Incentivizing Standards or Standardizing Incentives? Affirmative Action in India

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Abstract

This paper studies the impacts of affirmative action policies on schooling incentives in India. The theoretical model shows that when the probability of getting into college or of getting a job is increased, the marginal student from the minority group is incentivized to stay in school. This paper makes a unique contribution to the literature by looking at incentives in school (before the policy benefits come into play), focusing on a particularly understudied minority group: the OBCs (other backward classes); creating a comprehensive primary dataset using state commission reports which allows for a regression discontinuity analysis, and by confirming these results at the national level by using difference-in-differences and triple differences estimators. Together these estimators consistently show that affirmative action policies incentivize students to attain about 1.38 more years of education for the average student, and 2.2 more years of education for a student on the margin. Given the current debates in the media and policy spheres, this result is particularly significant.

JEL CODES: J15, J68, O12, O15, O53, I24, I25, I38, D63, D62

Key Words: Affirmative Action, Education, India, Reservations, Quotas, Regression Discontinuity, Difference in Differences, Other Backward Classes, OBC

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1 Introduction and Background

This paper looks at the impact of affirmative action policies on incentives in educational attainment. By focusing on affirmative action policies that make it easier to get into college or get a government job, it looks at the effect of such policies on the school grade completion of the minority group (that benefits from the policy of affirmative action). Affirmative action is an often discussed issue in both the public and academic spheres in the US, India, Sri Lanka, Malaysia, Nigeria and Brazil. This paper will focus on the Indian context where such policies are defined on the basis of caste or social class, and the policy interventions are much larger than in most other countries. The primary aim of this paper is to accurately and categorically discern the effects of these policies through rigorous empirical analysis. To that end, a comprehensive primary dataset on affirmative action policies was compiled using archived commission reports, petitioned from the Government of India. This step was necessary towards enabling a regression discontinuity analysis and a creating a double-difference and triple-difference estimator, making this paper a unique contribution to the affirmative action literature.

The caste system in India has stratified the society by instituting a historical hierarchy. While the nation is predominantly Hindu (80.5%), there are a significant number of Muslims (13.4%), Christians (2.3%) (Indian Census 2001) and other religious groups that have over time been absorbed into the hierarchy of the caste system. The Constitution has identified some of these castes as the most disadvantaged group and codified them as the Scheduled Castes (SCs). It also enumerates certain aboriginal tribal groups, which are referred to as Scheduled Tribes (STs). Over time there has been an attempt to identify groups that are better-off than SCs and STs but less well to do than upper caste members of the different communities. These groups are known as Other Backward Classes (OBCs), and are relatively under-studied in the literature.

Over time the Indian government has instituted laws whereby a certain percentage of seats in colleges or government jobs are set aside for certain castes or communities. This "reservation policy" primarily benefits groups from the Scheduled Castes, Scheduled Tribes and Other Backward Classes. The primary purpose of this law is to provide a level playing field for communities that have suffered from historical discrimination. The Constitution says that "the State shall promote with special care the educational and economic interests of the weaker sections of society (in particular, of the scheduled castes and aboriginal tribes), and shall protect them from social "injustice" and all forms of exploitation." This law allows states to reserve seats for different communities in state-run universities and in government jobs.

In 1980, a Commission was established to determine what percentage of seats should be reserved in national universities and government jobs for OBCs (Mandal 1980). Despite much opposition from the upper-castes, in 1993, OBC reservations in government jobs were implemented, (and reservations in colleges were finally implemented in 2006). [1] These community based reservations at the central level exist alongside the state laws, which vary across states. This paper will seek to exploit the variation across various dimensions: caste, age, region and eligibility in order to determine the impact of such policies. While state-level laws provide quotas in both educational institutions and government jobs, the federal law changes studied here will focus on OBC reservations in government jobs.[2]. Labor market reservation quotas, are unique to the Indian context.

The Regression Discontinuity (RD) approach will exploit certain policy features in a particular Indian state, whereas the Difference-in-Differences and Triple Difference ap-

[1]In 2005, a federal Committee suggested reservations for Muslims as well - these have not yet been implemented (Sachar 2005). Furthermore, reservations for women in local governing bodies were implemented in 1993.

[2]This is because the federal level implementation of OBCs in higher educational institutions only happened recently

proach will look at the entire country. All estimators consistently point towards an increase in educational attainment in response to reservations for OBCs in higher education and government jobs. By exploiting the discontinuity before and after these OBC reservations were instituted, this paper demonstrates a strong causal relationship between the reservations and the subsequent increase in educational attainment.

In the next section the relevant literature is reviewed, and the contribution of this paper is discussed. In the following section, a dynamic optimization model is discussed with testable implications. Unlike most of the other literature (which concentrates on outcomes in a sample of engineering colleges), the empirical section looks at nationally representative populations. Furthermore, filling a gap in the literature, OBCs will be the primary focus of this paper (the literature concentrates on reservations for SCs and STs). [3] Section 3 draws up a theoretical model that describes the expected impacts of such policies. Section 4 discuses the data and provides some summary statistics. The main focus of this paper is Section 5. It discusses the various empirical strategies used and their corresponding results using three different empirical strategies: (a) difference-in-differences, (b) triple differences, and a (c) regression discontinuity approach. The last section concludes, and discusses policy implications.

2 Literature

That quotas are a legitimate form of affirmative action, has been shown by several studies. For instance, Fryer and Loury (2005) show that equal opportunity is not enough to close educational inequalities that arise from historical discrimination. Affirmative action, via reserving seats in either universities or in government jobs may incentivize educational attainment through various channels. Increasing the probability of getting into college may motivate students to graduate from school and try to get into college. This may

[3] Nonetheless, impacts on the SC-ST will also be discussed.

help overcome what the literature refers to as "effort pessimism" (Fryer and Loury 2005). Similarly, certain government jobs require a minimum standard of education in order to qualify, and reservations in these jobs may incentivize students to attain that required level [4]. If peers are seen to benefit from this policy, then a "role model" effect may also have a positive impact on educational attainment. However, evidence in the American context may not support 'role model' hypothesis - it instead posits that benefiting minority students are less popular because they are accused of 'acting white' (Ogbu 2003, Fryer and Torelli 2010) [5]. On the other hand, such policies may lead to complacency and dependency if the minority group views the lower threshold to be "too easy." And if such policies lead the employers to devalue the minority group's achievements and give them less desired jobs, then it may discourage attainment of higher education.

The Coate and Loury (1993) theoretical model shows that under certain assumptions such policies can encourage effort. And over time the policies could lead to a 'benign equilibrium' where negative stereotypes about the minority group are eradicated. However, under other assumptions it could lead to a 'patronizing equilibrium' where the negative stereotypes persist, which could discourage education. The literature also mentions 'complacency' effects of such policies on incentives for schooling - for example, smarter sections of the minority group could put in less effort knowing that it is easier to get into college [6]. Furthermore, if employers devalue the credentials of any minority group candidate (because of the affirmative action policies) it can disincentivize members of the minority group from obtaining education. In the political and academic sphere these possible outcomes are the topic of contentious debate. Nonetheless, there is very little empirical evidence to back up these claims. Weisskopf (2004) provides a theoretical

[4] Anthropological studies in the American context suggest that difficulties faced by minority groups in finding employment ('job ceiling' hypothesis) discourage them from attaining education (Ogbu 2003)

[5] Teacher-student pairings of the same race, however, have been found to have positive impacts, which may be evidence in support of a role-model effect (Dee 2004)

[6] Assuncao and Ferman (2013) look at high-school tests scores in Brazil, and argue that affirmative action policies reduces human capital accumulation for the minority group.

comparison of affirmative action policies in the US and India, and discusses the various expected effects of such policies, including the impacts on incentives to stay in school. Looking at such policies in the US, Arcidiacono et al (2011, 2012) study the impact of affirmative action policies on college fit and mismatch. They show that laws banning the use of racial preferences in California public colleges lead to better match quality and higher graduation rates in colleges. Domina (2007) shows that the diversity programs enacted in Texas (after affirmative action was banned) boosted educational outcomes at the high-school level. On the other hand, Hickman (2013) uses a structural model (based on auction theory) and shows that race quotas (in the US) would induce more human capital investment by minorities, but would involve a larger welfare loss.

In the Indian context, there is some empirical work that suggests that affirmative action policies have "strong positive economic effects" (Betrand, Hanna and Mullainathan 2008). Their paper studies a sample of engineering colleges and argues that these policies are well targeted and improve the performance of the minority groups in question. Bagde, Epple and Taylor (2012) also look at a sub-sample of engineering colleges in a particular Indian state, and argue that reservations have a "significant and substantial positive effect both on college attendance and first-year academic achievement." Furthermore, using a nationally representative data set, Desai and Kulkarni (2008) show that educational inequalities have been falling over time for Scheduled Castes and Tribes (that do benefit from reservations), but have not been declining for the Muslim community (who are excluded from the current reservation policy). On the other hand, Krishna and Robles (2013) look at a detailed data set from an engineering college in India and show that affirmative action policies lead to mismatch - minority students end up earning less than they would have if they picked less selective majors. Many of these papers study a group of engineering colleges and focus on outcomes at the collegiate level. In contrast this paper, looks at educational attainment at all levels of schooling (before the policy benefits kick in), and studies the country as a whole. Furthermore, it also looks at reservations in governmental jobs (which is largely ignored by the literature). The hypothesis is that when the chance of getting a government job is increased, students are incentivized to achieve the schooling requirements of the job.

This paper speaks to the larger literature on human capital investment responses to changes in the returns to education. It finds that affirmative action policies increase the expected returns to education by increasing the probability of getting a job or getting into college, which is essentially a schooling-response to a change in the expected returns to education. A large literature exists on this in the US context (Freeman 1976, Katz and Murphy 1992, Heckman 1993, Kane 1994, Griliches 1996, Ryoo and Rosen 2004). And there is a constantly growing literature in the developing country context as well (and especially in the Indian context): Foster and Rosenzweig (1996) show how the Green-Revolution in India led to a direct increase in primary schooling. Kochar (2004) finds that households increase educational investments in response to higher returns in the nearest urban labor market, and Jensen (2010) finds that better jobs for women (in the IT sector of Delhi) increases schooling for girls. Similarly, Shreshta (2011) finds that a change in the eligibility requirements of joining the Army incentivized the Gurkha community in Nepal to increase their grade attainment. On the other hand, Jensen and Miller (2012) show that strategic incentives amongst rural Indian households can actually lower educational attainment in response to higher returns to education. They argue that parents want a child to remain at home and look after them, and so curb their migration opportunities by lowering their educational investments. Similarly de Brauw and Giles (2008) find that school attainment falls in rural China in response to better migration opportunities, because of higher opportunity costs of schooling. Therefore, the direct impacts of increased returns are not clear in the developing country context. [7]

[7] This literature will be re-visited in the last section when understanding the magnitudes of the impacts of affirmative action policies found in this paper.

Yet another strand of the literature focusing on possible policies that can incentivize education (Orazem and King 2008, Behrman 1999, Glewwe and Kremer 2005) is relevant to the results of this paper. In Chile, Dinkelman and Martinez (2011) show how financial aid information can reduce school absenteeism. Kazianga, Levy and Linden (2012) show how 'girl-friendly' schools increased enrollment and test scores in Burkina Faso. [8] This literature will be revisited at the end of this paper to understand the costs and benefits of the affirmative action policies relative to other policies.

This paper makes some unique contributions. It is amongst the first papers to empirically study the causal impacts on incentives before the benefits of the policy actually kick-in (the incentives of students in school). Unlike the other papers on India, it uses household survey data to look at the impacts on the entire country, rather than at a subset of engineering colleges. Furthermore, it also looks at labor market affirmative action policies (which is unique to the Indian context). And studies the impacts on the extensive margin (drop-outs) rather than the intensive margin (test-scores), making it consistent with certain papers that hypothesize that test scores may be adversely affected. Lastly, it compiles state-level laws, and exploits a state's law to perform a regression discontinuity to identify the causal impact of the policies.

3 Model

The paper uses a simple dynamic optimization problem where in every period the agent can choose to dropout or stay in high-school. If the returns to s years of schooling is

[8] Policies to incentivize education have also been discussed in the US context: Bettinger et al (2009), Hoxby and Turner (2013)

$w(s)$, then for a discount rate β, the agent's value function can be characterized by:

$$V_s = \max_{Dropout,Stay} (V(DropOut), V(Stay))$$

$$V_s = \max_{Dropout,Stay} (\sum_{t=s}^{\infty} \beta^{t-s} w(s), -c_i + \alpha_i + \beta(p_s \frac{1}{1-\beta} B + (1-p_s)V_{s+1})$$

In this equation, B is the expected net benefits from going to college or getting a government job. [9] The simplest version of the model doesn't allow for on-the-job search, and once the agent drops out and gets a job at wage $w(s)$ he/she earns that wage forever. [10] The cost of an additional year of schooling for person i is c_i. This varies by person, and is drawn from a distribution $F(c)$. α_i captures the preferences for schooling, and would then be affected by 'role-model' effects, if present. The probability of getting into college or getting a government job p is a function of various factors:

$$p = p(schooling, caste, quotas, grades, schoolquality, ability, Z)$$

Where Z is a vector of other individual characteristics that generate heterogenous responses to changes in the probability. Heterogenous responses to schooling are captured by a cost function c_i that varies by individual. The probability function can be different in various contexts. For example, different levels of government jobs require different levels of education, which means that the probability p_s could discretely jump across levels of schooling. Getting into college, however, requires one to complete high-school, therefore $p_s = 0$ for any s below the last year of schooling.

[9] Government jobs may not only pay a higher wage (over and above the going wage w(s)) but also provide job security

[10] Expectations of benefits can be made to depend on the information set of the agent. This will allow us to see the impacts of a change in the peer group that benefits from affirmative action, and incorporate the possibility of 'role model' effects.

For an increasing and concave wage function $w(s)$, the value function converges to an optimum under certain regularity conditions, [11] and can be solved by using backward induction. Let the last year of schooling be $\underline{S}$. Then, the last period in the value function is:

$$V_{\underline{S}+1} = p_{\underline{S}+1}\frac{1}{1-\beta}B + (1-p_{\underline{S}+1})\frac{1}{1-\beta}w(\underline{S})$$

Solving backwards, the penultimate period's value function is:

$$V_s(c_i) = \max_{Dropout,Stay}(\sum_{t=\underline{S}}^{\infty}\beta^{t-\underline{S}}w(\underline{S}), -c_i + \beta(p_{\underline{S}}\frac{1}{1-\beta}B + (1-p_{\underline{S}})V_{\underline{S}+1})$$

The optimal policy function has a threshold strategy, whereby a student chooses to drop out of school when his marginal value from an additional year of schooling is less than the cost he/she must bear. Let this threshold level of education be s^*.

When the probability of getting into college increases, it raises the expected value of an additional year of schooling and lowers dropouts. Thus reservations in colleges can incentivize the marginal student to stay in school for more years.

$$\frac{\partial s^*}{\partial quota} > 0$$

Similarly, reservations in government jobs increase the expected net benefits from additional schooling. This would thus incentivize students just below the job-qualification threshold to get at least as much education as the government job requires.

