***	
			(0.155)	
OBC*Post 94*Mandal State			0.794***	0.694***
			(0.251)	(0.223)
Observations	38,727	38,727	65,908	65,908
R-squared	0.051	0.229	0.067	0.270
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. OBCs are defined as those belonging to a state-jati where over 90% of jati members identify as OBC. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table I.2: Differential Effects: Caste Category Defined by Jati

VARIABLES	(1) Secondary	(2) Secondary	(3) Higher	(4) Higher
Post 94	1.590***		2.106***	
	(0.113)		(0.104)	
Ed. Father*1	5.973***		8.470***	
	(0.179)		(0.267)	
OBC	-0.108		-0.598***	
	(0.131)		(0.134)	
Post 94*Ed. Father	-0.806***		-2.289**	
	(0.210)		(0.303)	
Post 94*OBC	0.267	0.00761	0.559***	0.387**
	(0.192)	(0.187)	(0.175)	(0.170)
Ed. Father*OBC	-1.790***		-0.391	
	(0.378)		(0.734)	
Post 94*Ed. Father*OBC	0.935**	1.301***	-0.356	1.02
	(0.433)	(0.434)	(0.808)	(.872)
Observations	31,122	31,122	31,122	31,122
R-squared	0.255	0.361	0.120	0.280
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Ed. Father*State-Caste Category FE	NO	YES	NO	YES
Ed. Father*State-Birth Year FE	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. The definition of educated fathers is listed in the column headings. OBCs are defined as those belonging to a state-jati where over 90% of jati members identify as OBC. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table I.3: Middle Class Employment: Caste Category Defined by Jati

VARIABLES	(1) Middle Class	(2) Middle Class	(3) Middle Class	(4) Middle Class
OBC Caste	-0.0739***		-0.0606***	
	(0.0126)		(0.0125)	
Post 1994	-0.0201**		0.0343***	
	(0.0102)		(0.0126)	
Mandal State			0.0195	
			(0.0119)	
OBC*Post 94	0.0479***	0.0428**	0.0287	
	(0.0170)	(0.0171)	(0.0188)	
OBC Caste*Mandal State			-0.0133	
			(0.0178)	
Post 94*Mandal State			-0.0544***	
			(0.0163)	
OBC*Post 94*Mandal State			0.0191	0.0161
			(0.0253)	(0.0252)
Observations	16,847	16,847	30,598	30,598
R-squared	0.004	0.174	0.005	0.140
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with an indicator for middle class employment as the dependent variable. OBCs are defined as those belonging to a state-jati where over 90% of jati members identify as OBC. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table I.4: Association Membership: Caste Category Defined by Jati

VARIABLES	(1) Caste Association	(2) Caste Association	(3) Caste Association	(4) Caste Association
OBC Caste	-0.000344		0.0353**	
	(0.00477)		(0.0138)	
Post 1994	0.000103		-0.00938	
	(0.00283)		(0.00755)	
Mandal State			-0.111***	
			(0.00830)	
OBC*Post 94	-0.00185	-0.00130	-0.0139	
	(0.00479)	(0.00501)	(0.0138)	
OBC Caste*Mandal State			-0.0356**	
			(0.0146)	
Post 94*Mandal State			0.00948	
			(0.00806)	
OBC*Post 94*Mandal State			0.0120	0.0175
			(0.0146)	(0.0128)
Observations	33,915	33,915	57,329	57,329
R-squared	0.000	0.061	0.044	0.159
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household is a caste association member as the dependent variable. OBCs are defined as those belonging to a state-jati where over 90% of jati members identify as OBC. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table I.5: Contacts: Caste Category Defined by Jati

VARIABLES	(1) Caste Contact	(2) Caste Contact	(3) Caste Contact	(4) Caste Contact
OBC Caste	-0.0588***		-0.0543***	
	(0.0164)		(0.0162)	
Post 1994	-0.0347***		-0.0330***	
	(0.00912)		(0.0104)	
Mandal State			0.0284**	
			(0.0140)	
OBC*Post 94	0.0342**	0.0283*	0.0323**	
	(0.0161)	(0.0172)	(0.0161)	
OBC Caste*Mandal State			-0.00442	
			(0.0231)	
Post 94*Mandal State			-0.00162	
			(0.0139)	
OBC*Post 94*Mandal State			0.00191	-0.000241
			(0.0228)	(0.0233)
Observations	38,767	38,767	65,982	65,982
R-squared	0.002	0.089	0.003	0.102
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household knows a doctor, teacher police inspector or gazetted government officer as the dependent variable. OBCs are defined as those belonging to a state-jati where over 90% of jati members identify as OBC. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

