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Essays in Development and Education Economics

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Abstract

This thesis is a collection of three empirical essays investigating the effects of affirmative action for socially disadvantaged groups in India.

Using school census data, the first chapter examines enrolment trends of socially disadvantaged children post the Right to Education (RTE) Act, which mandated the reservation of 25% private school places for such children. Post-RTE, a significant increase was observed in disadvantaged children attending private schools. Difference-in-differences analysis revealed greater increases in schools previously below the 25% quota, especially those participating in the reservation policy. The results are however driven by a 'substitution' of places, where private schools are replacing free places under the policy with fee-paying disadvantaged children.

The second chapter examines the impact of the RTE Act's reservation policy on private school expenditure by socially disadvantaged households. Leveraging the age of school entry and using a difference-in-differences approach, the study finds a significant decrease in private school fees for disadvantaged children post-policy. This reduction was more pronounced in districts with higher enrolment rates under the policy. The change is attributed to a rise in low-cost private schools post-policy, facilitating cheaper education for disadvantaged students. Moreover, a strong correlation was observed between the growth of low-cost schools and increased policy enrolments in a district.

The third chapter provides new evidence on the causal impact of elected representatives on socio-economic development, using candidate data from state assembly elections (1974-2017). It exploits a discontinuity in constituency reservations for Scheduled Castes (SCs). Reservations do not just increase the chances of an SC representative but also increase the odds of a female representative, younger in age and affiliated with political parties. The study uses socio-economic indicators such as census outcomes, nightlight luminosity, and primary school outcomes. The estimates suggest no differences in census outcomes and nightlight luminosity between SC reserved and unreserved constituencies. However, SC representatives appear to have positively impacted private education after the RTE Act's introduction.

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This thesis is dedicated to the memory of my grandparents.

Contents

Introduction

This thesis is a collection of three empirical essays on development and education economics. It explores the effect of affirmative action targeting the socially disadvantaged communities in India, which include the Scheduled Castes (SCs), Scheduled Tribes (STs), and Other Backward Classes (OBCs). Affirmative action mainly entails a set of policies aimed at increasing opportunity for minority groups that have been historically discriminated against or underrepresented. Affirmative action in India has existed since Independence and has largely taken the form of 'quotas' or reservations in politics, government jobs, and education.

The first two chapters evaluate the impact of affirmative action in the context of primary education in India from both the supply side and the demand side. In August 2009, the government of India introduced an affirmative action policy under the Right to Education (RTE) Act. It entailed the reservation of at least 25 percent of seats in private schools for socially disadvantaged children. Moreover, children enrolled under the policy were entitled to free primary education which was publicly funded.

Chapter 1 investigates the effect of the policy on the enrolment of disadvantaged children in private schools. Using a large comprehensive administrative school-level data (District Information System for Education), I look at the evidence on policy implementation and takeup. Data shows that overall the policy did not operate on anywhere near the scale intended. However, initial findings illustrate a steep increase in the enrolment of disadvantaged children in private schools after the policy. One of the reasons for the increased enrolment is the growth of private schools. Using a difference-in-differences strategy, I also find a sharp increase in disadvantaged children's enrolment in private schools that had fewer than 25 percent of these children before the policy. Further, using a triple-difference model, I find that the post-policy increase was larger in schools that participated in the affirmative action policy.

However, the positive effect of the policy on disadvantaged children's enrolment was predominantly indirect. I find that a majority of private schools were not enrolling these children through the policy and were in fact substituting them for free seats. Even

though the indirect effect on enrolment cannot be interpreted as causal, it is suggestive of the role of the RTE Act. The RTE Act introduced various new reforms in education, which could have indirect effects on disadvantaged children's private school enrolment in association with the affirmative action policy.

Chapter 1 shows that many disadvantaged children were studying in private schools after the implementation of the affirmative action policy despite not receiving free seats. To understand what enabled disadvantaged children to afford private education after the policy, I investigate whether the policy had a spillover effect on their private school expenditure in Chapter 2.

Using a nationally representative survey of households (National Sample Survey), Chapter 2 studies the effect of the policy on private school tuition fees. The policy was only targeted at new entrants to schools, who are aged 5-9 in the data. Additionally, only children from socially disadvantaged communities were eligible to apply for free seats under the policy. I combine these two exogenous sources of variation and incorporate a difference-in-differences strategy to study the effect of policy exposure on private school fees. I find that the policy resulted in a significant reduction in private school fees for the younger disadvantaged cohort (5-9).

The effect is larger among the wealthier disadvantaged households who were more likely to apply for free seats and those in states that had a higher enrolment rate under the policy. However, the effects are not driven by free seats under the policy as almost no child in the younger cohort was studying in private schools for free. The effects are instead driven by an increased supply of low-fee private schools that entered the market after the RTE Act. The increased supply of low-cost private schools seems to be the result of an amplified demand for private education among disadvantaged groups, especially those more likely to apply for free seats.

Descriptive evidence from the District Information System for Education also shows a large district-level variation in the enrolment rate under the policy that is highly correlated with the entry of new low-fee schools. I further incorporate this district-level variation in the intensity of the policy by combining the household data with the administrative school data. Subsequently, I find that in districts with a higher enrolment rate under the policy, the reduction in fees for the younger disadvantaged cohort was larger.

The state governments' autonomy under the RTE Act has significantly influenced the implementation of the affirmative action policy within their territories. The variation in enrolment within states could also be potentially tied to political leadership, especially when political leaders belong to those minority groups affected by the policy.

The third chapter explores the role of affirmative action in the context of state elections in India. In state elections, some assembly constituencies are set aside for SC candidates depending on the SC population in each district. Chapter 3 investigates the effect of SC political representatives on socio-economic outcomes in assembly constituencies. While there are numerous studies investigating the effect of SC representatives on village and state-level outcomes, this chapter contributes to the very limited literature that looks at the constituency-level effects. I make five significant contributions to the existing literature.

First, I use a regression discontinuity design to explore the causal effect of SC representatives. Second, I study the effect of SC representatives on economic development following the allocation of state development funds. Third, I see if 'nightlights' is a better measure of constituency-level development than census outcomes. Fourth, I show that in reserved constituencies there are other representative characteristics that are significantly different. Fifth, I see if schooling outcomes were significantly different in SC constituencies with respect to the RTE Act using data from the District Information System for Education.

I find that constituencies reserved for SCs were also more likely to have female, younger and non-independent (affiliated to political parties) representatives, while also having a lower turnout percentage. Looking at outcomes, there is no difference in overall economic development between constituencies led by SC representatives and those led by non-SC representatives. However, using data on nightlights from the Defense Meteorological Satellite Program's Operational Linescan System as a proxy measure for development generates imprecise estimates. I conclude that using nightlight luminosity as an indicator of economic development requires better-quality data. Finally, when I study the effects on schooling outcomes, I do find a positive effect of SC representatives on private school enrolment of SC children, and on the overall stock of private schools.

Chapter 1

Direct and indirect effects of the RTE Act on school enrolment of disadvantaged groups

1.1 Introduction

Universal primary education has been one of the major global educational goals over the past few decades. In low and middle-income countries, the push towards universal primary education has been part of a broader agenda of promoting human development and reducing poverty. The UN's Millenium Development Goals and Sustainable Development Goals set a target to achieve universal primary education by 2015, and 'equitable quality education' by 2030. As a result, many countries have introduced policies that have successfully increased enrolment rates, improved infrastructure, and reduced gender disparity. However, there are still significant challenges such as high dropout rates, poor quality of education and high socio-economic barriers to accessing primary education.

At the same time, there has been a growing demand for private education in the last twenty years. While the advocates of private education believe that it is better than public education in terms of quality and accountability, others argue that it only caters to a privileged section of society. Private schools are often criticized because they lack inclusiveness and are not affordable for the poor. Yet, there has been a substantial increase in private school enrolment, especially in developing countries.

There are various studies that have linked increasing private school enrolment to the existence of low-cost private schools in developing countries (De et al., 2002; Tooley

and Dixon, 2003; Kingdon, 2020). These schools have a low per-child expenditure and charge a relatively lower fee than regular private schools. However, some other studies have found that these low-cost private schools are still not affordable for the poorest and those from socially marginalized communities (Härmä, 2009; Härmä, 2011; Hill, Samson, and Dasgupta, 2011).

Empirical evidence on whether private schools offer better quality education has been somewhat mixed. For instance, Angrist, Bettinger, and Kremer (2006) and Dixon et al. (2019) found that poor children attending private schools through free vouchers had better learning outcomes in Colombia and India respectively compared to children who did not receive the vouchers. However, Muralidharan and Sundaraman (2015) found no effect of such vouchers in Andhra Pradesh, India. On the supply side, public-private partnership (PPP) programs have been launched, where the government enters into a funding arrangement with private schools by offering them subsidies. Several studies have analyzed the role of PPP programs in schooling in the Asian (Tooley and Dixon, 2006; Amjad and Macleod, 2014; Ansari, 2020) and African (Mfum-Mensah, 2003; Tooley and Dixon, 2006; Akyeampong, 2009) context. These studies have found mixed results in terms of improved accessibility and learning outcomes for disadvantaged children.

In line with the Millenium Development Goals, India introduced the Right to Education (RTE) Act in August 2009, which became effective on April 1, 2010. It is a legal provision that made primary education a basic human right in India. It necessitates free and compulsory education for all children in the 6-14 age group in government[1] schools. The RTE Act also includes other norms aimed at improving infrastructure and the quality of education. To reduce socio-economic inequity in accessing good quality education, the government also implemented a public-private partnership under the RTE Act. It required all private schools to reserve at least 25% of their places for 'economically weaker sections' and 'socially disadvantaged groups', and offer them free primary education in return for a reimbursement from the government. It is this public-private partnership that I analyse in the first two chapters of the dissertation.

Like other developing countries, India has witnessed a sharp increase in private school enrolment. Between 2010 and 2016, private school enrolment increased by 38.5% (Kingdon, 2020). On the other hand, enrolment in government schools has sharply declined. However, whether the RTE Act had a role in explaining this shift towards private schools is understudied in the literature. Similarly, whether private school

[1]In India, all schools managed by the central, state or local governments are collectively known as government schools.

enrolment also increased for the economically and socially disadvantaged in India is yet to be explored.