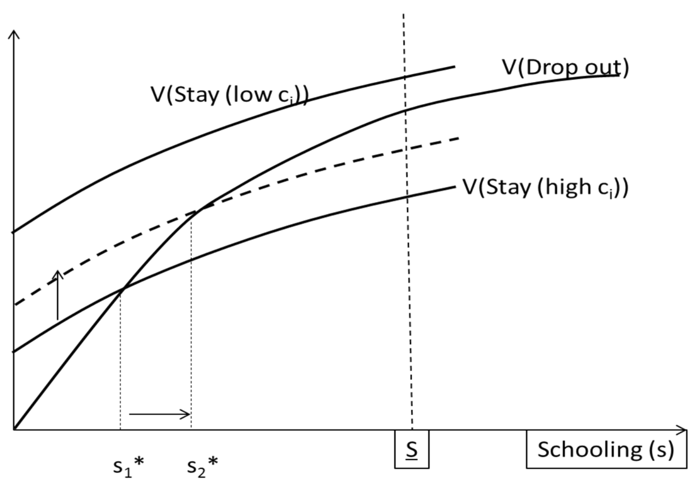
The graph presented in Figure 1 explains the mechanism behind the model. The values function $V(s)$ is the upper envelope of the two value functions $V(Dropout)$ and

[11] For example, we need the slope of the wage function to be steeper than probability function:

$$\frac{1}{1-\beta}w_s(s) \geq Bp_s$$

$V(Stay)$. The shape of the $V(Stay)$ depends on the shape of p_s, whereas the level depends on the cost of education c_i. The differences in cost of education provide heterogeneity in schooling attainment. Students with low costs of schooling (say from upper-caste households), may face a corner solution and obtain the maximum amount of schooling $\underline{\text{S}}$. For students with higher costs, they will stay in school till s_1^* (the point where the value from dropping out exceeds the value from staying in school). When quotas are introduced, it shifts up the value function for staying in school, and increases schooling for the minority group to s_2^*.

Figure 1: Incentivizing Schooling



Value function is upper envelope of V(dropout) and V(stay). An increase in the quotas, raises the V(stay) curve and increases optimal level of education from s_1^* to s_2^*

There are, however, factors that may confound the identification of these effects. If the quality of schooling and the number of schools increase, then costs of attending are lower, which also tends to prevent the agent from choosing to drop out of school $\frac{\partial s*}{\partial c_i} < 0$. This is an important result as it will be the primary confounding factor in the empirical specification. The government of India made large investments in schooling at around the same time that affirmative action policies were expanded. These investments were made under the National Policy of Education (NPE) program in 1986. Though the education reforms were not caste/class specific, they will still be a potential source of concern. Since school building and increasing the quality of education would prevent dropouts, the impact should be largest on disadvantaged groups that already have the highest drop out rates. These groups will be similar to those eligible for affirmative action. Therefore, the empirical strategies presented will need to tackle this issue. One important distinction between the two policies is that affirmative action policies may encourage the marginal student to stay in school (by increasing the probability p of getting a government job), whereas the school building policy may have the greatest impact on those students that have the highest costs of education (by lowering the costs c_i of schooling). [12]

Another testable implication is the result on test scores. The factors that determine the probability of getting into college p can be seen as substitutes. Marginal students who had a low probability of entering college may now seek to improve their test scores when it is easier to get into college due to reservations. [13] Whereas the marginal student who has a high probability of getting into college may actually lower their effort input when it is easier to enter college. This should thus lower the variance of the distribution (around the threshold) of test scores for the minority group in question. Assuncao and Ferman (2013) argue that in Brazil, there is a fall in high-school proficiency of the minority group. Since they focus on high-school proficiency, their results are fully consistent with the model in this paper. However, this paper will look at grade attainment, rather than 'effort' within a grade, and since certain grade-levels are required to take advantage of affirmative action policies, there should not be any fall in achieving that level of schooling. [14]

[12] These high-cost students are not the 'marginal,' in the sense that they are not the students who are just below the threshold level of education required to get a government job or get into college.

[13] In the model this can be seen if 'quotas' and 'test scores' are substitutes: $\frac{\partial testscores}{\partial quota} = \frac{\partial testscores}{\partial p}\frac{\partial p}{\partial quota} < 0$

[14] In a model that has costly education with credit constraints, affirmative action policies may also lead to more education. If a sibling or parent benefits from these policies, they have more income to pay for schooling of the younger members of their family.

Since the thrust of this paper is the empirical section, it will present a simplified version of the model in order to understand the magnitudes of the estimated impacts and the trade-offs made by the agents. The advantage of the stylized model will lie in its easy applicability to other contexts of affirmative action policies, (such as the US, Malaysia, Sri Lanka or Nigeria). Let us assume there are two periods in the model: youth and adulthood. Going to school costs c_i (drawn from a CDF $F(c)$). If the youth choses to not attend school, he/she can earn a wage w in both the youth and adulthood periods. Schooling forces the student to forgo a wage in their youth, but allows the student to earn a wage W^{ed} in their adulthood. The extra net benefit from attending college or obtaining a government job is B (including non-pecuniary benefits), and the probability of getting into college or a government job $p(s, quota)$ is a function of whether the person went to school and the affirmative action policies. An agent chooses to attend school in their youth if:

$$-c_i + (1 - p(s,q))W^{ed} + p(s,q)[W^{ed} + B] \geq w + w \tag{1}$$

Or

$$c_i \leq W^{ed} - 2w + p(s,q)B$$

For the upper-caste group, the costs of schooling are lower, and so this inequality is more likely to hold. Introducing quotas will increase the probability of attending college or getting a government job since $p_q(s,q) > 0$. This incentivizes beneficiaries of the quotas to attend school. The fraction of agents who attend school are $F(W^{ed} - 2w + p(s,q)B)$, which is an increasing function of quotas. The introduction of quotas, thus raises the minority-group's schooling for those below the cutoff (close to the inequality).

4 Data and Summary Statistics

This paper makes use of a number of data sources: a mix of survey data and governmental commission reports compiled specifically for this analysis. First, it uses the Indian National Sample Survey (NSS), which is a representative repeated cross-section carried out every five years. This data set has information on educational attainment, field of graduate study, caste, age, and host of other labor market outcomes along with a comprehensive consumption expenditure module. Since this paper will focus on affirmative action policies instituted in the early 1990s, the data set it uses is the 2000 module. The nationally-representative "thick" rounds of the data set are enumerated every 5 years. [15] (whereas "thin" rounds are collected every year). The 1995 round is too early to capture the effects of policies instituted in the early 1990s, since changes in schooling decisions take time. Whereas the 2005 round is too late and may suffer from other confounding policies introduced in the interim years, [16] and changes in definitions of the OBC group across waves of the survey.

The data set has information on *level* of education, rather than years of education. Such a measure is more useful in the Indian context where we may expect the level (rather than years) to matter a lot more for eligibility for jobs and colleges. For example, literacy (even with 0 years of formal schooling) may have an effect on the probability of getting a job. The various levels of education are (a) illiterate, (b) literate without formal schooling, (c) literate with formal schooling, (d) primary school, (e) middle school, (f) secondary school, (g) higher secondary school, (h) college educated. Nonetheless, the

[15]The NSS 55th Round was collected between July 1999 and June 2000 using a stratified two stage sampling design. First, clusters (rural villages or urban blocks) were sampled, and then 12 households within each cluster were sampled.

[16]One big policy change in 1999 was the introduction of OBC level scholarships under the Ninth Five Year Plan (see Gupta(2004)). Another was the implementation of the Millennium Development Goals in 2000. If the 2005 data set was used, then this policy would make it impossible to disentangle the direct effects of reservations in government jobs, because of the coincidental presence of scholarships and MDGs

paper will also discuss how to translate these levels into years (to be consistent with the rest of the literature, where 'years of education' is the measure used).

Primary source data was compiled on affirmative action policies instituted by the Federal government and the various Indian states. This was done by obtaining government reports via the Right to Information (RTI) Act. This dataset is comprehensive in that it has information on reservation policies for all states in the country. Furthermore, detailed knowledge on classification and identification of OBCs was found for a few states. The states in question had Committee Reports that laid out the methodology for identifying Other Backward Classes (OBCs) and their recommendations for reservation policy. Therefore, some estimation procedures will allow me to look at the effect on the entire country, while more detailed analysis has been done for the states where the in-depth reports were obtained.

The third source is the ARIS-REDS (Additional Rural Incomes Survey and Rural Economic and Demographic Survey 1999) data set. Unlike the NSS data, ARIS-REDS has information on disaggregated sub-castes. While the NSS is nationally representative, it only has information on four broad caste categories. ARIS-REDS on the other hand asks respondents their sub-castes, and thus has social-group information at a finer level. Unfortunately, neither of these data sets have information on educational aspirations and expectations, nor test scores, which would have been useful for additional analysis.

Table 1 uses NSS data to summarize the primary variables of interest by social groups. About one-third of the sample was self-reported to be OBCs. The proportion of SCs (16%) and STs (11%) are smaller. Looking at the mean education level by social group, it is clear that SCs and STs have the lowest rates of educational attainments, whereas OBCs do slightly better than them, but worse than the non-OBC/SC/ST group (known

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Table 1: Social Groups in India. *Source* : *NSS* 2000

	SC	ST	OBC	Others	Total
Sample Size	94098	66798	195579	237102	593577
Proportion of Sample (%)	15.85	11.25	32.95	39.94	100
Mean Education Level	3.62	3.90	4.26	5.55	4.63
Mean Years of Education (Approx.)	3.037	3.4042	3.9035	5.678	4.4186
Illiterate (%)	46.20	50.93	42.13	28.02	38.34
College Educated (%)	1.96	1.63	2.79	8.42	4.76
Household Month Exp (Rs.)	1245.89	1444.92	1440.81	2074.11	1609.51
Per Cap Month Exp (Rs.)	398.67	427.32	446.33	519.02	465.67
Urban (%)	30.87	22.61	33.21	48.17	37.62
Work in Agriculture (%)	56	72.89	53.31	40.36	51.53
Wage work (not Casual) %	26.61	32.65	40.46	68.38	45.85

'Others' are general category individuals (i.e. not SC, ST or OBCs). 'Mean Education Level' covers 8 levels of education from illiterate to college graduates. Nominal exchange rate: approx Rs. 50 to $ 1. Household Monthly Expenditure deflated by rural-urban-region-wise CPI.

as 'Others' or 'upper-caste'). The mean education level for the upper-caste group is 5.5, indicating that not a large proportion of them are in college either [17]. SCs , STs and OBCs have lower monthly expenditure compared to the rest of the population. Furthermore, these three disadvantaged groups are predominantly rural and work in the agricultural sector. They are also more likely to be employed as casual labor rather than in formal wage employment. Kohli (2001) discusses how the Indian growth story has largely been concentrated on urban, English-speaking, educated middle-class families, and the large-scale reforms of 1991 have been unable to bridge the inequalities between these social groups. [18]

The Indian Constitution determined the federal SC-ST lists (what sub-castes can be

[17]This is important, since if we expect the upper-caste to have reached the ceiling in educational attainment then the reservation policy should have no impact.

[18]Figure B.1 in the Appendix uses NSS data collected in 2000, to show a polynomial fit of the level of education by social group, and across various ages. The predicted fit shows that at any age group, those in the upper-caste category have more education than OBCs, and OBCs have more than SC-STs. With increases in age, the gap widens, but after an age of 25 years, the gap between the 3 groups is stable. This may provide suggestive evidence that the educational inequality has been falling for cohorts below the age of 25 - which is consistent with the empirical specifications discussed.

categorized as SC-ST) in 1950, and the OBC lists were created in 1980. Each state has the power to categorize certain communities as OBC [19] and the extent of reservations in state-run educational institutions and government jobs is a decision made autonomously by states. This produces variation in the 'intensity' of reservations faced by the different social groups, that will later be exploited in the empirical section of the paper. In addition to the state-wise reservations, the federal government also reserves seats for these groups in federal jobs and universities. While SCs and STs have been eligible for quotas since the 1950s, the reservations for OBCs are a relatively recent phenomenon. In 1980, a federal Commission was established to identify which communities should be classified as OBCs and what reservations they should have. The report recommended reserving 27% of the seats in government colleges and jobs for the OBCs that they identified. [20] This was met with large protests from the urban upper-class public who argued that they were being discriminated against, and that the disadvantaged groups already had a 'level playing field' (Kohli 2001). In 1993, the federal government implemented the first stage of the Mandal Commission recommendations by reserving 27% of government jobs for OBCs, and then in 2006 the reservations in colleges were implemented. This paper will focus on the 1993 reservations in government jobs, and the various state-level reservations. The Indian Supreme Court excluded the more well-off members of the OBC community (known as the 'creamy layer') from taking advantage of these policies, and this is another source of variation that is exploited. In the last empirical section, the paper will focus on the state of Haryana, which ranked sub-castes on the basis of their socio-economic disadvantage, and selected the worst-off castes as OBCs. This allows us to obtain a Regression Discontinuity estimate of the impact of these policies.

[19] This State list exists alongside the Federal list of OBCs

[20] This is a substantial change - compared to affirmative action policies in other countries.

5 Identification and Results

In order to make a comprehensive argument, this paper will explore three different identification strategies. Together the different estimators will provide a consistent picture of what the incentive effects of affirmative action policies are. The three identification strategies discussed here will be (a) Difference-in-Differences (DiD), (b) a Triple Difference Estimator, and (c) a Regression Discontinuity (RD) approach. While the Difference-in-Differences will identify the Average Treatment Effect on the Treated (ATET), and the Triple-Difference with produce a Heterogeneous Treatment Effect (HTE), the RD will identify a localized effect (in the neighborhood of the cutoff).

5.1 Difference-in-Differences

The double difference estimator will exploit variation on two fronts: (a) age and (b) social group. Some cohorts were too old to be affected by changes in the reservation policy. Others will be young enough (and still in school) and can thus change their level of educational attainment. Furthermore, only certain social-groups were eligible, providing variation in policy implementation on the social-group front. As discussed above, the federal government implemented reservations for OBCs in government jobs in 1993, whereby 27% of all public sector jobs were reserved for this group [21].

There are various kinds of government jobs that are applicable for reservations. Class I and II jobs refer to higher-level civil servants and require at least the completion of high-school (and usually other competitive selection exams) or college. Class III and IV jobs include lower skilled jobs like revenue inspectors, assistants, clerks and drivers. While these jobs have educational criteria, some of them do not require candidates to finish high-school (secondary schooling or even some basic literacy may be enough).

[21] This was after the Supreme Court upheld the implementation of reservations for OBCs in government jobs in the landmark case: *Indira Sawhney v. Union of India, 1993*

Therefore, the incentive effects will not just be seen in graduating from high-school, but also in attaining certain levels of education that make candidates competitive for these jobs. Rough calculations using the NSS data show a large increase in public-sector (and semi-public) employment for OBCs over time. In 1999-00 (six or seven years after implementation of the law), 22% of government and semi-public sector jobs were held by members of the OBC community, whereas in 2004-5 this number was about 27.7%. Therefore, representation of OBCs in government jobs has steadily increased since the implementation of the policy till about the amount of seats reserved for them (i.e. 27%). [22]

If such measures incentivize attaining a higher level of education, we should expect to see this for the OBC group. The average age for entering the last year of high-school lies between 17 and 18 years. At the time that reservations were implemented, anyone under the age of 17 or 18 years could have changed their educational attainment. Since the data was collected 6 to 7 years after that, by that time anyone who is above the age of 24 would not have been able to change their level of education. Furthermore, there would be many high-schoolers who have already dropped out of school and will thus find it hard to change their educational attainment. We should then see the impact of this policy being larger for younger individuals. For example, the impact on 15 year olds will be smaller than the impact on 10 year olds, since many 15 year olds would have already dropped out of school.