J Continuous Treatment Measure

Table J.1: Quotas as a Continuous Treatment

VARIABLES	(1) Ed. Years	(2) Ed. Years	(3) Prof. Contact	(4) Prof. Contact	(5) Caste Ass.	(6) Caste Ass.
OBC*Post 94 *OBC Reservation /OBC Pop.	0.624***	0.605**	0.0341	0.00826	-0.0102	-0.0178
	(0.242)	(0.305)	(0.0260)	(0.0309)	(0.0106)	(0.0168)
Observations	89,738	89,738	89,848	89,848	89,712	89,712
R-squared	0.236	0.239	0.085	0.087	0.137	0.138
State-Caste Category FE	YES	YES	YES	YES	YES	YES
State-Birth Year FE	YES	YES	YES	YES	YES	YES
Caste Category-Birth Year FE	NO	YES	NO	YES	NO	YES

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with the dependent variable indicatesd in the column heading. The independent variable of interest is the interaction of OBC status with the ratio of the OBC quota in the year the respondent turned 18 with the overall state percentage of OBCs in the sample$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

M No "Creamy Layer"

Table M.1: Education: No "Creamy Layer"

VARIABLES	(1) 18	(2) 18	(3) 14	(4) 14
OBC Caste	-0.851***		-0.822***	
	(0.116)		(0.114)	
Post 1994	2.150***		1.931***	
	(0.0856)		(0.0861)	
OBC*Post 94	0.527***	0.355**	0.591***	0.396***
	(0.140)	(0.139)	(0.141)	(0.139)
Observations	51,456	51,456	47,043	47,043
R-squared	0.049	0.194	0.045	0.181
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table M.2: Differential Effects: No "Creamy Layer"

VARIABLES	(1) 18	(2) 18	(3) 14	(4) 14
OBC Caste	-0.00583		-0.00582	
	(0.00415)		(0.00438)	
Post 1994	0.00206		0.00322	
	(0.00386)		(0.00486)	
OBC*Post 94	-0.00165	-0.00378	-0.00191	-0.00232
	(0.00503)	(0.00557)	(0.00616)	(0.00694)
Observations	43,687	43,687	39,860	39,860
R-squared	0.000	0.059	0.000	0.058
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with individual years of education as the dependent variable. The definition of educated fathers is listed in the column headings. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table M.3: Middle Class Employment: No "Creamy Layer"

VARIABLES	(1) 18	(2) 18	(3) 14	(4) 14
OBC Caste	-0.0628***		-0.0641***	
	(0.0111)		(0.0107)	
Post 1994	-0.0114		-0.00922	
	(0.00934)		(0.0104)	
OBC*Post 94	0.0369**	0.0310**	0.0446***	0.0386**
	(0.0151)	(0.0150)	(0.0166)	(0.0164)
Observations	22,289	22,289	19,694	19,694
R-squared	0.003	0.147	0.003	0.143
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with an indicator for middle class employment as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table M.4: Association Membership: No "Creamy Layer"

VARIABLES	(1) 18	(2) 18	(3) 14	(4) 14
OBC Caste	-0.00583		-0.00582	
	(0.00415)		(0.00438)	
Post 1994	0.00206		0.00322	
	(0.00386)		(0.00486)	
OBC*Post 94	-0.00165	-0.00378	-0.00191	-0.00232
	(0.00503)	(0.00557)	(0.00616)	(0.00694)
Observations	43,687	43,687	39,860	39,860
R-squared	0.000	0.059	0.000	0.058
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household is a caste association member as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table M.5: Contacts: No "Creamy Layer"

VARIABLES	(1) 18	(2) 18	(3) 14	(4) 14
OBC Caste	-0.0709***		-0.0837***	
	(0.0142)		(0.0138)	
Post 1994	-0.0280***		-0.0421***	
	(0.00852)		(0.00920)	
OBC*Post 94	0.0368**	0.0241	0.0643***	0.0556***
	(0.0146)	(0.0154)	(0.0153)	(0.0162)
Observations	51,514	51,514	47,099	47,099
R-squared	0.003	0.075	0.003	0.075
Controls	YES	YES	YES	YES
State-Caste Category FE	NO	YES	NO	YES
State-Birth Year FE	NO	YES	NO	YES
Caste Category-Birth Year FE	NO	NO	NO	NO

Household clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows the results of a series of linear regression models with a binary measure for whether someone in the household knows a doctor, teacher police inspector or gazetted government officer as the dependent variable. Models 1-4 correspond to Equations 1-4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.