The aim of this chapter is to investigate whether there was an increase in the enrolment of socially disadvantaged children in private schools, especially following the implementation of the RTE Act. Using descriptive evidence from a comprehensive school-level dataset (District Information System for Education), I first look at the trends in primary school enrolment across different types of schools. I find that private schools witnessed an increase in the enrolment and share of disadvantaged children relative to government schools. The increase was larger after the RTE Act was implemented. Seven years after RTE, the enrolment of disadvantaged children in grade 1 increased by 1.5 million in private schools. Much of this increase was driven by the entry of new private schools rather than an increase in school size.

However, there was also an increase in the enrolment of disadvantaged children in private schools that existed before the RTE Act. To understand the impact of the RTE Act on these enrolments, I employ a difference-in-differences strategy. I find that schools that previously had less than 25% disadvantaged children witnessed an increase post-RTE — their enrolment of these students grew by an additional 6 percentage points after the Act was implemented. To further examine this surge, I investigate whether the RTE Act's policy that mandates private schools to reserve 25% of their seats for disadvantaged children was the catalyst. Using a triple-difference model, I compare two sets of schools: schools that adopted the 25% reservation policy and schools that did not adopt this policy. Interestingly, the enrolment surge of disadvantaged children was not confined to just the policy-adopting schools. Schools that did not adopt the 25% reservation policy also saw increased enrolments. Nonetheless, the increase was more pronounced in schools that did adopt the reservation policy.

Furthermore, I find that the number of places filled under the reservation policy explains very little variation in the size of total disadvantaged children enrolled in the same grade. When enrolment under the policy increased by 10%, the enrolment of disadvantaged children only increased by 1.6%. This indicates a substitution of disadvantaged children paying private school fees for disadvantaged children getting free seats under the policy.

Yet, the increase in the enrolment of disadvantaged children does seem to be tied to the RTE Act. The sharp increase in their share is only prevalent in years after RTE was implemented. The increase is also higher in states where the RTE Act was enacted and where a higher proportion of private schools participated in the reservation policy.[2] These findings suggest a positive and 'indirect' effect of the RTE Act on disadvantaged children's enrolment in private schools. Subsidized private education under the reservation policy could have some indirect implications for the targeted children such as increased awareness about private education leading to increase in demand. At the same time, other provisions of the RTE Act such as free government education or establishment of more government schools could be correlated with the increase in private school enrolment. If that is true, it would be challenging to disentangle the effect empirically.

The findings from this chapter largely imply that many private schools which had a lower share of disadvantaged children before the policy, were encouraged to offer more places to them following its implementation. But they did not do so explicitly through the reservation policy. Nonetheless, schools that participated in the reservation policy offered free places to disadvantaged children in addition to enrolling fee-paying disadvantaged children. This resulted in a higher increase in the overall share of disadvantaged children in these schools, which is in fact a 'direct' effect of the policy.

The rest of the chapter is structured as follows. Section 1.2 describes the Right to Education Act in detail. Section 1.3 discusses the related literature and my contribution. Section 1.4 describes the dataset and presents some descriptive statistics from the data. Section 1.5 compares the enrolment and share of disadvantaged children across different types of schools. Section 1.6 estimates the effect of RTE on the share of disadvantaged children and discusses the results. Section 1.7 undertakes some robustness checks. Finally, Section 1.8 concludes.

[2]The RTE Act was not enacted in the state of Jammu and Kashmir while many other states do not seem to have implemented the reservation policy at all.

1.2 The Right to Education Act

1.2.1 Overview

The Right to Education (RTE) Act was introduced in India in August 2009. It is a national-level policy that became effective in April 2010 in all states except Jammu and Kashmir. The main aim of the RTE Act was to make primary education a fundamental right of every child in India. It mandates that all children in the 6-14 age group have access to free and compulsory education in government schools. Free education implies that no child enrolled in a government school is liable to pay fees or incur any expenses till the completion of primary education (grade 8). Compulsory education makes it mandatory for the government authorities to ensure admission and completion of primary education by all children in the 6-14 age group. Within three years from the commencement of the Act, the appropriate government (state or local) was also required to establish a school within 1km of residence, where no such school previously existed.

In addition, the RTE Act prescribes duties for schools which include maintaining infrastructure standards, teaching equipment standards, adequate training of teachers, school working days and a pupil-teacher ratio of 30:1. It also introduced a no-detention policy under which no student could be detained from being promoted if they failed exams in grade 5 or grade 8. However, in 2019, a bill was passed in the parliament to scrap the no-detention policy as a way of improving the quality of education in schools.

Furthermore, the RTE Act requires all private unaided[3] schools to be legally recognized by the state government. This implies fulfillment of certain requirements with respect to total expenditure, total area of the school, enrolment, number of lavatories for boys and girls, and prescribed curriculum till grade 8. Schools that fail to meet these requirements have to be shut down by the government under the RTE Act.[4] For the rest of the chapter, I refer to private unaided schools as simply private schools.

1.2.2 Reservation in private schools

The RTE Act also incorporated a policy under which all private (recognized) schools in India are required to reserve at least 25% of their seats, at entry level, for underprivileged children and provide them free education till the completion of grade 8. The main

[3]Private unaided schools are non-government schools that are managed by an autonomous private body and do not receive any maintenance grants or funds from the government.

[4]Despite this, a large number of private schools that are unrecognized continue to operate in India (Kingdon, 2020).

aim of this policy was to create a socially inclusive environment for children from different backgrounds and to give them the opportunity to access private education, which predominantly remains unaffordable for the poor.

The entry-level for reservation can either be grade 1 or a pre-primary grade at the discretion of the school. The RTE Act recognizes underprivileged children as those who either belong to **economically weaker sections** or **disadvantaged groups**. Economically weaker sections include children whose parents earn an annual income that is below a certain threshold determined by the state government. Disadvantaged groups mainly comprise three social categories in India— Scheduled Caste (SC), Scheduled Tribe (ST) and Other Backward Class (OBC).

The threshold levels set by the state government and the definition of disadvantaged groups vary largely across states. For instance, in the state of Madhya Pradesh, only children from families below the poverty line[5] are included under 'economically weaker sections', whereas in the state of Rajasthan, the threshold level is ₹2.5 lakh (USD 3,396) per annum, which is well above the poverty line. So, while both Madhya Pradesh and Rajasthan identify SC and ST as part of 'disadvantaged groups', Rajasthan also identifies children from OBC whose parents earn an annual income that is no more than ₹2.5 lakh (USD 3,396).

For each child admitted under the RTE Act, private schools are entitled to receive reimbursement from the state government. The amount of reimbursement is equal to the per-child expenditure incurred in state run government schools or the actual per-child fee charged by the private school, whichever is lower. In each state, the state government fixes the per-child reimbursement rate every year which is supposed to be equal to the per-child expenditure in the state's government schools. This means that private schools with a per-child fee lower than the reimbursement rate will be reimbursed the actual fee that they charge for each child admitted under RTE. On the other hand, private schools with a per-child fee higher than the reimbursement rate will be reimbursed an amount equal to the latter.

There is a large variation in the reimbursement rates fixed by different state governments. Table 1.1 shows the reimbursement rates in Rajasthan and Madhya Pradesh from 2012-13 to 2015-16. The reimbursement rates in both states have been increasing every year but the amount has been considerably higher in Rajasthan. In 2012-13, the reimbursement rate in Rajasthan was three times the reimbursement rate in Madhya Pradesh, while in 2015-16, it was almost four times that in Madhya Pradesh. The payment sched-

[5]In 2011-12, the poverty line was fixed at ₹9,372 (USD 128) per annum in rural areas and ₹11,580 (USD 158) per annum in urban areas.

ule also differs in both states. The reimbursement is made to private schools at the end of every academic year (in March) in Madhya Pradesh. In Rajasthan, the reimbursement is made in two installments, first, in October of the current academic year and second, in June of the next academic year.

The difference in the reimbursement rates can be attributed to the variation in the per-child expenditures in the states. According to Dongre and Kapur (2016), the calculated per-child expenditure in government schools in Rajasthan was ₹11,576 (USD 139) in 2011-12, while in Madhya Pradesh it was ₹8,066 (USD 97). Another potential reason for the difference in reimbursement rates could be the difference in the allocation of funds toward the implementation of the RTE Act. The RTE Act prescribes that the central and the state government must share equal responsibility in providing funds to carry out the provisions of the Act. However, according to the Ministry of Education, the central government did not contribute towards the reimbursement expenditures until 2014. As a result, between 2012 and 2015, the government of Rajasthan made reimbursements to private schools using its own budget. On the other hand, there was no separate budget for the RTE Act in Madhya Pradesh. To carry out its provisions, the state government used funds available under *Sarva Shiksha Abhiyan*[6], which is released by the central government to the states every year.

Table 1.1. Reimbursement rates fixed by the state government (Amount in ₹)

Year	Rajasthan	Madhya Pradesh
2012-13	9,748	3,065
2013-14	11,704	3,478
2014-15	14,141	3,826
2015-16	17,732	4,209

Notes: 1 USD = ₹83
Source: Report of the Comptroller and Auditor General of India for the year ended 31 March 2016.

[6]Sarva Shiksha Abhiyan (SSA) is a flagship programme of the Government of India that is aimed at creating a nation where all children aged 6-14 complete primary education. The RTE Act is the legal enforcement of SSA.

1.3 Related literature

1.3.1 Universal Primary Education in India

One of the earliest education reforms in India to promote universal primary education was the District Primary Education Program (DPEP). It was launched nationally in 1994 and was largely funded by external organizations such as the World Bank, the Department for International Development in the UK and the European Commission. While the program ended in 2002, its objectives were included under the Sarva Shiksha Abhiyan (SSA). A key objective of the DPEP was to make primary education accessible to all children, especially in districts where the female literacy rate was below the national average.

Combining the 1991 Census data with the National Sample Survey data, the study by Jalan and Glinskaya (2002) was one of the first to look at the impact of DPEP on the schooling outcomes of children from minority groups. They used a two-stage Propensity Score Matching method, where they first matched treated districts (where the female literacy rate was below the national average) with untreated districts and then matched households within the matched districts. Then using a difference-in-differences method Jalan and Glinskaya (2002) found that the enrolment rate of SC/ST children was 4.6 percentage points higher in treated districts for all age groups. Further, while the program had a positive effect on the retention rate of SC/ST children among the 6-11 age group, it had a negative effect among those in the 12-15 age group. Finally, there was no effect of the program for girls except in the state of Madhya Pradesh, where other state-specific programs targeted at girls could have been correlated with DPEP.