Equation (2) is the Differences-in-Differences regression (where $\boldsymbol{\alpha_a}$ and $\boldsymbol{\kappa_c}$ are vectors of dummies for age cohort and caste respectively). Here $\boldsymbol{\beta_{0ac}}$ is a vector containing the relevant coefficients, and is allowed to vary by age cohort a and caste c. The coefficient

[22] For a large fraction of the OBC population, a government job may be their best option given the level of job-security, and non-pecuniary benefits in addition to the pay. Furthermore, facing discrimination in the private sector employment market may make a government job the only option for some.

identifies the Treatment on the Treated ($\boldsymbol{\beta_{0ac}} = ATET_{ac}$) for caste c in cohort a. For $a > 24$, we expect $ATET_{c,a>24} = 0$. If this condition is violated, then we would not be satisfying the parallel trends assumption, which would then bias our coefficient of interest. For $a \leq 24$ and for the OBC group, we would expect $ATET_{c=OBC,a\leq 24} > 0$. Furthermore, the younger is the members of the OBC group, the greater would the expected impact be (i.e. $ATET_{c=OBC,a} > ATET_{c=OBC,a+1}$) since younger members find it easier to change their schooling. A person who was sixteen at the time the law was passed may have already dropped out of schools many years ago, and would therefore find it difficult to change their level of schooling; whereas a five-year old now knows the law is in place and can stay in school for much longer. [23]

$$edu_{ac} = \boldsymbol{\alpha_a} + \boldsymbol{\kappa_c} + \boldsymbol{\beta_{0ac}\alpha_a * \kappa_c} + \epsilon_{ac} \tag{2}$$

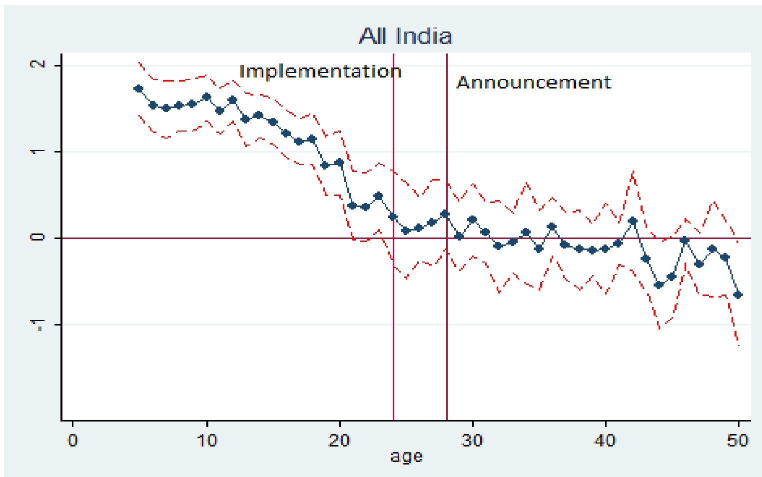
Since the NSS data only asks for education levels and not years of education, the results are produced for both measures. [24] The NSS data set has four broad social groups: (a) SCs, (b) STs, (c) OBCs and (d) Others. The 'Others' category includes the upper-caste section of the population ineligible for any reservations (i.e. not OBCs, SCs or STs). They comprise of 33% of the sample, have a higher monthly per capita expenditure than OBCs, SCs and STs, and are more likely to be urban and salaried (Table 1). More than 67% of Muslims fall into this category, and almost 70% of them are Hindu. The above regression specification was run where the 'Others' was the omitted social group, and ages above 50 were the omitted cohort category. It is then possible to plot the coefficients $\boldsymbol{\beta_{0ac}}$ for the three non-omitted social groups across the different

[23]Furthermore, since 42% of the OBC population cannot read or write, this will be the largest margin of change.

[24]A rough translation from the level of education to the years of education maintains the results. However, because there is no clear way to go from the level of education to the precise year of education, both forms have been presented. Furthermore, in the Indian contexts, certain changes in levels of education may be more relevant than the years of education. For example, the difference between being illiterate and literate without formal schooling will change the chances of acquiring a low-level government job.

age cohorts. Figure 2 plots these coefficients (for the 'levels of education' regression) for the OBC group across the various age cohorts, and clusters the standard errors across 32 states (and union territories).

Figure 2: OBC Coefficients of Diff-in-Diff Regression across age cohorts (Clustered)



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Plot of coefficients from Difference-in-Differences regression on 'levels of education'. Standard errors clustered at state-level. People above the age of 24 should be unaffected by implementation of policy. Vertical lines indicate year of announcement of the policy (on the right) and implementation (on the left).

The coefficients are close to zero and statistically insignificant for age cohorts above the age of 24. This confirms the absence of pre-treatment differential trends. For those below 24, however, the coefficient is positive and statistically significant. Furthermore, it is larger for younger cohorts as the model predicted. This is because younger cohorts have more time to change their educational decisions, whereas many in the older cohorts would have already completed or dropped out of school and will thus find it difficult to change their decisions. At its highest point, [25] the coefficient is around 1.5, indicating that the reservation policy caused an increase of about one level of education for the OBC group (this could be even something informal from a transition away from basic

[25] While the effects seem to be plateauing, the data also artificially truncates any larger effects for younger cohorts - since those cohorts had not yet reached schooling age at the time of the survey.

illiteracy to basic literacy). [26]

Since different states have, over time, passed different laws, this kind of analysis can be done for each state separately. In the graphs in Appendix Figure B.6, the vertical red line represents a marked change in reservation policy for the OBC group in that state. By restricting the sample to the corresponding state and plotting the coefficients, we can see that the state-wise changes in reservation policy have impacts similar to the federal law change.

In the Appendix, there are two other graphs. One of them reproduces the Difference-in-Differences figure but does not cluster the standard errors at the state level (B.3). This only narrows the confidence intervals. The other translates the dependent variable from levels of education to years of education (B.4). This translation to the years of education is crude (since many students will be between two levels, and there may be grade repetition), and may lead to measurement error, but the results are consistent with the levels of education.

One possible concern with the Difference-in-Differences strategy is that of violating the parallel trends assumption. However, if this assumption were to be violated, then it would be evident in the Difference-in-Differences figures. By looking at the figures we can see that older unaffected cohorts do not have a trending education gap with respect to the omitted categories (i.e. $ATET_{c=OBC;a>24} = 0$). Thus, the parallel trends assump-

[26] At the same time that the government implemented OBC reservations, they also upheld the decision to provide reservations in job *promotions* for the SC-ST groups, and established various National Commissions for the SC and ST groups. In Appendix Figure B.2 we can see that these policy changes had an effect on the SC-ST group's educational attainment. In 1990s, the Constitution was amended laying out guidelines for the formation and powers of a National Commission for SC-STs - and the first Commission under the amendment was established in 1992. Furthermore, Desai and Kulkarni (2008) show that how government policies in the early 1990s may have increased education levels for SC-STs. In the early 1990s, new policies were initiated to ensure that vacant quota seats were being filled by SC-STs and that upper-caste members were not appropriating the seats for themselves.

tion seems to hold in this context. There is also the concern of mean reversion. Since OBCs have less education than the general category, a theory of mean reversion would predict that over time this gap will fall. It is difficult to formulate a theory of mean reversion in educational attainment, especially when a lot of the educational inequalities literature argues that these gaps tend to widen over time (Halsey, Heath and Ridge 1980; Hauser and Featherman 1976) [27]. Furthermore, it is hard to see why this mean reversion should kick-in at exactly the same time as the reservation policy is implemented (in the absence of any other policy changes). Nonetheless, there is evidence (shown below) that mean reversion did not affect other disadvantaged social groups, and the other estimation strategies discussed in this paper will be unaffected by this issue of mean reversion.

Another concern arises if the omitted group is simultaneously 'treated.' Despite the fact that reservations are only applicable to OBCs, we may see a change in behavior of upper-caste members of society for various reasons. One possibility is akin to the John Henry effects discussed in the experimental literature. Upper-caste members of society may feel discouraged by the reservations and lower their educational attainment [28]. Such a reaction would bias the coefficients upwards. Another possible reaction by upper-caste members is to view these policies as increasing the competitiveness of getting a job, and thus working harder and attaining more education in order to compete for these spaces - these would bias the results downwards. As far as the federal law change is concerned, these reactions are unlikely since the number of government jobs were expanded to ensure that general category applicants were unaffected [29]. Many states also expanded seats in colleges and jobs in order to accommodate the quotas and ensure that general category applicants had the same number of seats as before. However, there still ex-

[27] These are models that show that because of intergenerational transfer of socio-educational capital can lead to divergence in educational attainment over time.

[28] In the US context, there is no evidence of this happening (Ogbu 2003)

[29] The major opposition to these policies come from affluent members of the upper-caste who would most likely not be affected in such a way

isted quite a few states where quotas were implemented without the expansion of seats and thus this may be a concern when interpreting some of the state-wise graphs above [30].

The general equilibrium effects of such policies may also affect the interpretation of the coefficients found. Increasing the number of seats could lower the wages paid in the government jobs (or jobs for college graduates), which may then attenuate the ATETs found. On the other hand, there may be peer effects in the classroom, which may affect the incentives for upper-caste students in attending school. Both these impacts should be of second-order in nature. [31]

The major concern to this approach is that of simultaneous policy changes. As discussed above, in 1986 the Indian government revamped the National Policy of Education (NPE) program and started spending on the improvement of schooling infrastructure and the building of new schools and recruited more teachers all across the country. They also expanded scholarships, provided access to adult education, and provided incentives for poor families to send their children to school regularly. This program was not OBC specific, but will still pose a problem to the double-difference identification strategy. The program will lower the costs of attending school, and should therefore matter the most for communities that have a higher cost of schooling, ex-ante. Since OBCs had lower educational levels than the omitted category (general students) they would reap larger benefits than the general category. Thus an improvement in schooling infrastructure would re-

[30] Furthermore, it is not clear how well the expansion of seats were handled at the Federal level and could lead to additional costs, and what margin these costs would lead to other cut-backs in expenditure

[31] Other general equilibrium effects include states changing policies in light of the federal government policy change. In order to tackle this I drop the states that introduced affirmative action policies around the same in a 5-year span around the federal government policy (this includes dropping West Bengal, Haryana and other small states). The results remain identical. Some states that had affirmative action policies for more than 20 years prior to the federal government change made minor changes to the amount of quotas, thus the parameter identified here may include that - giving us the policy relevant parameter that includes the inducement of minor state-level law changes. However, in the triple-difference section I show, that controlling for state-level laws, does not in any way affect the impacts of the federal level law change.

sult in a declining gap between the OBC and general category. The graphs above could merely be picking up this declining gap because of more teachers and smaller classrooms. One of the largest expenditures under the educational expansion policy came on hiring more primary school teachers. Chin (2005) shows that despite hiring new teachers, teachers-per-school didn't increase and class sizes didn't decrease. There was merely a redistribution of teachers from larger to smaller schools. And for girls, she finds that this may have impacted the primary school completion rate in states that had a higher 'intensity' of redistribution. I re-construct the intensity measures, and control for flexible forms of it in my analysis, and it doesn't affect my results. I also do the difference-in-differences exercise separately for low intensity and high intensity states (divided on the median), and the results are once again similar.

Furthermore, these school-building policies should also affect other disadvantaged groups like the low-income upper-caste population, and the Muslim population [32]. From table A.8 in the Appendix, we can look at the educational attainment and per capita expenditure for the Muslims and poorest-fifth of the upper-caste category (non-OBC/SC/ST). Both categories have mean per-capita expenditures and land assets that are *lower* than those of OBCs, and should thus be a relevant comparison group [33]. While the poorest-fifth of the upper-caste category have very slightly more years of education than the average OBC; Muslims have less years of education, (which would imply the possibilities of a larger impact on Muslims.) [34].

Comparing the graphs in figure 3, we can see that the largest impact is on the OBCs. Muslims seem to experience little or no-impact, but there is a slight impact on the poorest-fifth of the 'Others' category (many years after the policy was implemented).

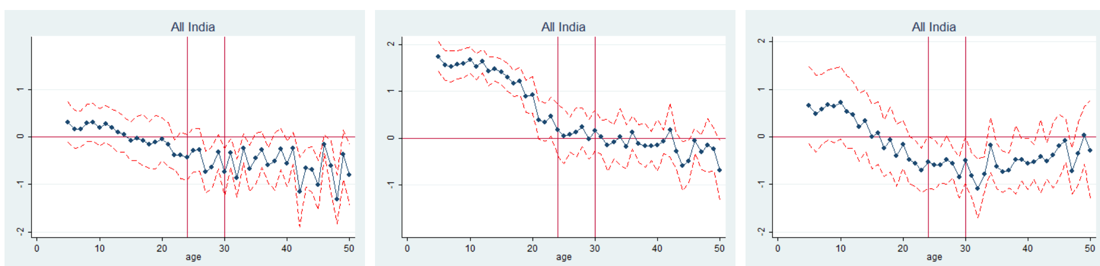
[32] Desai and Kulkarni (2008) propose a similar test- when looking at the impacts on SC-STs, they compare the it to the effect on Muslims

[33] They also have similar geographic dispersion

[34] We should expect the Muslims to have a larger impact (than OBCs) since they start out with a lower level of education (and should presumably have a higher cost of schooling). This is a prediction from the model. Lowering the costs of schooling should have the largest impact on the high-cost students

Nonetheless, the effect on this population is less than half of the total impact on the OBCs. Thus, even if there is an effect of the infrastructure building program of the early 1990s, there still remains a large impact on OBC schooling that can only be explained by the affirmative action policies. Furthermore, the other identification strategies used in this paper, will not be threatened by this issue of simultaneous treatment. The figures also show little or no immediate impact of launching the National Policy of Education in 1986 (persons between the ages of 24 and 30 should be affected by the National Policy of Education but not by reservations).

Figure 3: Comparing Impacts on OBCs with Muslims and the Poorest 20% of Others



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(a) Muslims (b) OBCs (c) Others - poorest 20%

Standard errors clustered at state-level. Persons above 24 unaffected by Reservations; Persons above 30 unaffected by National Policy of Education. ‘Others’ defined as non-(OBC, SC or ST). In the regression with the Muslims, the omitted category is Hindus. In the regression with the poorest 20% of upper-caste members, the omitted category is the richest 80% of the upper-caste population.