Using the District Level Household Survey (DLHS) conducted in 2007-08 and a difference-in-differences method, comparing younger (treatment) and older (control) cohorts across DPEP and non-DPEP districts, Azam and Saing (2017) found that DPEP had a larger, positive effect for girls than boys. The program was found to increase the probability of attending school, the probability of completing school, and the years of schooling. However, for SC/ST children, the increase in the probability of attending and completing school was lower than for non-SC/ST children. Furthermore, the program had no effect on the total number of years SC/ST children attended school.

A recent study by Khanna (2023) looked at the long-term effects of a school expansion policy in DPEP districts using a regression discontinuity design. Khanna (2023) used district-level data from multiple sources including the District Information System for Education (DISE), the National Sample Survey (NSS), the Census, the Annual

Survey of Industries and the Annual Survey of Education Report (ASER). He found a positive effect on education and earnings for students in targeted regions, including a reduction in the cost of education. Leveraging variation in cohort exposure, Khanna (2023) found a positive effect for the younger cohort only, who directly benefited under the policy. The policy also had some general equilibrium effects, notably, it led to a decrease in the wages of skilled workers due to an increase in their supply.

However, not all education reforms introduced have attained a similar level of success as the DPEP. Unlike the DPEP, there have been multiple challenges involved in the proper administering of the RTE Act. As a result, it has not been able to achieve many of its objectives. This chapter finds that the effects of the RTE Act, especially its reservation policy have been largely indirect. Private schools were not following the actual rules even 7 years into the policy and were enrolling disadvantaged children who could afford to pay private school fees. The RTE Act has therefore not been successful in providing private education to the very poor and there appears to have been little effort made by the government to rectify these issues.

Using data from the Ministry of Human Resource Development (MHRD) Mehrotra (2012) was the first to examine the cost and financing of the RTE Act. He found that the majority of the budget for the RTE Act was spent on teachers' salaries in government schools. Only the remaining was used to fund resources such as textbooks, uniforms and stationary. There were additional challenges to financing the RTE Act due to the 2008 financial crisis that led to an increase in India's fiscal deficit. There was also not much clarity in terms of how expenses would be shared between the central and the state governments.

The current literature on the RTE Act also includes state-specific studies. In the state of Haryana, there were improvements in terms of enrolment and basic infrastructure following the RTE Act, but there was a huge lag between expectations related to quality improvements and real outcomes (Ojha, 2013). Ojha (2013) collected data on RTE awareness among teachers, parents and children through questionnaires and observational recordings and conducted a qualitative analysis. Ojha (2013) found that there was very little awareness of the norms of the RTE Act among the stakeholders. In terms of infrastructure, most schools did not have access to safe drinking water or a library. Even though most schools had a pupil-teacher ratio of 30:1, there was no proper mechanism in place to improve teachers' training. Most parents were also dissatisfied with the quality of education in government schools.

Malakar and Mahato (2015) studied the effect of the RTE Act on girls' enrolment in the state of Tripura. They observed that the enrolment rate of girls in primary and upper

primary schools in the state was almost 50% in each of the three years between 2011 and 2013. The enrolment of SC/ST children also increased during this period. However, Malakar and Mahato (2015) did not explicitly use a comparison group so it is not clear if this increase was caused by the RTE Act or not.

Singh (2016) also used descriptive analysis to evaluate the effect of the RTE Act on enrolment in Himachal Pradesh. He used data from multiple sources such as the District Information System for Education (DISE), National Achievement Survey (NAS) and the National Council of Educational Research and Training (NCERT). Singh (2016) found that primary and upper primary enrolment decreased between 2009 and 2012 in government schools. However, there was a small increase in the enrolment of girls and SC children. Most facilities and infrastructure including the pupil-teacher ratio improved in schools while they still did not meet the required standards.

Using national level data on children's enrolment status, test scores in math and reading, pupil-teacher ratios and infrastructure for 2005-2014, Shah and Steinberg (2019) found enrolment in grades 1-8 to have significantly increased post-RTE, particularly for girls. However, it is not clear how much the increase in total enrolment is associated with the RTE Act as Shah and Steinberg (2019) also found a significant jump in enrolment after 2008, two years before the Act came into effect. They also found that the learning achievements of children deteriorated in the period after RTE despite an upward trend in overall enrolment and improvements in pupil-teacher ratios. Shah and Steinberg (2019) attributed this effect to the no-detention policy of the RTE Act where all students till grade 8 had to be compulsorily promoted to the next grade even if they failed exams, which may have disincentivized learning.

Disaggregating enrolment by state and type of school, Bhattacharjee (2019) found that there were significant differences in enrolment across states and between school types. From 2014 to 2016, Bihar, Rajasthan and Uttar Pradesh were the top three states which saw an increase in enrolment in upper primary education, with the increase being highest in Bihar (6.5%). On the other hand, Assam, Madhya Pradesh and West Bengal saw a significant decrease in enrolment in upper primary education, with the decrease being highest in Assam (5.1%). Examining this further, Bhattacharjee (2019) concludes that the increase in enrolment was driven by improved sanitation and not just the RTE Act. With respect to school type, Bhattacharjee (2019) found that enrolment in government schools declined, while that in private schools increased. This was driven by a large increase in the number of private schools.

The study by Sarin et al. (2015) is one of the few to have looked at the implementation of the RTE Act's reservation policy in private schools. Using state-level data from

DISE and the MHRD, Sarin et al. (2015) calculated total enrolment and total seats filled under the policy in rural and urban areas. Only 29% of the total available seats were filled under the policy by 2013-14. Moreover, only 22% of all private schools were participating in the policy in the same year. Sarin et al. (2015) also found large variations across states. For example, Andhra Pradesh had not implemented the RTE Act 5 years after its introduction. In Uttar Pradesh, both the seat fill rate and the school participation rate were the lowest despite the state government formally administering the policy.

Most studies of the RTE Act have primarily focused on its overall implementation and effectiveness. Private schools' response to the reservation policy under the RTE Act has been largely understudied. While the report by Sarin et al. (2015) studies the policy's enforcement at the state level, this chapter investigates the policy's effect at a more granular level. Specifically, it uses school-level data from DISE to look at the response to the policy from the school side, both at the national and state level. Additionally, using a difference-in-differences model with school-fixed effects it investigates the effect of the policy on the enrolment of disadvantaged groups in private schools.

1.3.2 Private schooling in India

The demand for private education in India has amplified in the last two decades. This is largely due to the perception that private schools offer better quality education. There is evidence that suggests that private schools in India outperform government schools on a variety of quality indicators. Even after controlling for confounding factors, students in private schools have higher test scores than their government school counterparts (French and Kingdon, 2010; Tooley et al., 2010). Moreover, private schools have better infrastructure and less teacher absenteeism (Tooley et al., 2010; Kingdon, 2020).

Using data from the Annual Survey of Education Report (ASER) from 2005 to 2007, French and Kingdon (2010) examined the relative effectiveness of private and government schools in rural India. French and Kingdon (2010) used multiple non-experimental techniques including OLS, fixed effects models and a selection on observables method. The results were consistent across all methods. Children attending private schools demonstrated cognitive achievement levels between 0.18SD and 0.25SD higher than those in government schools.

A similar study was conducted by Tooley et al. (2010) in low-income areas of Hyderabad using survey data on households and private schools. An IQ test and standardized tests in Math, Urdu, and English were also conducted for a random sample of students from the households. Using factor analysis and multilevel modeling, Tooley et

al. (2010) found that children in private schools performed better in Math and English, but there was no difference in Urdu test scores. They also found that boys in private schools scored relatively lower in English and Math than girls.

The growing demand for private education in India has been met by an increase in the supply of private schools, especially 'low-fee' private schools. This has resulted in an increase in the overall enrolment in private schools. However, studies have found that even such low-fee private schools are not economically or socially equitable and the poorest in India still cannot afford private education (Härmä, 2009; Härmä, 2011; Hill, Samson, and Dasgupta, 2011).

Using survey data collected from rural areas of a district in Uttar Pradesh in 2005, Härmä (2009) investigated whether low-fee private schools are affordable for the poor. Härmä (2009) undertook a quantitative analysis of household surveys using the information on income and asset index score. The results indicated that parents often make a choice between government and low-fee private schools. Furthermore, even though a majority of households preferred low-fee private schools over government schools, less than 50% of them were able to access these schools. The fraction was even less among disadvantaged groups (SC/ST) despite high demand. For the poorest, the cost of educating a child in private schools was 1/5th of the household's income.

Härmä (2011) builds on their previous work by incorporating asset index scores in a logit regression and using explanatory and factor analysis. The results are consistent with the previous findings. A higher asset index score was positively associated with the likelihood of attending low-fee private schools. Asset index was the strongest factor determining the choice of low-fee private schools. Härmä (2011) also found that a low perception of government schools was associated with a high enrolment in low-fee private schools. On the other hand, being a girl, SC and a Muslim were negatively associated with the likelihood of attending low-fee private schools.

Using qualitative evaluation and descriptive evidence from a village in Rajasthan, Hill, Samson, and Dasgupta (2011) found similar results. Enrolment in private schools significantly increased by 2006 but it was accompanied by an increase in social inequity and exclusion. Leveraging the Public Report of Basic Education (PROBE) Survey and data from DISE, Hill, Samson, and Dasgupta (2011) found that there was a large proportion of SC and ST children in government schools in 2006-07. Girls were also more likely to be in government schools than boys. Overall there was an increase in the number of private schools which was followed by an increase in private school enrolment. Even though there were many low-fee private schools, Hill, Samson, and Dasgupta (2011) argue that the average cost of private education significantly increased over time.

Thus, the increased private school enrolment despite higher fees might be indicative of a greater demand for private education.

In general, there has been a nationwide increase in private school enrolment in the last ten years in India (Kingdon, 2020). Using data from DISE, NSS, and ASER, Kingdon (2020) compares private and government schools on the basis of size, growth, teachers' salaries, fee levels and per-child costs. Kingdon (2020) found that between 2010 and 2014, there was a 44% increase in the number of private schools in the country. This was almost 12 times the growth in government schools. Total enrolment in private schools increased in the same period while government school enrolment declined. Kingdon (2020) found that in urban areas, almost half of all primary school-going children attended private schools. On comparing the costs, it was found that most private schools charge a fee that is lower than the per-child expenditure in government schools. Lower per-child expenditure in private schools is because of the relatively lower salaries of teachers.

The current literature has established a shift from government to private schools in India in terms of enrolment, especially following the growth of low-fee private schools. However, the accompanied increase in social inequity and exclusion of the poorest have raised some concerns. In the midst of that, the reservation policy under the RTE Act was a landmark step that made school choice 'free' for the poor, at least in principle. This chapter adds to the literature by finding that there are more SC/ST children attending private schools following the RTE Act's implementation. This suggests that there has been an increase in the social equity of children from minority groups in the private education sector. But a majority of these children are not directly enrolled under the reservation policy and are in fact paying fees to attend private schools. This implies that economic equity for the poorest has still not improved.

1.4 Data

For the analysis in this chapter, I use the District Information System for Education (DISE), which is a nationwide database of roughly 2 million registered[7] schools of India. DISE database was created by the National University of Educational Planning and Administration (NUEPA) under the Ministry of Human Resource Development (MHRD) in 1995 and was later redesigned in 2001. Each year, DISE publishes school annual report cards on its official website. These report cards consist of state-level and

[7]DISE does not collect information from unregistered/unrecognized schools.

district-level school statistics on key variables such as total number of schools (government and private), total number of classrooms, grade-wise enrolment by gender and social category, enrolment ratio and total number of teachers.

DISE also includes raw data at the school level. It is a panel data of schools, which is presently available for all academic years from 2005-06 to 2017-18. Relevant variables include grade-wise enrolment by gender and by social category, type of school (government or private), category of school (primary, upper-primary etc.) and enrolment of students with special needs.

From 2010 onward, DISE raw data of schools also includes information on key variables related to the reservation policy of the RTE Act in private schools. Specifically, from 2010 to 2012, all private schools were asked how many students applied and enrolled under the 25% reservation policy in grade 1. From 2013 to 2017, they were asked how many students enrolled under the reservation policy at entry level and how many continued from previous years.

The DISE data has information on the enrolment of children by social category from grades 1 to 8 only. So, I consider grade 1 to be the entry-level. Since DISE does not have information on the family income of children, I cannot identify the economically weaker sections. Therefore, I only focus on the enrolment of disadvantaged groups in this chapter. I use the definitions of disadvantaged groups prescribed by the state governments in their official RTE notices[8] to calculate the grade-wise enrolment of the groups. So, disadvantaged groups technically include all children who are eligible for the reservation under the policy.

States such as Haryana, Mizoram and Tamil Nadu do not enrol SC, ST, OBC children or children with special needs under the policy. Similarly, Jharkhand, Meghalaya and Tripura only include SC and ST children from families below the poverty line. As a result, I cannot precisely define disadvantaged groups in these states and thus, exclude these states from the analysis. I also remove schools from Jammu and Kashmir, where the policy was not implemented, and Sikkim, where there was no official definition of disadvantaged groups available.

Data collected under DISE is self-reported by schools, and submitted by the school head teacher. However, the data is checked[9] for inconsistencies at multiple stages by the district and state level authorities before it is published. DISE is currently the largest, centralized database of all registered/recognized schools in India. Figures 1.1-1.3 show

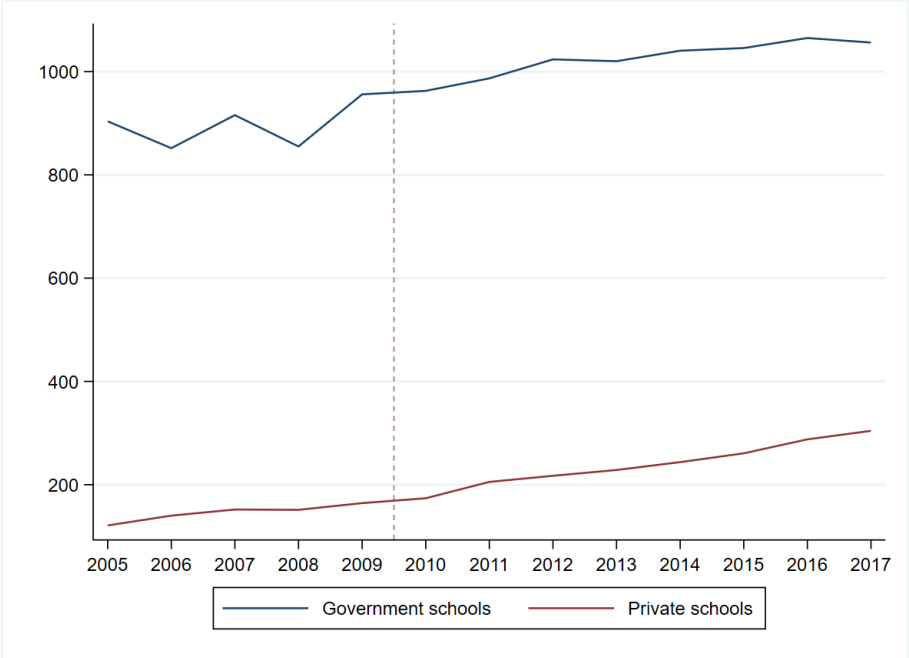
[8]For official definitions see: https://www.education.gov.in/hi/rte_dw

[9]For further information on how the data is checked see: http://schoolreportcards.in/src-new/AboutDISE/Reliability.aspx

some descriptive evidence from DISE. Since the RTE Act was implemented in August 2009, any effect of the policy would reflect in the academic year starting in April 2010 (2010-11).[10] So, a vertical line has been drawn between the academic years 2009-10 and 2010-11 to capture the timing of the policy.

The number of schools has increased over time across both school categories (Figure 1.1). However, I observe that total enrolment in grade 1 has sharply declined in government schools as opposed to private schools, where enrolment has increased over time (Figure 1.2). This is consistent with the existing literature that has observed a shift away from government schools to private schools at the primary and upper primary levels (Krishna et al., 2017; Bhattacharjee, 2019; Kingdon, 2020). Moreover, the decline in government school enrolment is larger than the increase in the number of government schools. As a result, the average enrolment in grade 1, which is equal to the ratio of total enrolment in grade 1 to the total number of schools, has seen a steep decline in government schools (Figure 1.3). Compared to that, the average enrolment in grade 1 in private schools has remained quite stable.

Figure 1.1. Number of schools (in thousand)



[10] A school year in India starts in April and ends in March of the following year.

Figure 1.2. Total enrolment in grade 1 (in million)

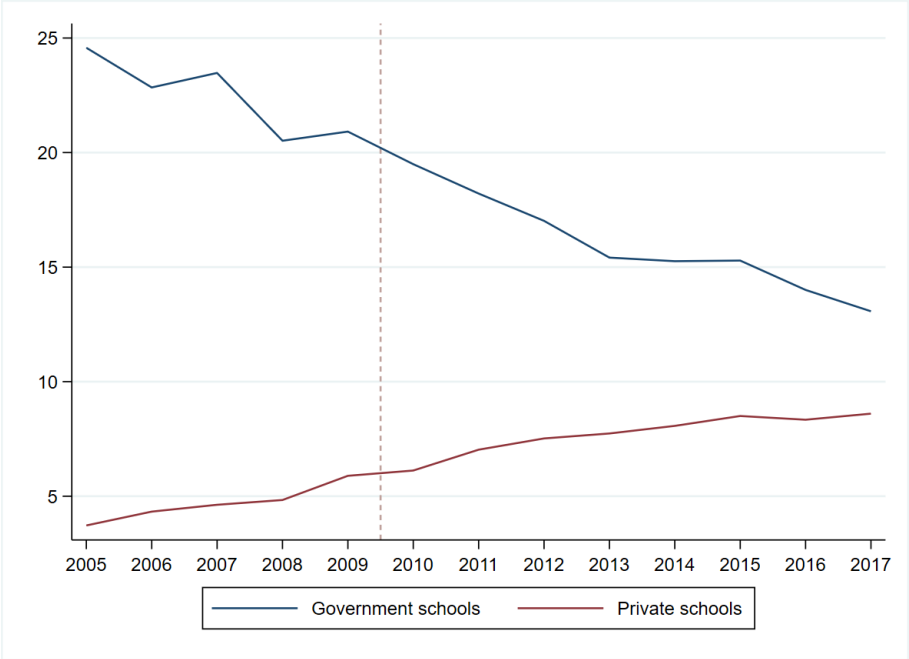


Figure 1.3. Average enrolment in grade 1

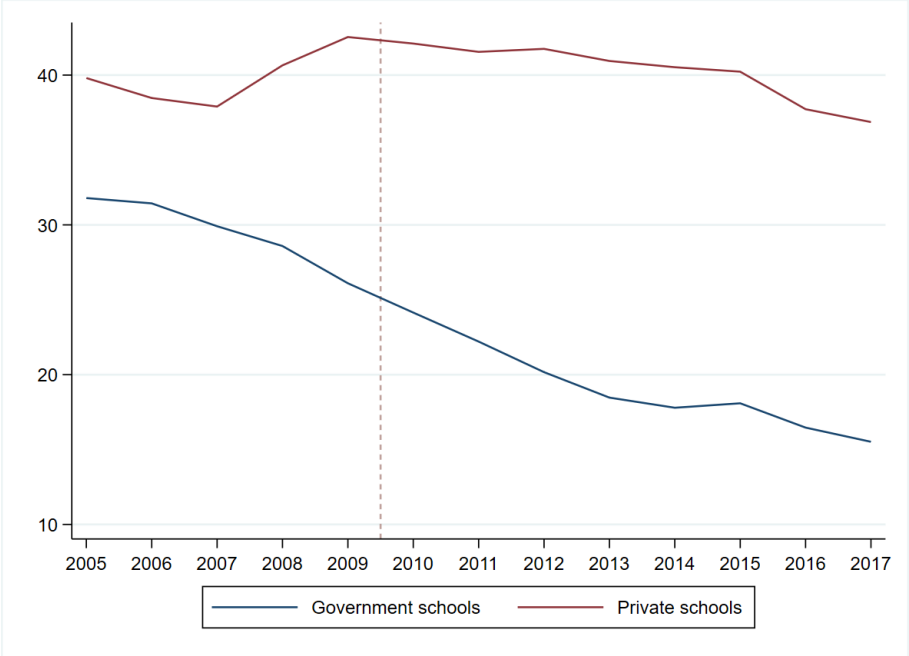
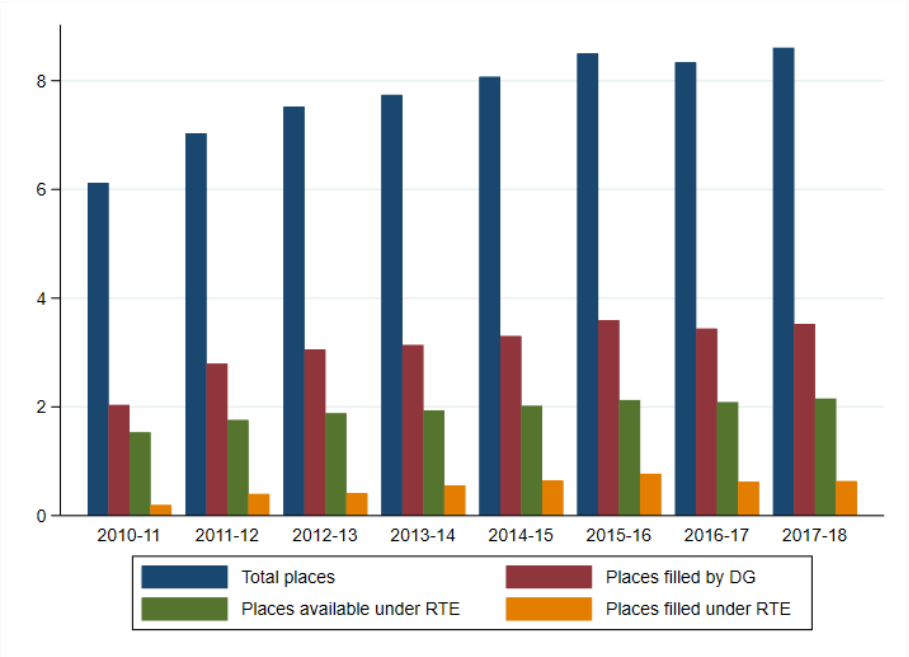