The Difference-in-Differences tables can be made by dividing the sample into younger and older cohorts; and OBCs and upper-caste. Looking at the Difference-in-Differences results in Table 2 we see that the largest impact is on the OBC population. Being an OBC in an age category eligible for education corresponds with a statistically and economically significant increase in educational attainment (of about 1.07 educational levels on average, and 1.38 years of education). The tables with ‘levels of education’ as the dependent variable can be found in Table A.9. While the impact on Muslims is statistically significant, it is economically small, being less than one-fifth of the effect on OBCs [35]. The impact on the poorest 20% of the upper-caste category is both economically and statistically insignificant. The Difference-in-Differences result therefore indicates that the policies incentivized a rise in education by 1.07 levels (approximately 1.38 years) of education on average. The ATET (in the tables) is the weighted average of all the $ATET_{ca}$s seen in the figures, where the weights are the cohort sizes. This parameter is different from the ones identified by the other empirical strategies discussed below.

These tables and pictures can also be produced by excluding college-goers. Artificially truncating the sample by dropping all people who have college education allows us to focus on human capital accumulation at the pre-collegiate level. [36] Looking at Figure B.5, in the Appendix, we can see that there is no impact on the Muslim population, and only a slight increase in educational attainment of the poorest upper-caste individuals (about 10 years after the policy), but the impacts on the OBC group is still visible. It is natural that the impacts of these reservations lead to an increase in educational attainment even at the pre-collegiate level, since many lower-level government jobs don't require collegiate education.

5.2 Transition Between Education Levels

While the Difference-in-Differences estimate shows that on average, there was an increase of about 1.4 years of education for OBCs, it says little about the transition between the different levels of education. In being eligible for government jobs, these levels of education are important milestones in the qualification criteria. In order to see how the transition takes place, one can make Difference-in-Differences tables for each level of education (using the highest attained grade as a 1/0 indicator). For example, looking at Secondary School grade attainment in table A.10, it can be seen that only 8.7% of

[35] The slight impact on Muslims can also be explained by the fact that some Muslim groups are also categorized as OBC and could benefit from affirmative action policies

[36] Since we are look at reservations in jobs and not colleges (in this section) there is no *a priori* reason to drop college goers, other than to focus on pre-collegiate education.

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Table 2: Difference-in-Differences Table - Years of Education

Education Years	**Panel A:**	**OBC vs. Others**	
	Younger Cohort	**Older Cohort**	**Difference**
OBC	4.439	4.129	-0.310
	(0.013)	(0.016)	(0.020)
Others	5.579	6.654	1.076
	(0.013)	(0.016)	(0.020)
Difference	-1.140	-2.526	**-1.386**
	(0.018)	(0.022)	**(0.029)**
	Panel B:	**Hindus vs. Muslims**	
	Younger Cohort	**Older Cohort**	**Difference**
Muslim	4.031	3.961	-0.071
	(0.018)	(0.025)	(0.030)
Hindu	4.762	4.952	0.190
	(0.009)	(0.011)	(0.014)
Difference	-0.731	-0.992	**-0.261**
	(0.021)	(0.030)	**(0.036)**
	Panel C:	**Rich vs. Poorer Others**	
	Younger Cohort	**Older Cohort**	**Difference**
Others-Poorest 20%	4.111	5.083	0.972
	(0.025)	(0.037)	(0.044)
Others-Richest 80%	5.989	6.983	0.993
	(0.014)	(0.017)	(0.023)
Difference	-1.879	-1.900	**-0.022**
	(0.030)	(0.041)	**(0.051)**

Using NSS 1999-2000 data. Standard Errors in Parentheses. Difference-in-Differences value in bold. 'Others' are general category individuals (i.e. not SC, ST or OBCs).

older OBCs had secondary school as their highest grade attained, whereas this number is 14.6% of the older individuals in the upper-caste category. The difference-in-difference coefficient (0.0281) shows that there is a relative (to the upper-caste group) transition of the OBCs into having secondary school as their highest grade attained.

These tables can be produced for every level of education to look at the relative transition of OBCs in and out of certain grade levels. The difference-in-differences coefficients for each grade level are reproduced in table A.11. These tables were also made for the sample excluding college goers (i.e. by artificially truncating the data and dropping all college-goers) in order to focus on transitions in the pre-collegiate level. The table indicates that the relative transition, of OBCs before and after the policy, has been away from illiteracy (and away from below primary and primary levels of education) and into secondary school and college [37].

5.3 Triple Difference Estimator

The triple difference estimator will provide evidence similar to the double difference, and also address the issues of mean reversion and simultaneous policy changes mentioned above. While variation in social group and age were exploited in the difference-in-differences section, it is possible to investigate another dimension of variation: 'the intensity of reservation policy.' (Later, a triple-difference will be done using the fact that $affluent$ OBCs are excluded from the reservation policy.) Since each state has its own reservation policy, there is variation in terms of which states are more pro-reservations and which are less so. Let us define the 'intensity of reservation' as the ratio between the percentage of quotas and the population percentage for each group: $\frac{quotas\%}{population\%}$. For example, in the state of Karnataka, this ratio is $\frac{53}{36} = 1.47$, whereas in the state of Madhya Pradesh it is only $\frac{13}{40.5} = 0.32$, thus making the intensity higher in Karnataka than in Madhya Pradesh [38].

In the following regression specification, edu_{ics} is the education level obtained by a person i belonging to caste c and residing in state s. $\boldsymbol{\kappa_c}$ is a vector of dummies for the different caste-groups. Most states made significant changes to reservation policies in the

[37]Between 2001 and 2002, the government tried to implement policies to universalize elementary education and the Millennium Development Goals, but the effects of these policies are not being captured here since the dataset was collected before these policies were implemented.

[38]Note that it is possible to have intensity values greater than 1

early 1990s [39]. The variable *young* equals 1 for cohorts that were still in school or will attend school after the changes in reservation policy have been implemented. $\boldsymbol{Z\beta}$ is a vector of controls. [40] The coefficient of interest is $\boldsymbol{\gamma_c}$. This is the triple difference estimator, and according to the model above, should be positive in sign, since the older members of the reserved castes should have relatively less education than the younger members, and this disparity should be higher in states that had larger changes to the intensity of reservations. The parameter $\boldsymbol{\gamma_c}$ can also be interpreted as the Heterogenous Treatment Effect (HTE), where we expect the affirmative action ATET to be larger in states that had a higher 'intensity' of reservations. Furthermore, β_{0c} is the same ATET estimated before, and should produce similar results as the difference-in-differences parameter if the intensity of state reservations doesn't affect the impact of the federal government policies.

$$\begin{aligned} edu_{ics} = young_i + \boldsymbol{intensity_{cs}} + \boldsymbol{\kappa_c} + \boldsymbol{\beta_{0c}\kappa_c} * young_i + \boldsymbol{\beta_{1cs}intensity_{cs}} * young_i + \\ \boldsymbol{\beta_{2cs}\kappa_c * intensity_{cs}} + \boldsymbol{\gamma_c\kappa_c * intensity_{cs}} * young_i + \boldsymbol{Z\beta} + \epsilon_{cs} \quad (3) \end{aligned}$$

As Gruber (1994) explains, the triple difference approach allows us to control for caste-specific trends ($\boldsymbol{\beta_{0c}\kappa_c} * young$), and state specific trends in laws ($\boldsymbol{\beta_{1cs}intensity_{cs}} * young$). Controlling for these trends allows us to tackle the issue of simultaneous timings of policy; even if the Federal government did improve the schooling infrastructure at around the same time as the quotas were implemented, there is no reason to believe that the state-wise intensity of reservations should be correlated with federal invest-

[39] The reason that the law changes from the early 1990s are used (as opposed to previous changes) is because the Federal law also changed at that time. The Federal law change should not differentially impact residents of different states because people are competing for Federal seats with people all over the country. If state-law changes from periods both before and after the 1990s were studied, then they would be confounded by other changes like the Federal law change. For example, studying the impact of state law changes in the 1980s will be different from changes in the 1990s because of the Federal law changes in the early 1990s.

[40] However, no additional controls have been used in the main specification.

ment in schooling infrastructure. Furthermore, this method also allows us to control for state-specific caste preferences $\boldsymbol{\beta_{2cs}\kappa_c * intensity_{cs}}$, since certain states may care more about certain castes, and the intensity variable would then be picking up these preferences. Lastly, this approach also solves the (automatic) mean-reversion problem, since there is no reason to believe that (non-policy driven) mean-reversion should be higher in states that have more favorable reservation policies than others [41].

Instead of defining the *old* dummy used above, we can introduce a continuous *age* variable. Quotas have almost always been ratcheted up over time, so younger members of the minority groups would enjoy more quotas than older members. Relatively higher quotas today would imply a more intensive ratcheting up of seats over time. In which case the coefficient $\boldsymbol{\gamma_{c=OBC,SC,ST}}$ in the regression below would be of negative sign.

$$edu_{acs} = age + \boldsymbol{intensity_{cs}} + \boldsymbol{\kappa_c} + \boldsymbol{\beta_{0c}\kappa_c} * age + \boldsymbol{\beta_{1cs} intensity_{cs}} * age + \boldsymbol{\beta_{2cs}\kappa_c * intensity_{cs}} + \boldsymbol{\gamma_c\kappa_c * intensity_{cs}} * age + \boldsymbol{Z\beta} + \epsilon_{cs} \quad (4)$$

An additional issue with the triple difference estimator is that since we are using state-level policies, we may want to cluster the standard errors at the state level (Be-

[41] It may be interesting to see if the 'intensity' variable is correlated with the minority group's situation in society. If greater socio-economic disadvantage in the state is positively correlated with more intensity, then the treatment effect will probably be larger (since there is potentially a larger gap to bridge). If however, more advanced minority groups, can (say via political power) influence greater 'intensity', then the treatment effect will potentially be smaller. Thus there is potential for heterogeneity in impacts depending on what predicts 'intensity.' However, on doing some rough calculations, there doesn't seem to be strong correlation between 'intensity' and socio-economic disadvantage of the minority group The regression I ran was the following:

$$intensity_{state} = \boldsymbol{\kappa_c} + \boldsymbol{\beta_{1c}\kappa_c} * eduold_i + eduold_i + \epsilon$$

Where *eduold* is the education level for people old enough to be ineligible for treatment and κ_c is the caste-specific indicator. The coefficient β_{1c} should show how educational disadvantage would be correlated with intensity of reservations. This coefficient was found to be economically and statistically insignificant. The statistical insignificance may be an issue of low power.

trand, Duflo and Mullainathan 2004). Since there are only 32 states in India, this poses an issue of power, especially because a triple difference estimator soaks up a lot of degrees of freedom. The regression results in table 3 will present the coefficient of interest γ_c under both the clustered and unclustered standard errors regression specifications.

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Table 3: Triple Difference Caste, Young and Intensity of Reservations

VARIABLES	Unclustered	Clustered	State FE Clustered
OBC*Young	0.991***	0.991***	1.073***
	(0.0325)	(0.148)	(0.130)
OBC*Young*Intensity	0.0732**	0.0732	0.0192
	(0.0293)	(0.0936)	(0.0753)
SC*Young*Intensity	1.583***	1.583*	1.324***
	(0.108)	(0.821)	(0.466)
ST*Young*Intensity	0.158***	0.158	0.175
	(0.0422)	(0.169)	(0.175)
Constant	5.390***	5.390***	6.518***
	(0.0141)	(0.180)	(0.104)
Clusters		32	32
State FE			Y
Observations	593,095	593,095	593,095
R-squared	0.067	0.067	0.105

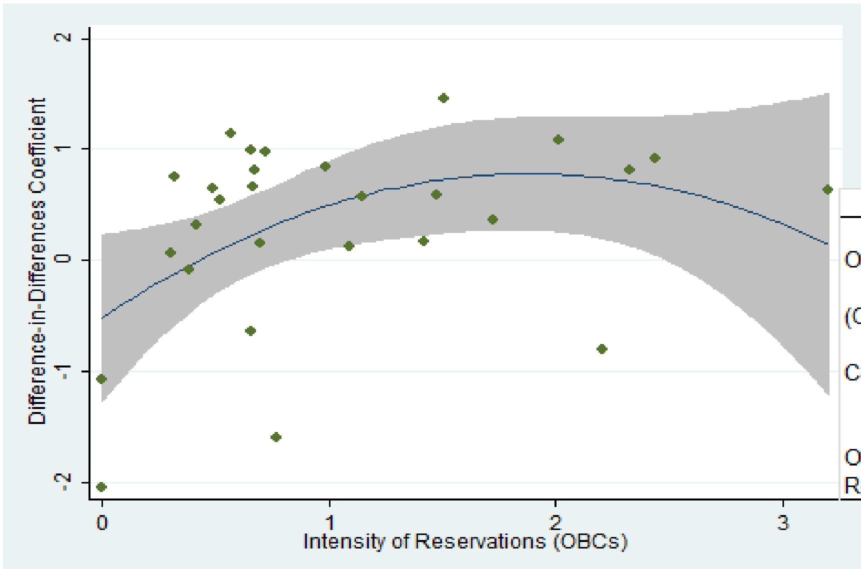
Dependent variable: levels of education
Standard Errors in Parenthesis
Level of significance: *** 0.01; ** 0.05; * 0.1
Young: Less than 25 years old
Intensity variable defined as ratio of percentage quotas to percentage in population

In the regressions performed, the omitted group is the general category. The regressions with unclustered standard errors are significant in the direction we expect them to be: a higher intensity leads to a higher treatment effect on younger OBCs. However, clustering standard errors at the state level doesn't give us much power to estimate the impacts, and the statistical significance is lost. Nonetheless, the coefficients are in the expected direction. In Table 3 we see that the effect of affirmative action policies is larger in states that have a higher intensity of reservations. An increase in the intensity by one unit, increases the treatment effect of these policies by 0.0732 levels of education for OBCs. This parameter can be interpreted as the Heterogeneous Treatment Effect (HTE), and the sign of the parameter is consistent with the underlying model. In Appendix Table A.12 we can see that replacing the 'young' variable with a continuous 'age' variable produces similar results: due to the ratcheting up of quotas over time, the older members of benefit less from reservations. Another important result from this regression is that the coefficient on the OBC and Young indicators re-produce the ATET (for levels of education) from the previous section. This shows that the impacts of the federal level law is unaffected by controlling for state-level policies.

The HTE can also be studied across other dimensions. We can use the triple difference method to identify heterogeneous treatment effects across levels of parents' education. For example we can compare the differential effects on students from highly educated families with those from less-educated families. Educated families may be closer to the corner-solution described in the model above, since they send their children to school no matter what. Therefore, the larger impact should be seen on less educated families. The regression specification below identifies the heterogeneous treatment effect in the parameter γ_c. The variable $ParentsEdu_i$ is the average level of education by the parents of the child, and κ_c is a caste dummy. We would expect the $\gamma_{c=OBC,SC,ST}$ parameter to be negative. In Table A.13 in the Appendix, we see a significant and negative value for $\gamma_{c=OBC,SC,ST}$.

$$edu_{cs} = Young + ParentsEdu_i + \boldsymbol{\kappa_c} + \boldsymbol{\beta_{0c}\kappa_c} * Young + \boldsymbol{\beta_{1cs}} * ParentsEdu_i * Young + \boldsymbol{\beta_{2cs}\kappa_c} * ParentsEdu_i + \boldsymbol{\gamma_c\kappa_c} * ParentsEdu_i * Young + \boldsymbol{Z\beta} + \epsilon_{cs} \quad (5)$$

Figure 4: Relationship between treatment effect in a state, and state-level OBC intensity of quotas



	DID Coeff
OBC Intensity	1.385**
	(0.632)
(OBC Intensity)^2	-0.367*
	(0.211)
Constant	-0.523
	(0.366)
Observations	28
R-squared	0.198

.
Auxiliary Regression of state-by-state relationship between the ATET and intensity of OBC reservations in each state. (without outliers)

In order to tackle the issue of the small number of clusters, I do a two-stage estimation procedure by first computing the treatment effect for each state, and then regressing that treatment effect on the intensity of reservations (in the spirit of Donald and Lang (2007)). In order to find the treatment effect in each state, I do a simple difference-in-differences using only the sub-sample of each state. I then plot the difference-in-differences coefficient across the intensity of reservation by each state in order to find the relationship. In Figure 4 I plot the relationship and display the auxiliary regression that captures this relationship - which is increasing at a decreasing rate [42]. As the intensity of of OBC reservations increase, the treatment effect of quotas increases but at a decreasing rate.