Figure 1.4 shows that in 2010, private schools in India filled around 6 million places in grade 1 (total enrolment). Out of these, around 2 million places were filled by disadvantaged groups. In other words, 33% of seats in grade 1 were filled by children who were eligible under RTE's reservation policy. As the RTE Act required private schools to offer at least 25% of all places in grade 1 for free to disadvantaged groups and economically weaker sections, I calculate the total available places under RTE as 25% of total places in grade 1 in private schools. Figure 1.4 shows that in the year 2010, at least 1.5 million places were available under the policy, of which only around 500 thousand places were filled. Moreover, despite enrolling 2 million disadvantaged children who were eligible, private schools offered less than 500 thousand free places to them under the policy. I do observe that the number of places filled under RTE increased over time, albeit slowly.

Figure 1.4. Places in grade 1 in private schools (in million)



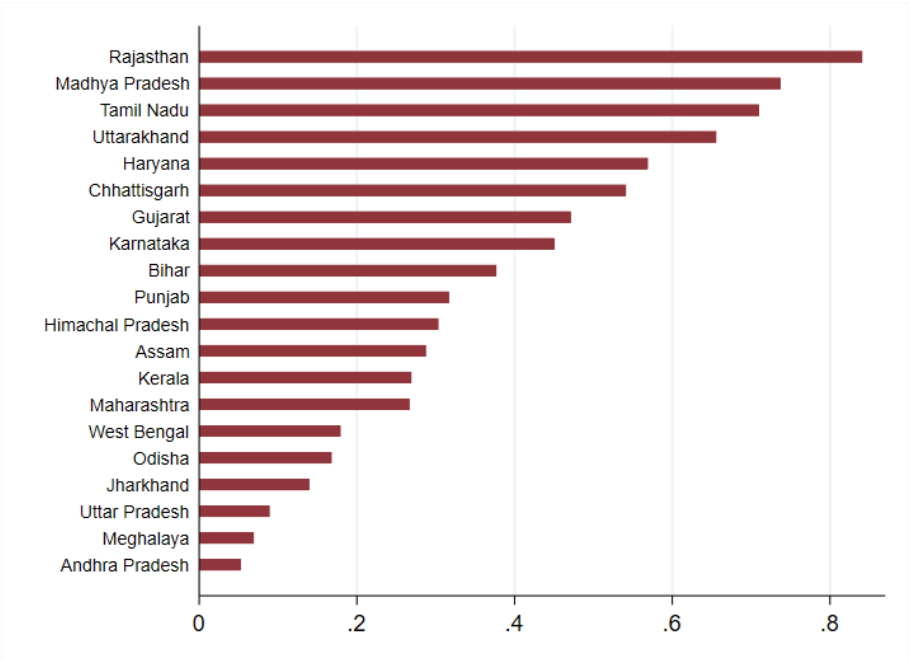
Notes: 'Places available under RTE' is calculated as 25% of total places. 'Places filled under RTE' is the enrolment under the reservation policy as a percentage of total places. 'Places filled by DG' is the percentage of total places filled by all disadvantaged groups.

At the state level, I compare the proportion of RTE schools and the proportion of places filled under RTE. 'RTE schools' are defined as those private schools which reported to have enrolled at least 1 student under the reservation policy in any year after 2009. Non-RTE schools are those that reported to have never enrolled any student under the policy after 2009. Figure 1.5 shows the number of RTE schools as a proportion of the total number of private schools in the largest 20 states of India. The values are averaged over a period of 8 years (from 2010-11 to 2017-18). I find that in Rajasthan, Tamil

Nadu and Madhya Pradesh, more than 80% private schools were RTE schools. This was followed by Uttarakhand and Chhattisgarh, where almost 70% of private schools on average were RTE schools. In states such as Jharkhand, Uttar Pradesh, Meghalaya and Andhra Pradesh, less than 20% of private schools had any RTE enrolment on average.

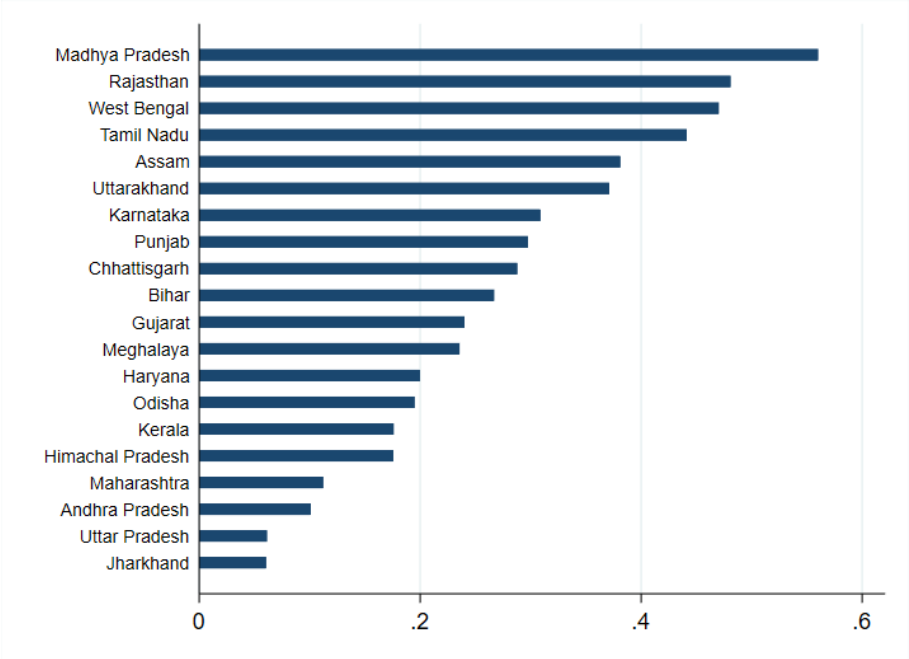
In terms of the average proportion of places filled under RTE's reservation policy, Madhya Pradesh surpassed all other states by filling more than 60% of all available places (Figure 1.6).[11] In contrast, states such as Andhra Pradesh, Uttar Pradesh and Jharkhand, left more than 90% of available places unfilled.

Figure 1.5. Average proportion of RTE schools in largest 20 states (2010-2017)



[11] Average proportion of places is the proportion of places filled under the reservation policy in grade 1, averaged across 8 years. The required proportion is at least 0.25.

Figure 1.6. Average RTE enrolment as a proportion of available places in largest 20 states (2010-2017)



1.5 Response to the reservation policy: A comparison of schools

As the RTE Act's reservation policy mandates subsidized private education for disadvantaged groups, it should in principle increase private school enrolment, especially given the high demand for private education. As the price gap narrows between government and private schools, some disadvantaged families might view private schools as a more attainable substitute for government schools. To study how the enrolment of disadvantaged groups changed with the introduction of the RTE Act, I first compare the trends in enrolment across both government and private schools in Section 1.5.1. I show that enrolment of disadvantaged children in private schools increased post-RTE and was accompanied by a decline in their enrolment in government schools.

To attribute the increasing enrolment in private schools to the reservation policy, it is essential to delve deeper into the private school sector itself. So, in Section 1.5.2, I compare the trends in the enrolment of disadvantaged children across schools participating in the reservation policy and schools not participating. If schools participating under the policy show a remarkably different trend in the enrolment of disadvantaged children, it lends credibility to the policy's direct impact.

Even if participating schools did increase the enrolment of disadvantaged children, the overall success of the policy depends on the number of schools participating. Many private schools, however, did not enroll any students under the reservation policy (Sarin et al., 2015). There are various reasons why some private schools opt not to participate in the policy, with financial incentives being a potential major deterrent. According to the policy's rules, private schools with fees exceeding the government's per-child expenditure only receive reimbursement equivalent to that expenditure, rather than their actual fees (see page 15). This setup might discourage 'high-fee' private schools from participating, as they would be unable to recover their full costs. Similarly, 'low-fee' private schools, which charge fees that are below or on par with the government's per-child expenditure, might have little financial incentive to participate. These schools would only be reimbursed an amount they already charge (presumably low), which does not provide a significant benefit.

Moreover, if private schools were already admitting disadvantaged children up to the stipulated 25% quota, they might have little incentive to offer those seats for free under the policy. This is especially true if the financial costs of participating in the policy outweigh the benefits. Indeed these schools were previously filling those seats with disadvantaged children who were paying fees. These schools might also not increase the total number of seats for disadvantaged children as an expansion of seats requires additional resources and infrastructure. Additionally, increasing the proportion of disadvantaged students might not appeal to parents from non-disadvantaged groups which might potentially affect the reputation of private schools. I investigate this in Section 1.5.3.