[42]Figure 4 drops outlier states that have very large intensity values because of almost non-existant OBC populations. These states are amongst the smallest in the country (Andaman and Nicobar Islands, Goa, Meghalaya and Mizoram). In order to see the relationship without dropping outliers, see figure B.7

5.4 The Creamy Layer: Triple Difference

The *Indira Swahney v. Union of India, 1993* case prompted the Supreme Court to exclude the relatively wealthier members of the OBC group from being eligible for these reservations. This excluded group was referred to as the 'creamy layer,' and consists of sons and daughters of people with high-ranking Constitutional Posts (the President, Supreme Court Judges, etc.), high-ranking civil service posts, and large landowners. It also excludes sons and daughters of richer members of certain occupations (doctors, lawyers, dentists, film professionals, authors, sportsmen, etc.). The members of these occupations are subject to an income test, where their annual household income must be below Rs. 100,000 (approx. $2000) [43] in order to be eligible for reservations.

Using the NSS Labor Force Survey data, one can identify certain occupational groups and industrial sectors, and classify persons as whether they should be classified as 'creamy layer' or not. Then using the income-information in the Labor Force Survey, it is necessary to construct the total household income for adults. However, this constructed measure will be far from perfect as (a) the labor force survey only identifies broad occupational groups and not the specific occupations, and (b) persons close to the income cutoff may find it easy to manipulate their bank statements/income tax returns, etc. in order to qualify for reservations [44]. Therefore, the creamy layer indicator will be at best, a close approximation of whether the persons took advantage of these policies or not.

Table 4 produces the Difference-in-Differences tables for the creamy layer and non-creamy layer groups separately. While there is some impact on the creamy layer group (which could be a result of income-reporting manipulation, or other ways of getting around the eligibility criteria), the impact on the non-creamy layer group is more than

[43] since then this threshold has been raised and now stands at Rs. 600,000 (approx. $12000).

[44] Furthermore, the law stipulates that the income criteria will be applicable to 'household' income, where the definition of 'household' is also subject to manipulation

double the size than that of the creamy layer group [45]. The triple -difference estimator is the difference between the two double difference estimates in the table, and is a statistically significant 0.614 years of education. One can also run the triple-difference regression (results shows in Appendix table A.14), which produces the same estimate (clustering standard errors at the state-level). The tables therefore show that the bulk of the impact was on the non-creamy layer households.

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Table 4: Years of Education: Creamy Layer vs. Non-Creamy Layer

Panel A:	**Creamy Layer**		
	Old	**Young**	**Difference**
OBC	10.674	7.263	-3.412
	(0.13)	(0.16)	(0.21)
Others	11.734	7.711	-4.023
	(0.06)	(0.08)	(0.10)
Difference	-1.060	-0.448	0.612
	(0.14)	(0.18)	(0.22)
Panel B:	**Non-Creamy Layer**		
	Old	**Young**	**Difference**
OBC	4.046	4.415	0.370
	(0.02)	(0.01)	(0.02)
Others	6.406	5.523	-0.883
	(0.02)	(0.01)	(0.02)
Difference	-2.360	-1.108	1.253
	(0.02)	(0.02)	(0.03)

Dependent variable is (constructed) years of education. Standard Errors in Parentheses. Panel A consists of 9133 observations and Panel B has 370500 observations. Households with no income or occupational information are excluded. The Triple Difference estimate is the difference between the two double difference estimates: 0.614 years of education (statistically significant).

[45] stricter occupational criteria produce even smaller impacts on the creamy-layer population

5.5 Regression Discontinuity

This section will exploit the state-determined methodology of identifying/classifying OBCs to produce a Regression Discontinuity (RD) estimate of the the impacts of reservations. Such an analysis does not exist in the literature, and provides a causal impact of affirmative action policies. The biggest advantage of an RD estimate is that it is not encumbered by issues such as mean reversion and simultaneity of government policy. Government spending on school infrastructure should have uniform impacts on castes just below and above the cutoffs determined by the eligibility methodology. Thus there should be no confounding effects of the government's investment in schooling program. There is also the benefit of identifying a different and interesting parameter - the effect of such policies on a student from the *marginal* sub-caste (the Difference-in- Difference was looking at the average effect over all sub-castes, and the Triple Difference identifies an HTE).

Classification and identification of OBCs for state-level reservation policies is the prerogative of the state government. States appoint Committees to determine who the OBCs are and what reservations they should be eligible for. Some Committees conduct a socio-economic survey and collect data. They use this data to rank the different sub-castes on the basis of socio-economic indicators. Castes above a certain cutoff of 'backwardness' are eligible for reservations. This set-up allows us to estimate the impacts of the reservation policy using a regression discontinuity design. If we have information on the index of 'backwardness', we can compare sub-castes just above to those just below the cutoff to see what the causal impacts of reservations are. The analysis in this section will focus on the state of Haryana, which had one such methodology for classifying the OBCs.

In the state of Haryana, an index of 'backwardness' for each sub-caste is published, thus it is possible to conduct a sharp RD. The 1990 Haryana Committee was the first ever backward classes commission in the state. Being the first is an added bonus, since it prevents any lingering policies from contaminating the before-after analysis. [46] The Committee conducted a survey and created a score out of a total score of 60. Any caste that had more than half the total score was considered an OBC. A half-way mark is an intuitive cut-off point and it is thus unlikely that the cut-off itself was manipulated to include certain castes. It is also unlikely for people of different castes to manipulate their score as the index is based on survey data where the respondents were probably unaware of the utilization purpose of this data. If there was manipulation then a simple eyeballing of the RD scatter plot should show bunching of castes just above the cutoff. [47] Manipulation of the methodology from the government's side is also unlikely, since they use the same methodology formulated by the 1980 Federal Commission. In order to find the causal effect, we need the treatment to be discontinuous at the cutoff and everything else to vary continuously, which will be shown to hold in this context. [48]

Haryana's 1990 Gurnam Singh Committee identifies the OBCs by creating an index of 'backwardness' based on (a) social, (b) educational, and (c) economic disadvantage. The social disadvantage criterion looks at 10 indicators, including employment in manual labor, the unorganized sector, and lack of access to proper sanitation and other civic amenities. The educational criterion studies 10 other indicators related to drop-out rates, female literacy, test scores and vocational education. And the economic index looks at 15 indicators such as family assets, consumption expenditure, maternal mortality rates, unemployment rates, etc. The survey was done in 53 villages and 4 towns, and the report

[46] The handful of other states that used similar methodologies had lingering policies; furthermore, the other states don't publish the tables used to formulate the index

[47] This would not be a valid way of testing manipulability if there were certain groups that wanted to move in opposite directions (i.e. some castes wanting to move above the cut-off and others below). But since it is reasonable to believe that the marginal caste wants to be eligible for reservations, we should see bunching just above the cutoff (if there was manipulation of data from the respondents' side.)

[48] In 1995, the Ramji Lal Committee (the second backward classes commission in Haryana) added 4 more castes to the list. In the dataset used, this adds two castes below the cutoff to be eligible for reservations. However, since these castes will have only felt the benefits for less than 3 years (the data was collected in 1999), they have been coded as ineligible. Doing so doesn't change the results.

produces caste-wise tables on each of the 35 indicators used in the final index. Using these tables one can replicate the index. The criteria used to make the index is the same one proposed by the Federal Commission of 1980. Since they use the same methodology as the Federal Commission from a decade ago, it is unlikely that any manipulation of method occurred to favor certain castes.

The data set used for the RD analysis is the ARIS-REDS (1999) data set. The nationally representative NSS data cannot be used since it doesn't have disaggregated sub-caste categories, which we require for the RD analysis. Unlike the NSS data set, ARIS-REDS collects information on years of education rather than levels. Therefore, the results in this section analyze the impact of affirmative action policies on the years of education. In the RD results in Figure 5, the dependent variable is the difference in mean years of education between the older and younger members of that caste. [49] Once again 'older' is defined as being too 'old' to enjoy the benefits of this reservation policy. There are 27 sub-castes for which the ARIS-REDS and the Haryana Committee Report have matching caste names [50]. Thus, the scatter plot in Figure 5 is for those 27 castes only.

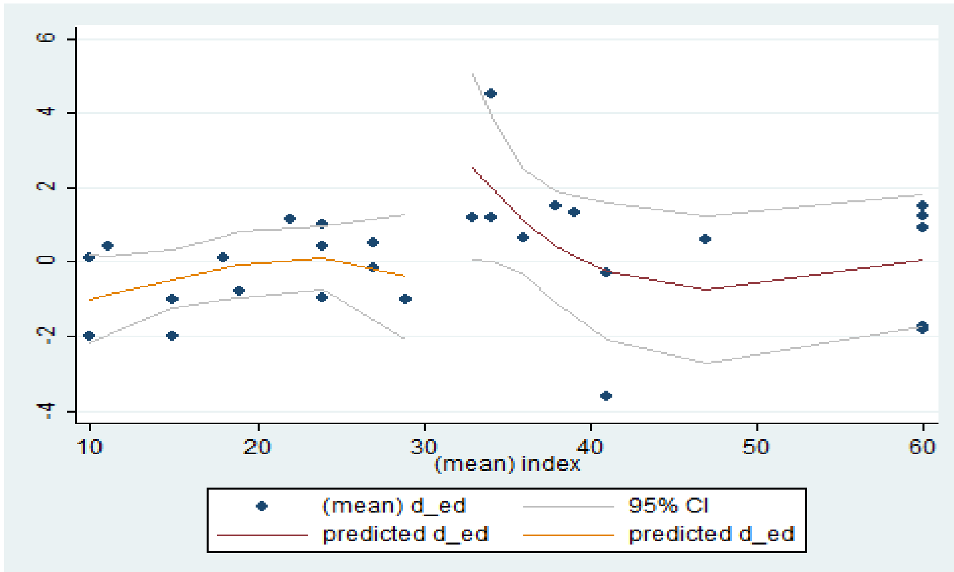
If, however, we look at the mean education level of the population that is too old to be affected by the reservation policy, we see no discontinuity at the cutoff (Figure 6). Furthermore, we can see a slight downward trend, since a higher index indicates a larger socio-economic disadvantage. Looking at regression Table A.15 in the Appendix, we can see that the cutoff isn't significant for the educational attainment of the older population.

There are various regression specifications we can look at to estimate the impacts of

[49] dependent variable = mean education of young_c − mean education of old_c

[50] While 34 of the ARIS-REDS castes could be matched to the names in the Committee Report, there wasn't any data on 7 of these castes in the data-set - since the data set is much smaller than the NSS. Furthermore, the Scheduled Castes were assigned highest possible index values as they were already eligible for these policies (and are therefore not castes near the threshold) - this shows up in the bunching at an index value of 60

Figure 5: RD: Haryana: Average change in years of education by caste



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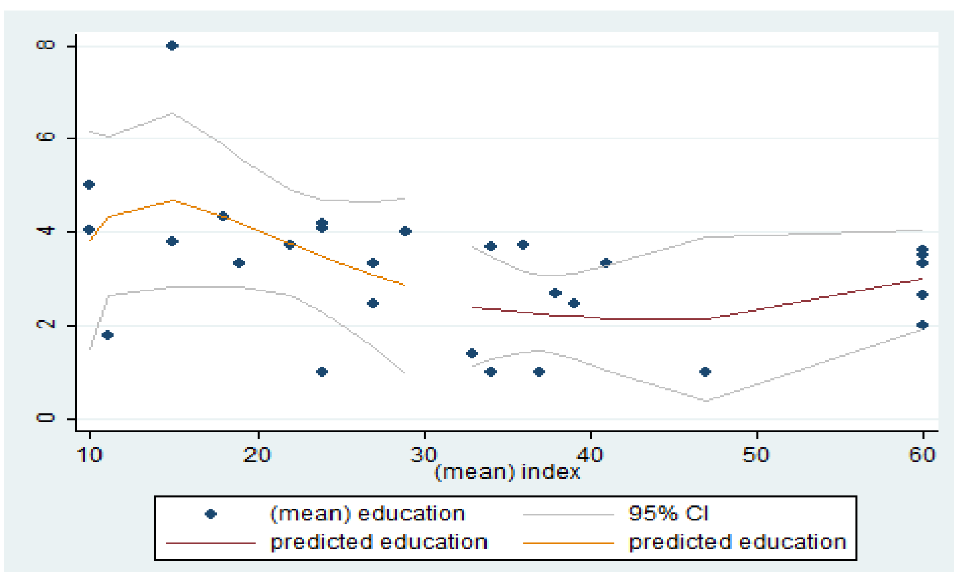
Regression Discontinuity on d_{ed}, defined as: mean ed young$_c$ − mean ed old$_c$.

Figure 6: RD: Haryana: Mean Education by Caste of Older Population



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Sample restricted to population above the age of 27 (too old to benefit from the reservation policy). Regression Discontinuity on years of education.

the policy. Imbens and Lemieux (2007) suggest changing the bandwidth and seeing if the results are robust to restricting the sample to a small area just around the cut-off. Van der Klaauw (2008) suggests using a semi-parametric approach of local linear regressions with higher order polynomials. In the tables below, various regression specifications with higher order polynomials ('Control Function Approach' (Heckman and Robb 1985)) and restricted sub-samples are presented. Column headings have the index's degree of polynomial order, and if 'Restricted' is mentioned, then the sample only includes half the index-span around the cutoff (i.e. index values of 15 to 44).

The RD framework identifies the localized treatment effect in the neighborhood around the cutoff. Since these are students who are presumably close to the cutoff of attaining more education, they should have the largest impacts of these policies. The coefficient of interest is known as the Neighborhood Average Treatment Effect (NATE) since it's the average impact of the policies in the neighborhood around the cutoff of eligibility. This NATE will presumably be larger than the ATET found via the Difference-in-Differences methodology because the ATET is pulled down by students who have the highest costs of schooling (and who therefore do not respond to any changes in affirmative action policies). The students with higher costs of attending school will be further away from the RD threshold - and since a large number of high-cost students will not increase their schooling despite these policies - the ATET is lower than the NATE. Another way to think about this parameter is to think of it as a weighted average treatment effect, where the weights are the probability that each caste's assignment value lies in the neighborhood of the threshold (DiNardo and Lee 2010).

The first regression specification (A Discontinuity-in-Differences) is what Figure 5 is trying to plot. In the following equation, the dependent variable is the mean difference in education between the younger and older members of the caste:

$$\text{mean ed young}_c - \text{mean ed old}_c = \beta_0 cutoff_c + \text{polynomial index} + \epsilon_c$$

.