While understanding the trends in the enrolment numbers of disadvantaged groups across different school types provides a broad picture, it might not convey the complete story. A more refined approach is to compare the trends in the average share, which is the proportion of enrolment of the disadvantaged groups relative to the total enrolment. There might be an increase in pure enrolment numbers, but if the overall school population grows at a faster rate, disadvantaged groups' share might still be declining. Moreover, an increasing share indicates not just increased enrolment, but that the growth rate of enrolment of the disadvantaged groups is higher than that of non-disadvantaged groups.

For comparison of disadvantaged children's enrolment trends, I focus on grade 1, which is the typical entry point for primary education. Following RTE, private schools were mandated to reserve seats specifically at this entry level. Once students secured these reserved spots, they would then continue their schooling in subsequent grades

without the need for further reservations. The pre-RTE period means all academic years from 2005-06 to 2009-10, while post-RTE period means all academic years from 2010-11 to 2014-15 such that the enrolment is averaged over a period of 5 years.

1.5.1 Government vs private schools

At the national level, government schools on average are enrolling fewer children in grade 1 in the post-RTE period relative to the pre-RTE period (Table 1.2). However, the average share of disadvantaged groups, which is the ratio of the enrolment of disadvantaged groups to enrolment of all children in grade 1, is increasing in government schools. This is because the decline in the enrolment of disadvantaged groups is less than the decline in total enrolment.

In private schools, despite the increase in the number of schools, the average enrolment in grade 1 remains more or less the same in the post-RTE period. In fact, the average enrolment increases for disadvantaged groups. This means school size has not increased in private schools but per school, there are more disadvantaged children after RTE. As a result, the average share of disadvantaged groups also increases. However, this cannot be taken as evidence of the effect of the reservation policy because the trends in the enrolment of disadvantaged groups between private and government schools were different even before RTE (see Figure 1.A.1).

Table 1.2. Enrolment in grade 1 in government and private schools

	Pre-RTE	Post-RTE
Government schools		
Average enrolment	29.63	20.80
Average enrolment of disadvantaged group	18.59	13.99
Average share of disadvantaged group	0.61	0.65
Observations	3,407,045	3,719,140
Private schools		
Average enrolment	40.15	40.71
Average enrolment of disadvantaged group	15.88	18.03
Average share of disadvantaged group	0.38	0.43
Observations	538,611	794,277

Notes: Haryana, Mizoram, Tamil Nadu do not enrol SC, ST, OBC or children with special needs under RTE. Jharkhand, Meghalaya and Tripura only include SC and ST from BPL families. No official definition of disadvantaged group is available for Sikkim. Schools from these states are therefore, excluded.

Given the heterogeneity across Indian states in terms of the reimbursement rates, and participation and enrolment under the reservation policy, it is important to see what happened at the state level. Therefore, I measure the changes in the average enrolment and share of disadvantaged groups between pre and post-RTE periods in the largest 20 states of India. In all 20 states, there is a positive change in the average enrolment of disadvantaged groups in private schools (Figure 1.7). In government schools, the change in the average enrolment of disadvantaged groups is negative in all states.

Furthermore, Figure 1.8 shows that there is a strong correlation between the change in the average share of disadvantaged groups in government schools and that in private schools. Most states that witnessed an increase in the share of disadvantaged groups in private schools witnessed a similar increase in their share in government schools. This could be because the decrease in government school enrolment was larger among non-disadvantaged groups, such that the share of disadvantaged groups actually increased despite a decrease in their enrolment numbers. Whereas in private schools, the increased share of disadvantaged groups can be attributed to their increased enrolment. The change in the share of disadvantaged groups is also more spread out across states. This can be explained by the large variation in the change in the average enrolment of all children across states, as shown in Figure 1.9.

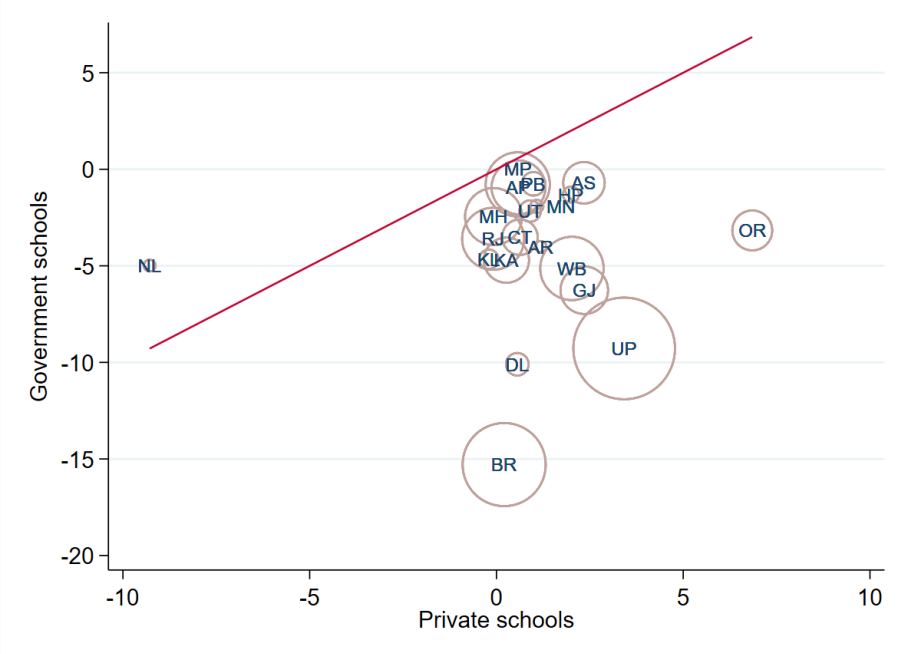
The state-level trends are similar to the national-level trends for most states. The average enrolment of disadvantaged groups post-RTE increases in private schools and decreases in government schools, while the average share increases across both categories in most states. Figure 1.A.2 shows the population of children aged 6 from SC and ST categories as a percentage of the total SC, ST population in the top 20 states. I observe that in almost all states, the population of these children, who would potentially be enrolled in grade 1, decreases between 2001 and 2011. However, the percentage of these children attending schools increases between 2001 and 2011 in all states except Andhra Pradesh, Delhi, Kerala and Rajasthan (Figure 1.A.3). This means that an increase in the enrolment of SC/ST children is not due to a higher share of 6 years olds. It is in fact because there are fewer SC/ST out-of-school children.

A large number of children in India are also enrolled in unrecognized private schools which are not included in DISE. At the same time, there are many children enrolled in private aided[12] schools. When I examine the enrolment data from National Sample Survey of India, I find that about 10% of primary school-aged children were enrolled in private-aided schools in 2014-15. However, I do not consider private-aided schools

[12]Private-aided schools are partly funded by the government and partly managed by a private committee of individuals.

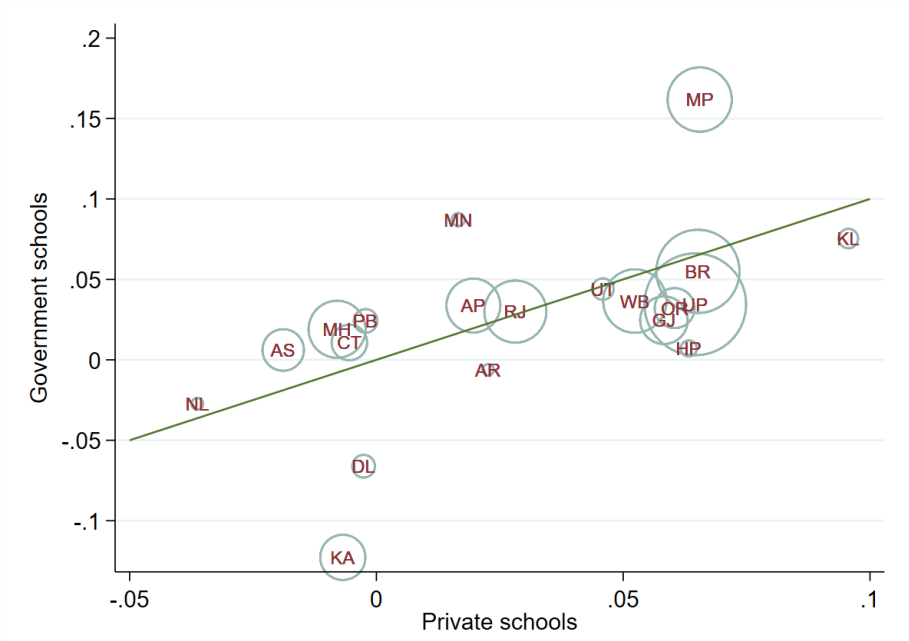
in this chapter. Therefore, even though the number of schools has been increasing and more children are attending schools than before, the overall enrolment is still under reported in Table 1.2.

Figure 1.7. Change in the average enrolment of disadvantaged groups across government and private schools



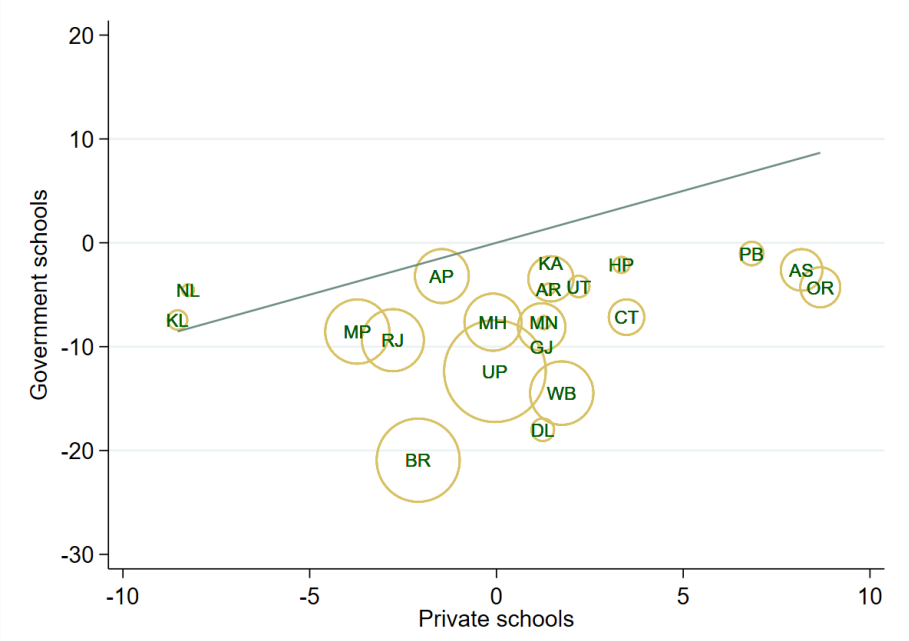
Note: The numbers are weighted by the total primary enrolment in each state. So a larger bubble implies a larger state.

Figure 1.8. Change in the average share of disadvantaged groups across government and private schools



Note: The numbers are weighted by the total primary enrolment in each state. So a larger bubble implies a larger state.

Figure 1.9. Change in the average enrolment of all children across government and private schools



Note: The numbers are weighted by the total primary enrolment in each state. So a larger bubble implies a larger state.

Private schools have clearly outperformed government schools in terms of increasing the enrolment of disadvantaged groups after the RTE Act. This is in spite of free government school education. Studies on private schooling in India have observed an upward trend in private school enrolment predominantly for children from socially and economically better-off families. Based on my findings, post the implementation of the RTE Act, even disadvantaged children showed a similar shift towards private schools. However, the shift from government to private schools was stronger among the non-disadvantaged groups, which explains why the share of disadvantaged groups increases in government schools despite a decline in the enrolment.

1.5.2 RTE vs non-RTE schools

In this section, I compare the changes in the average enrolment and average share of disadvantaged groups in RTE and non-RTE schools within the private sector. RTE schools are defined as those private schools which reported to have enrolled at least 1 student under the reservation policy in any year after 2009. Non-RTE schools are those that reported to have never enrolled any student under the policy after 2009. I find that 39% of private schools are RTE and 61% of schools are non-RTE in the data. This means that 61% of all private schools reported no enrolment under the reservation policy even 7 years after its implementation.

Table 1.3 reports the change in the average enrolment and share of disadvantaged groups in RTE and non-RTE schools. Private schools which are present only in the pre-RTE period or only in the post-RTE period have been removed for consistency. However, a complete version with all schools is given in Table 1.A.1, which shows similar results. In RTE schools, the average enrolment of all children in grade 1 is almost the same in the post-RTE period but the average enrolment of disadvantaged groups increased (Table 1.3). Subsequently, their share also increased. In non-RTE schools, the average enrolment of all children in grade 1 increased in the post-RTE period, and the increase is in fact higher for disadvantaged groups. As a result, their share also increased. The increase in both enrolment and share is higher in non-RTE schools, which suggests that the increased enrolment of disadvantaged groups in private schools was not driven by the reservation policy.

Table 1.3. Enrolment in grade 1 in RTE and non-RTE schools

	Pre-RTE	Post-RTE
RTE schools		
Average enrolment	36.81	36.49
Average enrolment of disadvantaged groups	12.33	13.52
Average share of disadvantaged groups	0.32	0.37
Observations	176,433	247,669
Non-RTE schools		
Average enrolment	44.54	46.23
Average enrolment of disadvantaged groups	19.79	23.29
Average share of disadvantaged groups	0.43	0.50
Observations	266,936	259,340

Notes: Haryana, Mizoram, Tamil Nadu do not enrol SC, ST, OBC or children with special needs under RTE. Jharkhand, Meghalaya and Tripura only include SC and ST from BPL families. No official definition of disadvantaged groups is available for Sikkim. Schools from these states are therefore excluded.

On comparing the change in the average enrolment of disadvantaged groups in RTE and non-RTE schools in the top 20 states, I find that the trend is very similar across both categories. In Figure 1.10, the majority of the states are close to the 45-degree line. Figure 1.10 suggests that the increase in average enrolment of disadvantaged groups is not systematically higher in schools that participated in the reservation policy.

Table 1.A.2 reports the average enrolment of disadvantaged groups in the pre and post-RTE periods as well the change in each of the 20 states. In states such as Delhi, Karnataka and Maharashtra, the average enrolment of disadvantaged groups increased in RTE schools but declined in non-RTE schools. In Gujarat, Odisha, Uttarakhand and West Bengal, the average enrolment enrolment of disadvantaged groups increased in both RTE and non-RTE schools but the increase was higher in RTE schools. In contrast, Assam and Uttar Pradesh witnessed a higher increase in the average enrolment of disadvantaged groups in non-RTE schools. In Bihar, Kerala and Manipur, there was no change in the average enrolment of disadvantaged groups in RTE and non-RTE schools as shown in Table 1.A.2.

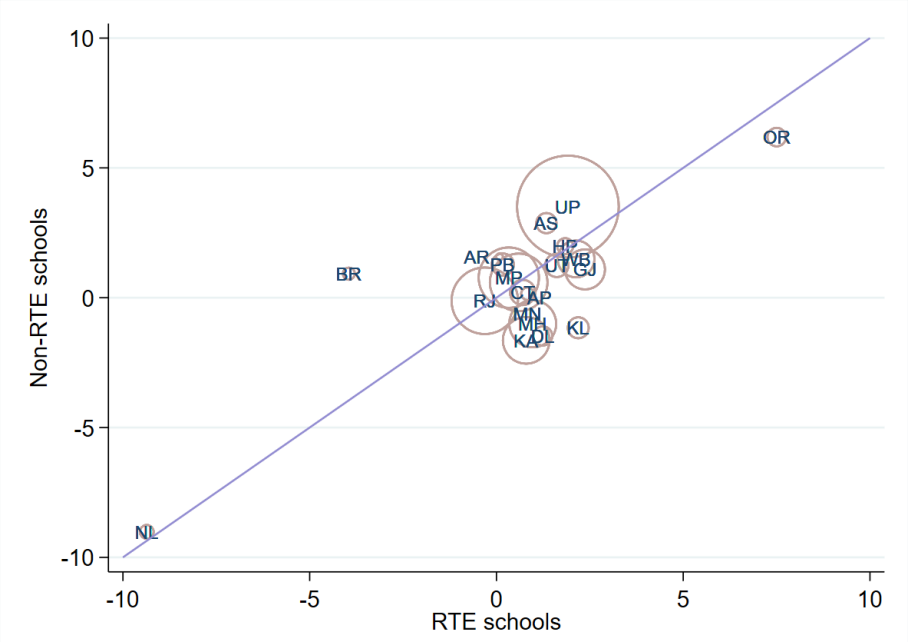
The increase in the average share of disadvantaged groups is higher in RTE schools compared to non-RTE schools in states such as Gujarat, Himachal Pradesh, Odisha and West Bengal (Figure 1.11). In Chhattisgarh and Manipur, the average share increases in RTE schools but falls in non-RTE schools. Table 1.A.3 reports the average share of disadvantaged groups in the pre and post-RTE periods and the difference in all 20 states.

In states such as Assam, Bihar, Delhi and Karnataka, the increase in the average share of disadvantaged groups in RTE schools is insignificant.

Compared to the enrolment of disadvantaged groups, the change in their average share in RTE and non-RTE schools is more scattered across states (Figure 1.11). This is due to the fact that the change in the average enrolment of all children in grade 1 is drastically different across states (Figure 1.12). However, the majority of the states witness a one-to-one change in the average enrolment of all children across both categories of schools. In the remaining states, the increase in the share of disadvantaged groups is almost equal between RTE and non-RTE schools.

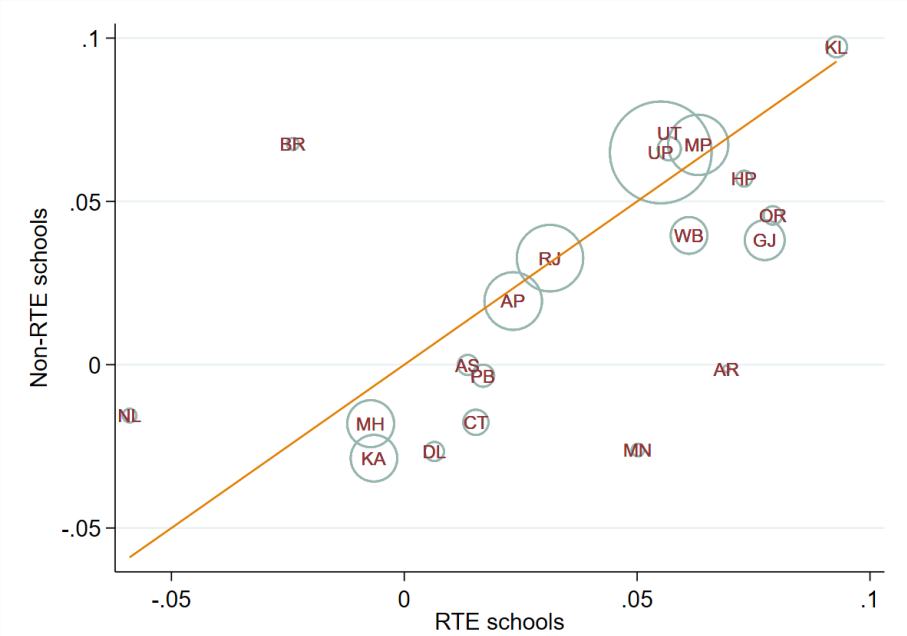
Gujarat, Odisha and West Bengal are the only three states where RTE schools outperformed non-RTE schools in terms of both increased enrolment and share of disadvantaged groups. Even in the states of Madhya Pradesh and Rajasthan, where the proportion of RTE schools was the highest, RTE schools had a relatively lower average share of disadvantaged groups post-RTE. In Delhi, Karnataka and Maharashtra, while the average enrolment of disadvantaged groups increased in RTE schools only, the average share did not. This is because, in these states, the increase in average enrolment of all children was higher than the increase in the enrolment of disadvantaged groups (Figure 1.12).