Table 5: Collapsed RD

Polynomial	3rd	4th	5th	1st	2nd
Cutoff	3.274**	2.908**	3.862*	5.716**	21.25
	(1.256)	(1.285)	(1.947)	(2.183)	(12.57)
Flex				X	X
Slope					
R-sq	0.400	0.427	0.439	0.381	0.417

Dependent variable is years of education. Standard Errors in Parenthesis. Level of significance: *** 0.01; ** 0.05; * 0.1. Regressions consist of 27 sub-castes in the state of Haryana.

Due to having only 27 sub-castes to work with, we may expect power issues. Nonetheless, the coefficient of interest is both economically and statistically significant. Looking at the third order polynomial column, the coefficient shows that the causal effect of reserving seats for backward classes is to increase their high-school education by about 3.27 years (Table 5).

In order to tackle issues with smaller sample size we can look at various other regression specifications. We can restrict the sample to young cohorts who would be able to change their schooling decision, and control for the mean education level of the older population in that caste. We can then run the regression without collapsing the data into only 27 castes. However, it would be necessary to cluster the standard errors at the caste level. The added advantage of just performing the regression for the younger population is that we can make sure that the discontinuity isn't merely arising out of the older populations education, and reconfirm the results of Figure 6. The regression of interest is:

$$edu_{ic} = \beta cutoff_c + \text{ index polynomial}_c + \text{ mean of old edu}_c + \epsilon_{ic}$$

.

Table 6: Young Sample

Polynomial	Flex Slope	Restricted	β_1	Std Err	R-sq
3rd			3.105***	(0.746)	0.105
3rd		X	3.513**	(1.231)	0.121
4th			2.959***	(0.854)	0.106
4th		X	2.378	(1.490)	0.122
5th			3.448***	(1.222)	0.106
5th		X	3.951**	(1.572)	0.124
1st	X		0.473	(0.650)	0.101
1st	X	X	5.985*	(3.173)	0.118
2nd	X		19.11**	(8.051)	0.105
2nd	X	X	-13.83	(46.45)	0.122

Dependent variable is years of education. Level of significance: *** 0.01; ** 0.05; * 0.1. 'Restricted Sample' consists of half the index span around the cutoff (index values 15 to 44). 'Flexible slope' allows the slope of the regression specification to vary on either side of the cut-off.

Table 6 shows similar coefficients as before: the causal impact of reservations is to increase years of high-school education by about 3 years for the average student in the neighborhood of the cutoff.

We can also conduct an RD using a Differences-in-Discontinuities approach (for a recent example see Grembi, Nannicini and Troiano 2012 for another example of this approach). This incorporates the discontinuity along the caste index, and differences it across the older and younger age cohorts. In the following specification, we interact the cutoff with the variable $Young$. This interaction term should have a positive sign since the younger group will benefit from the reservation policy. When $Young = 0$, the discontinuity should be insignificant (as seen in Figure 6 and Table A.15), but when $Young = 1$ those above the 'backwardness' cutoff should increase their educational attainment. Therefore, the model predicts that the coefficient β_1 will be positive and significant:

$$edu_{ic} = \beta_0 cutoff_c + \beta_1 cutoff_c * Young_i + \beta_2 Young_i + (\text{ index polynomial and Young}_i) + \epsilon_{ic}$$

.

Table 7: Difference in Discontinuities

Polynomial	β_1	Std. Err.	Flex Slope	Restricted	R-sq
3rd	2.128***	(0.650)			0.102
3rd	2.806**	(1.020)		X	0.103
4th	1.923***	(0.607)			0.103
4th	2.313*	(1.317)		X	0.107
5th	2.890***	(0.929)			0.103
5th	3.722**	(1.623)		X	0.109
1st	2.020***	(0.652)	X		0.105
1st	1.509**	(0.588)	X	X	0.102
2nd	1.031***	(0.152)	X		0.103
2nd	1.797***	(0.378)	X	X	0.110

Dependent variable is years of education. Level of significance: *** 0.01; ** 0.05; * 0.1. 'Restricted Sample' consists of half the index span around the cut-off (index values 15 to 44). 'Flexible slope' allows the slope of the regression specification to vary on either side of the cut-off.

Once again, the results are economically and statistically significant and of a similar magnitude, giving us a consistent story across all the different possible specifications. Table 7 shows an increase in education for the OBCs. The average value for the coefficients is about 2.22 years of education. This last specification is the preferred specification, since it utilizes the entire data set and has the highest power.

While the RD is the most 'internally valid' of all the identification strategies used here, it could be less externally valid than the other strategies that use the nationally-representative data. While the double difference and triple difference specifications were done for the entire country, the RD analysis looks at the state of Haryana. Haryana may be similar to many North Indian states, but may be quite different from South Indian states. In Appendix Table A.17 the means of the major variables are studied comparing Haryana with the Rest of India. The one stark difference is that Haryana has virtually no Scheduled Tribes (STs). The other differences are economically insignificant: the average Haryanvi is richer than the average Indian by only Rs. 61 per month (about $1.1), is half a year older, and has about one-tenth more levels of education. This differences are small, and not statistically significant, making it a representative North Indian state. [51]

It is important to check that other factors are not discontinuous at the same cutoff, since the RD design requires all other factors (income, assets, etc.) to vary smoothly at the cutoff. Looking at table A.16 in the Appendix, we see that there are no other significant discontinuities at the same threshold (an index value of 30). The table presents results on total expenditure, medical expenditure and work in casual labor, but robustness checks were done on other variables as well. We can also look for educational discontinuities at any other value of the index. When studying the impact on the average change in education between the younger and older cohorts, no other values of the index have significant discontinuities. The only value that the discontinuity is visible, is at the true cutoff (i.e. a value of 30 on the index). Figure B.8 shows cutoffs at 20, 25, 35 and 40 - none of which have significant discontinuities.

5.6 Summary of Empirical Section

So far this paper has used three different approaches to answer the primary question of interest: does affirmative action incentivize students to stay in school? The double-difference strategy uses a nationally representative dataset to identify the average treatment effect on the treated ($ATET_{ca}$) for each age cohort a and caste c. Exploiting variation in caste and age, the estimator finds that the students eligible for reservations increased school attainment. This was found to be true in response to the change in

[51] Nonetheless, South Indian states are culturally different from Haryana and have a history of reservations unlike Haryana.

Federal Law, as well as various states' changes in law. The concern of confounding policies - like large expenditures on school building - was tackled by looking at placebo groups that should've been affected by school building but not by reservations. But, there wasn't a large impact on educational attainment for the Muslim population and the low-income non-OBC/SC/ST population, suggesting that the bulk of the impact on lower-caste members was due to the affirmative action policies.

The triple-difference strategy exploits variation on a third front: the intensity of reservation policy. The paper finds that the impact is larger in states that have a more generous reservation policy. Using a 2-stage estimation procedure, I show the treatment effect of quotas is increasing with the intensity of reservations (increasing at a decreasing rate). The parameter identified by the triple difference could be interpreted as the Heterogeneous Treatment Effect (HTE), and its sign is in the expected direction. The triple-difference can also be performed by looking at the differential impact between the creamy layer and non-creamy layer populations. The non-creamy layer population was seen to have more than twice the impact than that of the creamy layer group.

The regression discontinuity approach looks at the introduction of OBC reservations in the state of Haryana. OBCs were classified on the basis of an index of 'backwardness,' which provides the running variable for the RD. Across specifications, the paper consistently finds an increase in educational attainment for the population eligible for reservations (and having no discontinuities in other dimensions). While the RD analysis was done for only one state, it has not been used in this literature before and confirms a powerful finding on affirmative action.

The Difference-in-Differences estimator identifies the Treatment on the Treated (ATET) of about 1.38 years of education. Whereas the NATE (or alternatively, the weighted average treatment effect) from the RD strategy is somewhere between 2.2 and 3.13 years of education. This implies that even though the student belonging to a caste near the cutoff is incentivized to increase their years of education by a little less than 3 years of education, the average impact is only about 1.38 years of education. [52] The NATE may be the relevant estimate of interest if the government is considering adding another sub-caste to the list of OBCs; whereas the ATET may be the relevant estimate if the government wants to know the overall impact of changing the amount of quotas for all OBCs.

6 Conclusion

This paper seeks to understand the effects of affirmative action policies on incentives in schooling. According to the model, when the probability of getting into college or of getting a government job is increased, the marginal student from the minority group is incentivized to increase their educational attainment. The empirical section uses various strategies to tease out a comprehensive picture of the plausible impacts. The double difference strategy shows a marked increase in educational attainment of a little more than one level of education (or about 1.38 years of education on *average*). The triple difference estimator also shows that the effect is larger for states with higher 'intensity' of reservations, and that the bulk of the impact is on the non-creamy layer population. The RD approach uses various specifications, which all consistently point to a causal impact of reservations: an increase of about 2.2 to 3 years of high-school education for the student in the *marginal* caste.

The results therefore show that these policies encourage students to increase their education by one more schooling-level. This has major implications as it indicates the

[52] However, it is important to remember that the RD and Difference-in-Differences are looking at the impacts of different policies: the difference-in-differences looks at the impact of reservations only in governmental jobs and not colleges.

possibility of encouraging students just below the threshold (of a certain level of education) to cross that threshold and get to the next highest level. This result can be compared to that of Shreshta (2011) who finds that the Gurkha community in Nepal attains one more year of education (on average) in response to a change in the mandatory employment eligibility law of the British army. However, it is hard to translate the results in most of the other literature into years of educational attainment. Kazianga, Levy and Liden (2012) show that enrollment rises by 20% when schools are made more girl-friendly, and Dinkelman and Martinez (2011) show that absenteeism falls by 14% when information is provided about financial aid. Using the booming IT sector near Delhi as a sign of an increase in returns to education, Oster and Millet (2011) find that school enrollment rises by 4% to 7% when a new IT center is opened in the area. On the other hand, Jensen and Miller (2012), and de Brauw and Giles (2008) show that schooling investments may actually fall in response to higher returns. [53]

Furthermore, the paper tells us that contrary to popular belief, lowering standards may actually have some positive incentive effects. There is no indication of a 'patronizing equilibrium' discussed in the theoretically possible outcomes in the literature (Loury 1992) [54]. While the model may be generalizable to other contexts (the US, Sri Lanka, Malaysia), the empirical results may differ depending on the context. For example, in the US, quotas are illegal and affirmative action lacks the backing of certain salient features (like explicitly reserving seats for certain groups) found in the Indian context. Furthermore, interventions in the US are minor in size, compared to a 27% reservation of seats in all government jobs. This lack of salience, and difference in policy-size may lead to

[53] Policies to incentivize education have also been discussed in the US context. Bettinger et al (2009) show families that were randomly provided with assistance in filling up their Federal Student Aid Applications (FAFSA) were more likely to enroll in college, and Hoxby and Turner (2013) show that information on the college application process and costs of attending can encourage high-achieving low-income students to apply and enroll in colleges.

[54] However, the patronizing equilibrium may not necessarily be immediate, and may take many years to set in if we use models of imperfect information or learning-by-doing.

different results.

The policies may come with certain costs if there is a crowding out of educational attainment for upper-caste members. The government has tried to mitigate this concern by increasing the seats in colleges and government jobs so that the absolute number of seats available to the upper-castes does not change, but it is not clear how well implemented this increase in seats is (and what the possible costs of increasing seats are). Furthermore, such a large policy is sure to have other general equilibrium effects in terms of the work-force composition and composition of classrooms. Peer-effects, due to these changing compositions, may play a large role - but it is not clear what these effects may be. On the one hand, interaction with other lower castes may encourage amicable cross-caste relations, and on the other hand foster resentment. In terms of the benefits for the minority group however, an increase in 2.2 years of education can translate into high wage gains since the estimated returns to education in developing countries vary between 7% and 12% (Duflo 2001, Behrman 1999, Strauss and Thomas 1995) . There are also various non-pecuniary benefits of education, like greater participation in the political process, better health, etc. Lastly, lowering educational inequalities (and therefore possibly wealth inequalities in the long run) may be something intrinsically valuable to policy-makers. In light of these results, therefore, policy-makers should keep in mind the externalities of such affirmative action policies.

7 References

- Arcidiacono Peter, Esteban Aucejo, Patrick Coate, and V. Joseph Hotz "Affirmative Action and University Fit: Evidence from Proposition 209" Working Paper (2012)

- Arcidiacono Peter, Esteban Aucejo, Hanming Fang, and Ken Spenner, "Does Affirmative Action Lead to Mismatch? A New Test and Evidence" Quantitative Economics, Vol. 2, No. 3 (November 2011), 303-333

- Assuncao Juliano and Bruno Ferman (2013), "Does affirmative action enhance or undercut investment incentives? Evidence from quotas in Brazilian public universities" (unpublished)

- Bagde, Surendrakumar, Dennis Epple and Lowell Taylor "Dismantling the Legacy of Caste: Affirmative Action in Indian Higher Education" NBER Summer Institute 2012

- Behrman, Jehre "Schooling in Asia: Selected microevidence on determinants, effects, and policy implications" Journal of Asian Economics 10 (1999) 147194

- Betrand, Marianne, Esther Duflo and Sendhil Mullainathan "How Much Should we Trust Difference in Differences?", QJE 119(1) (2004)

- Betrand, Marianne, Rema Hanna and Sendhil Mullainathan "Affirmative Action: Evidence from College Admissions in India," Journal of Public Economics, February 2010.

- Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos and Lisa Sanbonmatsu, 2009. "The Role of Simplification and Information in College Decisions: Results from the HnR Block FAFSA Experiment," NBER Working Papers 15361, National Bureau of Economic Research, Inc.

- de Brauw, Alan and John Giles. "Migrant Opportunity and the Educational Attainment of Youth in Rural China," World Bank Working Paper Series (2008)

- Chin, Aimee "Can redistributing teachers across schools raise educational attainment? Evidence from Operation Blackboard in India", Journal of Development Economics 78 (2005) 384 405

- Dee, Thomas S. "Teachers, Race, and Student Achievement in a Randomized Experiment," The Review of Economics and Statistics, February 2004, Vol. 86, No. 1, Pages 195-210

- Desai, Sonalde and Kulkarni, Veena "Changing Educational Inequalities in India in the Context of Affirmative Action", Demography, V45.II, May 2008

- DiNardo, John and David S. Lee. "Program Evaluation and Research Designs," NBER Working Papers 16016, National Bureau of Economic Research, Inc, 2010

- Duflo, E. "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment," American Economic Review, American Economic Association, vol. 91(4), pages 795-813, September 2001.
- Foster, Andrew D. and Mark R. Rosenzweig . "Technical Change and Human Capital Returns and Investments: Evidence from the Green Revolution," American Economic Review, 86(4), p. 931-53. (1996)
- Freeman, Richard, "The Overeducated American", New York: Academic Press, 1976.
- Fryer, Roland and Glen Loury "Affirmative Action and Its Mythology", Journal of Economic Perspectives, (Summer 2005)
- Fryer, Roland and Paul Torelli " An Empirical Analysis of 'Acting White'", Journal of Public Economics (2010)
- Glewwe, Paul and Michael Kremer "Schools, Teachers, and Education Outcomes in Developing Countries" Handbook on the Economics of Education (2005)
- Grembi, Veronica, Tommaso Nannicini and Ugo Troiano "Policy Responses to Fiscal Restraints: A Difference-in-Discontinuities Design" (forthcoming (2012))
- Griliches, Zvi, "Education, Human Capital, and Growth: A Personal Perspective," Journal of Labor Economics, 1997, 15, S330-S344
- Gruber, Jonathan. "The Incidence of Mandated Maternity Benefits." A.E.R. 84 (June 1994): 62241.
- Gupta, VS (2004) "Communication, Development and Civil Society: Essays on Social Development", Concept Publishing Company
- Haryana 1990 Backward Classes Commission Report
- Heckman, James, "Private Sector Skill Formation: International Comparisons", University of Chicago Press, 1993.
- Hoxby, Caroline, and Sarah Turner. "Expanding College Opportunities for Low-Income, High-Achieving Students," NBER Working Paper 18728, 2012.
- Imbens, Guido and Lemieux, Thomas "Regression Discontinuity Designs: A guide to practice" Journal of Econometrics, 142 (2008)
- Kane, Thomas, "College Entry by Blacks since 1970: The Role of College Costs, Family Background and the Returns to Education," Journal of Political Economy, 1994, 102 (5), 878-911
- Katz, Lawrence and Kevin Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," Quarterly Journal of Economics, (1992), 107 (1), 35-78

- Kochar, Anjini "Urban Influences on Rural Schooling in India," Journal of Development Economics, 74, p. 113-136. (2004)
- Kohli, Atul "The Success of India's Democracy", Cambridge University Press (2001)
- Krishna, Kala and Veronica Frisancho Robles "Armative Action in Higher Education in India: Targeting, Catch Up, and Mismatch" (unpublished (2013))
- Lang, Kevin and Stephen Donald "Inference with Difference-in-Differences and Other Panel Data," The Review of Economics and Statistics, May 2007, Vol. 89, No. 2, Pages 221-233
- Loury, Glen "The Incentive Effects of Affirmative Action," Annals of the American Association of Political and Social Science, No. 523, (September, 1992), pp. 19-29.
- Ogbu, John " Black American Students in an Affluent Suburb: A Study of Academic Disengagement" Routledge (January 3, 2003)
- Orazem, Peter and Elizabeth King "Schooling in Developing Countries: The roles od supply, demand and government policy" Handbook of Development Economics Vol. 4 (2008)
- Oster, Emily and M. Bryce Millett . "Do Call Centers Promote School Enrollment? Evidence from India," mimeo, University of Chicago .(2011)
- Ryoo, J. and Rosen, S. "The engineering labor market," Journal of Political Economy 112 (S1), S110-S140. February 2004.
- Sachar Committee Report, Gov. of India 2005
- Strauss, J and Thomas, D. "Human Resources: Empirical Modelling of Households and Family Decisions," in J Behrman and TN Srinivasans ed. Handbook of Development Economics, vol. 3, Amsterdam, North Holland, chapter 34, 1995.
- van der Klaauw, Wilbert"Regression-Discontinuity Analysis: A Survey of Recent Developments in Economics", Labour 22(2) (2008)
- Weisskopf, Thomas "Affirmative Action in the United States and India: A Comparative Perspective," Routledge (2004)

8 Appendices

A Tables

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Table A.8: Social Groups and Religions

	Years of Education	**Land owned (acres)**	**Per Cap Month Exp (Rs.)**
ST	3.40	1.17	427.32
SC	3.04	0.39	398.67
OBC	3.90	0.99	446.33
Others	5.68	1.10	519.02
Richest 80%	6.07	1.14	578.00
Poorest 20%	4.10	0.96	283.17
Hindu	4.46	1.01	465.57
Muslim	3.61	0.49	424.17

'Others' are general category individuals (i.e. not SC, ST or OBCs). 'Education' is constructed years of education. Nominal exchange rate: approx Rs. 50 to $ 1. Household Monthly Expenditure deflated by rural-urban-region-wise CPI.

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Table A.9: Difference-in-Differences Table - Levels of Education

	Panel A:	**OBC vs. Others**	
	Younger Cohort	**Older Cohort**	**Difference**
OBC	4.279	3.673	-0.605
	(0.010)	(0.013)	(0.016)
Others	5.185	5.652	0.467
	(0.009)	(0.012)	(0.016)
Difference	-0.906	-1.978	**-1.072**
	(0.014)	(0.018)	**(0.023)**
	Panel B:	**Hindus vs. Muslims**	
	Younger Cohort	**Older Cohort**	**Difference**
Muslim	3.965	3.565	-0.400
	(0.015)	(0.021)	(0.025)
Hindu	4.527	4.293	-0.234
	(0.007)	(0.009)	(0.011)
Difference	-0.562	-0.728	**-0.166**
	(0.017)	(0.024)	**(0.029)**
	Panel C:	**Rich vs. Poorer Others**	
	Younger Cohort	**Older Cohort**	**Difference**
Others-Poorest 20%	4.059	4.420	0.361
	(0.020)	(0.030)	(0.035)
Others-Richest 80%	5.500	5.909	0.409
	(0.010)	(0.013)	(0.017)
Difference	-1.441	-1.489	**-0.048**
	(0.022)	(0.032)	**(0.039)**

Dependent variable is levels of education. Using NSS 1999-2000 data. Standard Errors in Parentheses. Difference-in-Differences value in bold. 'Others' are general category individuals (i.e. not SC, ST or OBCs). Levels of education determined by NSS.

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Table A.10: Proportion of Students with Secondary School

Secondary School	Old	Young	Difference
OBC	0.0877 (0.0009487)	0.0736 (0.0008772)	-0.0141 (0.0012922)
Others	0.1463 (0.001044)	0.1041 (0.0009521)	-0.0422 (0.0014241)
Difference	-0.0586 (0.0014502)	-0.0305 (0.0013096)	**0.0281** **(0.0019609)**

Standard Errors in Parentheses. Difference-in-Differences value in bold. ‘Others’ include that section of the population ineligible for reservations (i.e. not SCs, STs, or OBCs)

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Table A.11: Relative Transition of OBCs between grades

	Difference-in-Differences Coefficient	
Level of Education	**Including College**	**Excluding College**
Illiterate	-0.0862 (0.003)	-0.0661 (0.003)
Below Primary Education	-0.0132 (0.002)	-0.0083 (0.003)
Primary Education	-0.0149 (0.002)	-0.0065 (0.002)
Middle School	0.0077 (0.002)	0.0217 (0.002)
Secondary School	0.0281 (0.002)	0.0455 (0.002)
Higher Secondary School	0.0047 (0.002)	0.0139 (0.002)
College Graduate	0.0741 (0.002)	

Standard Errors in Parentheses. Levels of education determined by NSS 1999-2000. Sample of ‘excluding college’ drops all people with at least some college education.

.

Table A.12: Triple Difference Coefficient: caste, intensity and age

VARIABLES	Unclustered	Clustered	State FE Clustered
obc*intensity*age	-0.00280***	-0.00280	-0.00116
	(0.000816)	(0.00264)	(0.00200)
sc*intensity*age	-0.0116***	-0.0116	-0.0206**
	(0.00364)	(0.0100)	(0.00917)
st*intensity*age	-0.00345***	-0.00345	-0.00354
	(0.00110)	(0.00438)	(0.00426)
Constant	4.238***	4.238***	5.511***
	(0.0166)	(0.201)	(0.114)
State Fixed Effects			X
Observations	593,095	593,095	593,095
Clusters		32	32
R-squared	0.069	0.069	0.105

Dependent variable is levels of education.
Standard Errors in Parenthesis
Level of significance: *** 0.01; ** 0.05; * 0.1

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Table A.13: Heterogeneous Treatment Effects by Parents' Education: Levels of Education

VARIABLES	Education Level
OBC	-1.089***
	(0.0652)
SCST	-1.683***
	(0.0698)
Young	-1.595***
	(0.0479)
Parents Education	0.618***
	(0.00730)
OBC*Young	0.518***
	(0.0683)
SCST*Young	0.869***
	(0.0726)
ParentsEdu*Young	-0.353***
	(0.00781)
OBC*ParentsEdu	0.0667***
	(0.0136)
SCST*ParentsEdu	0.128***
	(0.0166)
OBC*ParentsEdu*Young	**-0.0310****
	(0.0143)
SCST*ParentsEdu*Young	**-0.0995*****
	(0.0172)
Constant	4.966***
	(0.0455)
Observations	330,227
R-squared	0.178

Dependent variable is levels of education.
Standard Errors in Parenthesis
Level of significance: *** 0.01; ** 0.05; * 0.1

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Table A.14: Creamy Layer v Non Creamy Layer

VARIABLES	**Years of Education**
OBC	-2.360***
	(0.297)
SC-ST	-3.392***
	(0.274)
Young	-0.883***
	(0.107)
Creamy Layer	5.328***
	(0.155)
OBC*Young	1.253***
	(0.0944)
SC-ST * Young	1.682***
	(0.125)
OBC* Creamy layer	1.301***
	(0.305)
SC-ST * Creamy Layer	1.647***
	(0.364)
Young* Creamy Layer	-3.140***
	(0.170)
OBC*Young* Creamy Layer	**-0.641****
	(0.274)
SC-ST*Young* Creamy Layer	-0.943***
	(0.297)
Constant	6.406***
	(0.150)
Observations	521,063
R-squared	0.093

Dependent variable is years of education.
Standard Errors in Parenthesis
Level of significance: *** 0.01; ** 0.05; * 0.1

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Table A.15: Education for the Older Population - i.e. Not eligible for reservations

Polynomial	Flex Slope	Restricted	β_1	Std Err	R-sq
3rd			-0.165	(0.109)	0.189
3rd		X	-0.0615	(0.152)	0.175
4th			-0.112	(0.106)	0.189
4th		X	-0.0361	(0.129)	0.175
5th			-0.153	(0.109)	0.189
5th		X	-0.465*	(0.240)	0.175
1st	X		0.0545	(0.0641)	0.189
1st	X	X	-0.648	(0.427)	0.175
2nd	X		-1.876**	(0.869)	0.189
2nd	X	X	7.224	(5.678)	0.175

Dependent variable is years of education. Sample restricted to older population. Level of significance: *** 0.01; ** 0.05; * 0.1. 'Restricted Sample' consists of half the index span around the cutoff (index values 15 to 44). 'Flexible slope' allows the slope of the regression specification to vary on either side of the cut-off.

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Table A.16: RD: Robustness Checks: Other Discontinuities?

Polynomial	Restricted	Variable	β_1	Std Err	R-sq
3rd		Edu Expenditure	-0.0587	(0.0502)	0.016
3rd	X	Edu Expenditure	-0.0772	(0.0809)	0.013
4th		Edu Expenditure	-0.0834*	(0.0471)	0.017
4th	X	Edu Expenditure	0.0315	(0.0798)	0.014
5th		Edu Expenditure	0.0230	(0.0588)	0.019
5th	X	Edu Expenditure	0.0491	(0.116)	0.014
3rd		Med Expenditure	0.0273*	(0.0156)	0.008
3rd	X	Med Expenditure	0.00234	(0.0166)	0.005
4th		Med Expenditure	0.0223	(0.0142)	0.008
4th	X	Med Expenditure	-0.0309*	(0.0172)	0.006
5th		Med Expenditure	0.00726	(0.0187)	0.009
5th	X	Med Expenditure	-0.0181	(0.0152)	0.006
3rd		Total Expenditure	30.73	(30.97)	0.072
3rd	X	Total Expenditure	-29.21	(25.01)	0.094
4th		Total Expenditure	9.403	(20.71)	0.094
4th	X	Total Expenditure	-59.37*	(32.23)	0.097
5th		Total Expenditure	10.06	(35.61)	0.094
5th	X	Total Expenditure	-95.38***	(29.56)	0.100
3rd		Casual Labor	-0.686*	(0.390)	0.151
3rd	X	Casual Labor	0.289	(0.226)	0.189
4th		Casual Labor	-0.381	(0.259)	0.194
4th	X	Casual Labor	0.253	(0.303)	0.189
5th		Casual Labor	-0.360	(0.372)	0.194
5th	X	Casual Labor	0.489	(0.287)	0.190

Variable 'Edu Expenditure' is expenditure on education-related goods. 'Med Expenditure' is medical expenditure. 'Total Expenditure' is expenditure on all items. 'Casual Labor' is 1/0 indicator of occupation. Level of significance: *** 0.01; ** 0.05; * 0.1. 'Restricted Sample' consists of half the index span around the cutoff (index values 15 to 44).

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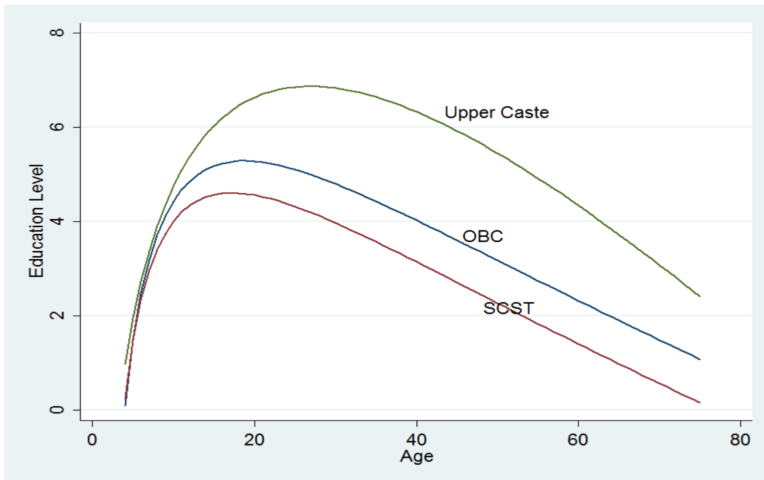
Table A.17: Comparing Haryana to the Rest of India

	Rest of India	Haryana	Difference
Sample Size	583422	10155	
Mean Education Level	4.629	4.763	-0.134
Monthly per cap Expenditure (Rs.)	464.612	526.433	-61.821
Male (%)	0.515	0.529	-0.014
Age	26.133	25.551	0.582
Urban (%)	0.376	0.363	0.013
Agricultural sector (%)	0.516	0.503	0.013
OBC (%)	0.33	0.278	0.052
SC (%)	0.158	0.165	-0.007
ST (%)	0.114	0.007	0.107

Using NSS 1999-2000 data. 'Mean Education Level' covers 8 levels of education from illiterate to college graduates. Nominal exchange rate: approx Rs. 50 to 1 dollar. Household Monthly Expenditure deflated by rural-urban-region-wise CPI.

B Figures

Figure B.1: Predicted Education Level By Caste



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Fractional polynomial prediction of mean education levels across age for each social group.

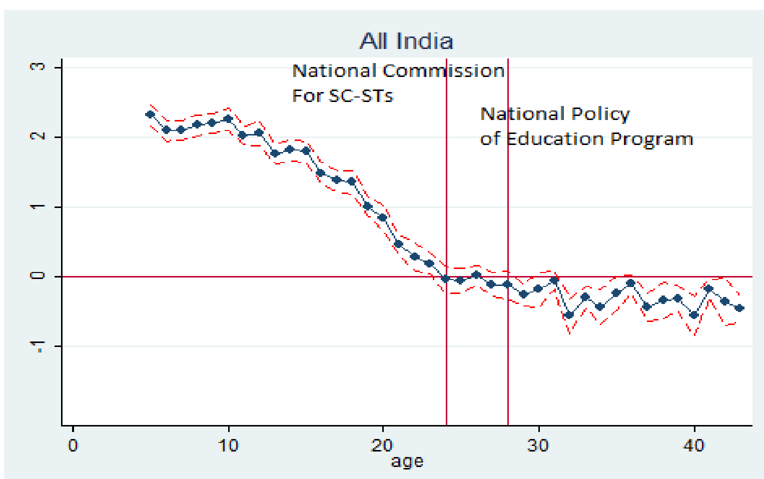

Figure B.2: Double Difference Coefficients for the SC-ST group

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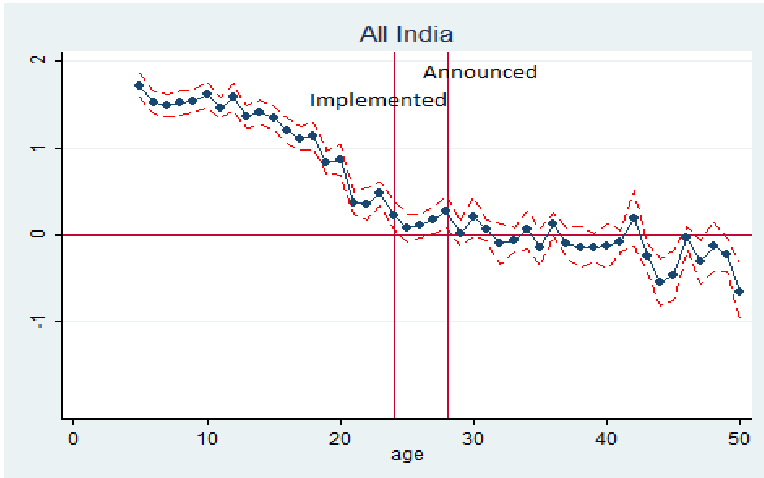

Figure B.3: OBC Coefficients of Diff-in-Diff Regression across age cohorts (Unclustered)

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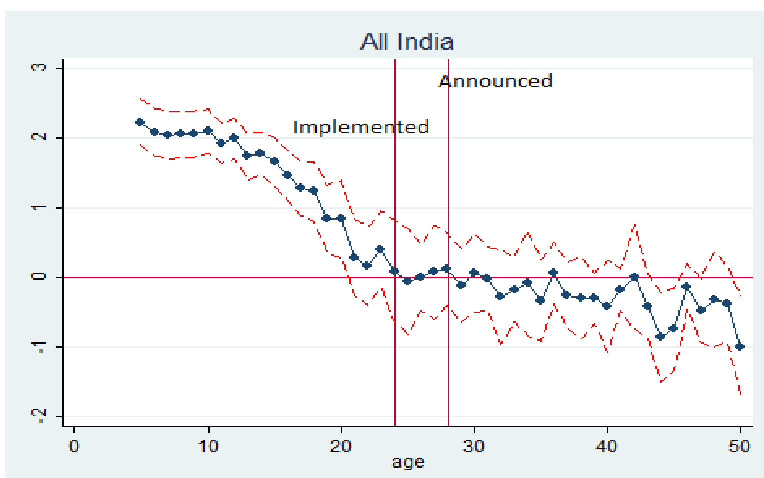
Figure B.4: OBC Coefficients of Diff-in-Diff Regression across age cohorts (Years of Education, Clustered Standard Errors



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Dependent variable is years of education. Standard errors clustered at state-level. Vertical lines indicate year of announcement (on the right) and implementation (on the left)

Figure B.5: Pre-collegiate education: Impacts on OBCs v Muslims and the Poorest 20% of Others

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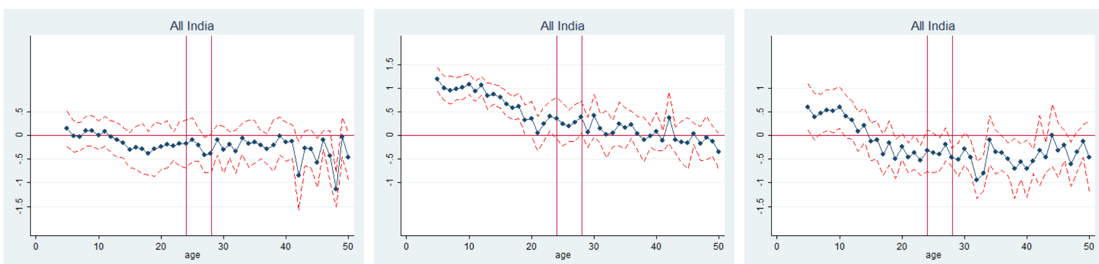

(a) Muslims (b) OBCs (c) Poorest 20% of Others

Standard errors clustered at state-level. Vertical lines indicate year of announcement (on the right) and implementation (on the left). ‘Others’ indicates non OBC/SC/ST

Figure B.6: State-Wise Changes in Reservation Policy for OBCs

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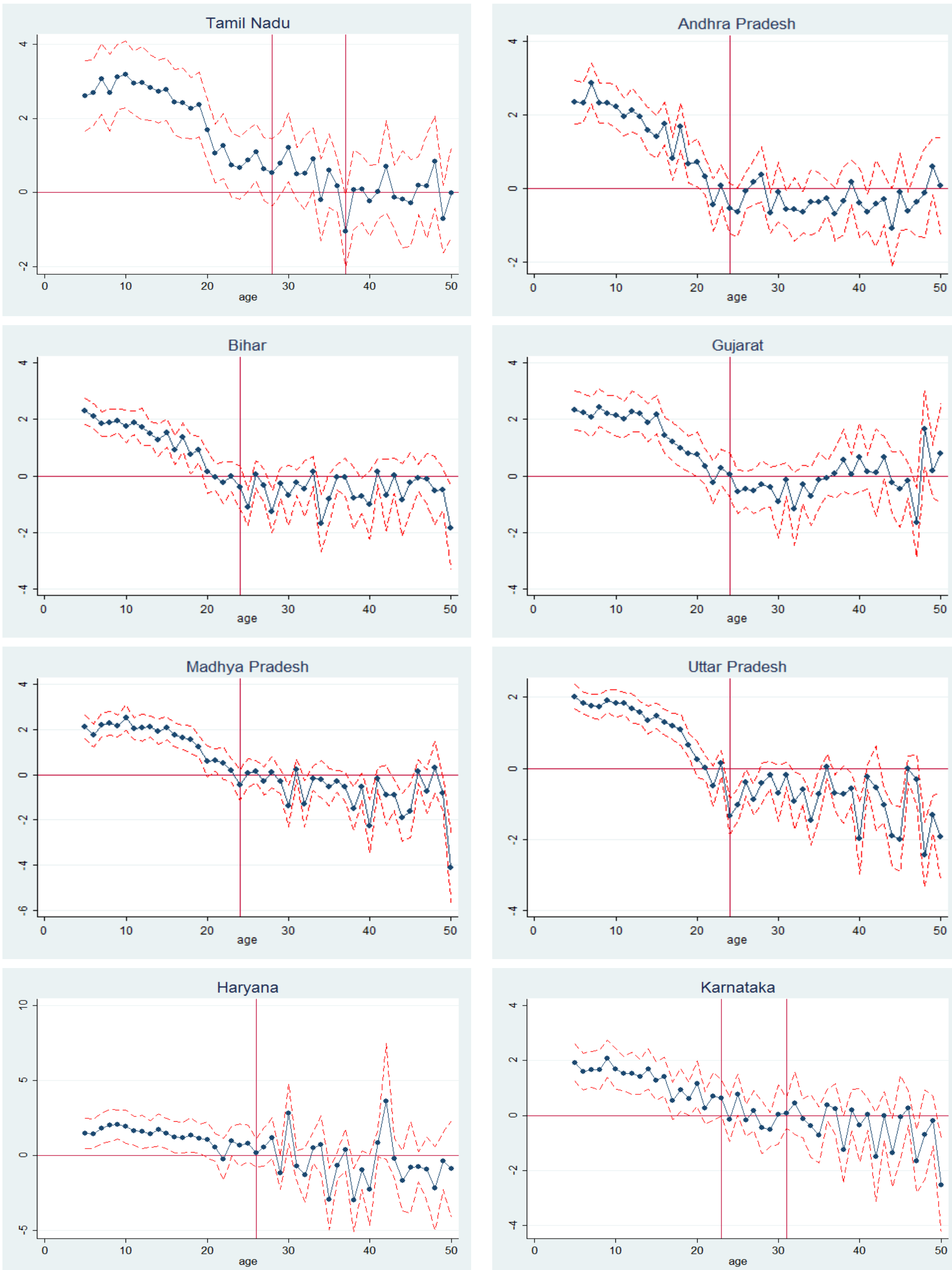
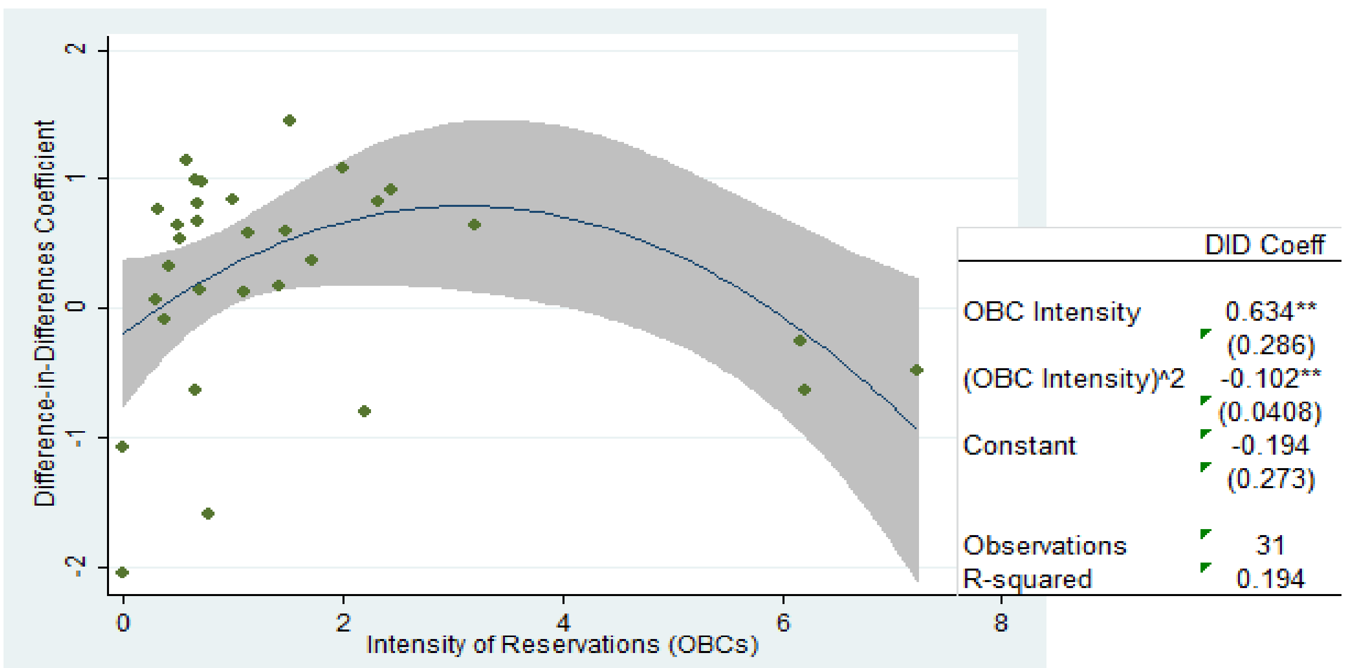


Vertical lines indicate year of implementation of significant changes in state-wise policies. Primary source data on reservation policy changes collected via Right to Information (RTI) Act petitions.

Figure B.7: Triple Difference- Auxiliary Regression



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Auxiliary Regression of state-by-state relationship between the ATET and intensity of OBC reservations in each state. (dropping AN Islands with extremely large intensity value due to lack of OBC population.)

Figure B.8: Looking for other Discontinuities at index values: 20, 25, 35 and 40

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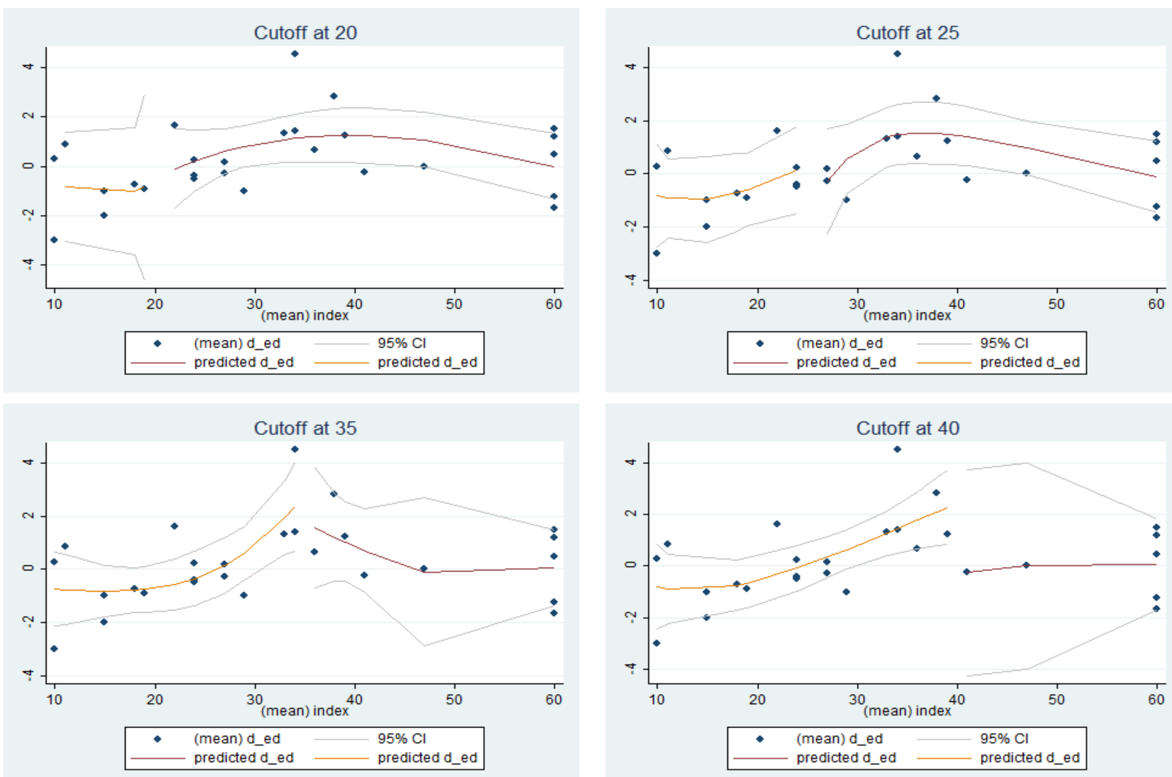

Placebo test: looking for discontinuities at other values of the index. True cutoff value is 30.