Figure 1.10. Change in the average enrolment of disadvantaged groups across RTE and non-RTE schools



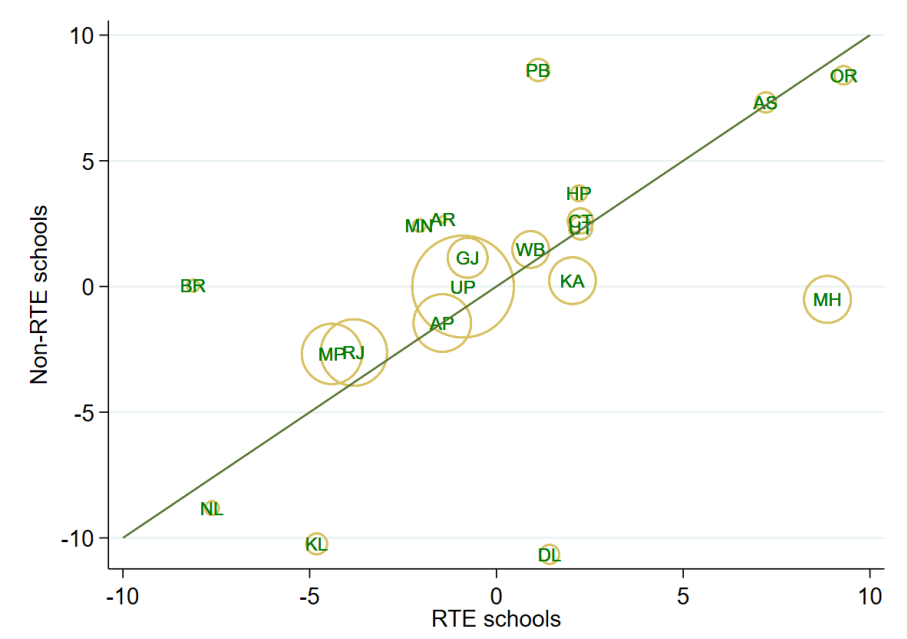
Note: The numbers are weighted by the total primary enrolment in each state. So a larger bubble implies a larger state.

Figure 1.11. Change in the average share of disadvantaged groups across RTE and non-RTE schools



Note: The numbers are weighted by the total primary enrolment in each state. So a larger bubble implies a larger state.

Figure 1.12. Change in the average enrolment of all children across RTE and non-RTE schools



Note: The numbers are weighted by the total primary enrolment in each state. So a larger bubble implies a larger state.

Results show that the increased private school enrolment of disadvantaged children did not just pertain to schools enrolling students under the reservation policy. In fact, the increase was larger in schools that did not enrol any student under the policy. This suggests that subsidized private education did not drive the increased private school enrolment of disadvantaged children post-RTE.

1.5.3 Schools above 25% quota vs schools below 25% quota

The increase in enrolment of disadvantaged children in private schools could have been a result of a surge in demand from disadvantaged groups who had the means to pay the fees. However, the success of these groups securing admission in private schools depends on the availability of places. Private schools with a pre-existing high share of disadvantaged children might find little reason to significantly expand their intake post the RTE Act.

A striking observation is that even before the RTE Act was implemented, on average, nearly 40% of places in grade 1 were filled by disadvantaged groups in private schools (Figure 1.13). Since all children belonging to disadvantaged groups are eligible for free places under the reservation policy, if private schools were already meeting the 25% cut-off, they might not have a financial incentive to enrol these children for free. In fact, they might have a disincentive to do so if their per-child fee is lower than the reimbursement rate set by the government (see page 15). Therefore, in principle, after 2009, the share of disadvantaged groups in grade 1 would not increase much in schools that enrolled at least 25% students from disadvantaged groups in the pre-RTE period.

To better understand these dynamics, I classify private schools based on their share of disadvantaged children relative to the 25% quota before the RTE Act. Specifically, I compare the enrolment trends of disadvantaged children between two categories of schools: those that had already met the 25% quota and those that were below this benchmark.

Figure 1.13. Average share of disadvantaged groups in grade 1

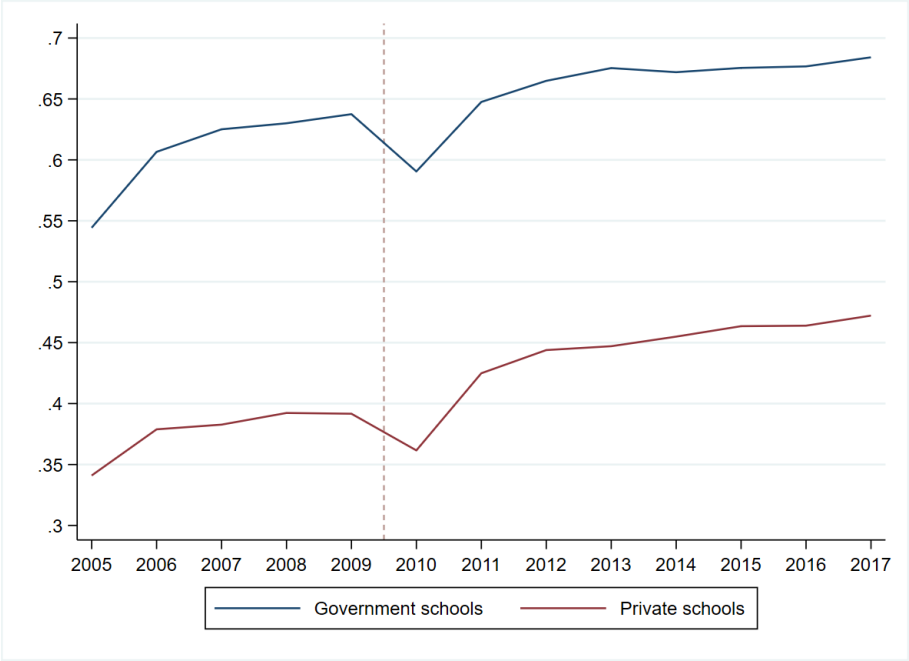


Table 1.4 shows the change in enrolment in grade 1 in private schools above and below the 25% quota. I define schools above the quota to be those that had at least 25% disadvantaged children in grade 1 in any year before 2010, while schools below the quota had less than 25% disadvantaged children in all years before 2010. Schools that exist only in the pre-RTE period or only in the post-RTE period have been removed. I observe that in schools below the quota, there is a 15 percentage points increase in the share of disadvantaged groups in the post-RTE period, whereas, in schools above the quota, the increase in the share is only 3 percentage points.

Table 1.4. Private school enrolment in grade 1 based on the pre-RTE share of disadvantaged groups

	Pre-RTE	Post-RTE
More than 25%		
Average enrolment	41.08	40.96
Average enrolment of disadvantaged groups	22.31	23.75
Average share of disadvantaged groups	0.52	0.55
Observations	318,777	336,141
Less than 25%		
Average enrolment	42.46	42.45
Average enrolment of disadvantaged groups	2.79	8.39
Average share of disadvantaged groups	0.06	0.21
Observations	124,592	173,225

Notes: Haryana, Mizoram, Tamil Nadu do not enrol SC, ST, OBC or children with special needs under RTE. Jharkhand, Meghalaya and Tripura only include SC and ST from BPL families. No official definition of disadvantaged groups is available for Sikkim. Schools from these states are therefore excluded.

From Table 1.3 it is clear that the reservation policy was not directly responsible for the increase in the enrolment of disadvantaged groups in private schools. However, the descriptive evidence in Table 1.4 suggests that schools that had a low pre-RTE share of disadvantaged groups did offer relatively more places to these children following the implementation of the policy.

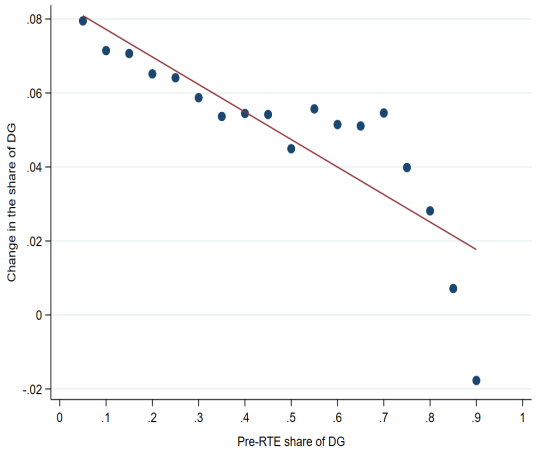
This is true even when I divide the schools into narrower intervals based on their pre-RTE share of disadvantaged groups (Figure 1.14a). I find that there exists a monotonic negative correlation between the pre-RTE share of disadvantaged groups and the change in their post-RTE share. In schools with 10% disadvantaged children in the pre-RTE period, the share increased by around 8 percentage points in the post-RTE period. Whereas, in schools with a pre-RTE share of 85%, the share increased by only 1 percentage point in the post-RTE period.

To see if this negative correlation existed in the years before RTE, I look at the change in the share of disadvantaged groups first between 2005 and 2007 (Figure 1.14b), and then between 2007 and 2009 (Figure 1.A.4). In both figures, I find that a lower pre-RTE share of disadvantaged groups is associated with a lower increase in this share upto a certain point, after which the relationship is non-linear. This implies that before the RTE Act was implemented, schools that offered relatively fewer places to disadvantaged children, continued to offer them fewer places. Whereas, after the policy was

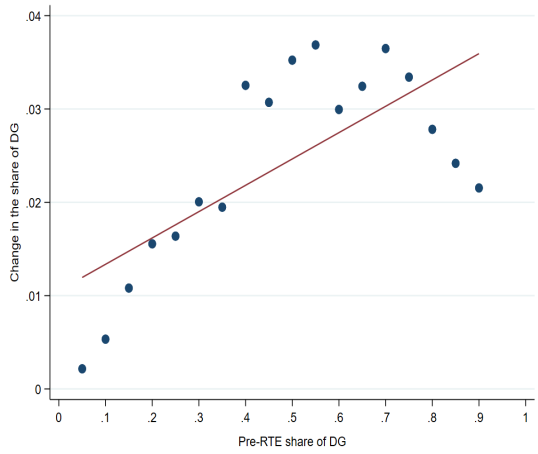
implemented, they offered them relatively more places compared to schools that admitted more of these children before the policy.

Figure 1.14. Change in the share of disadvantaged groups

(a) After RTE



(b) Before RTE



Notes: The x-axis denotes the average share of disadvantaged groups in schools from 2005 to 2009. Figure 1.14a shows the average change in the share from 2005 to 2014 on the y-axis, while Figure 1.14b shows the average change in the share from 2005 to 2007 on the y-axis.

I find that the increase in the enrolment of disadvantaged children was largely in private schools that were below the 25% quota before RTE was implemented. This means that schools that already catered to a significant portion of disadvantaged children prior to the policy's enactment did not see a marked increase in their enrolment.

1.5.4 General equilibrium effects

Private schools' response to the RTE reservation policy could also be largely influenced by the availability of government schools and other private schools nearby. A major provision of the RTE Act was the construction of government schools in areas where no such school previously existed. As seen in Figure 1.1, there has been a steady increase in the number of government and private schools post-RTE. Therefore, the availability of new schools in close proximity could significantly impact the dynamics of school enrolment and the ability of private schools to meet the stipulated quota for disadvantaged groups under the reservation policy.

The opening of new schools, both government and private, increases competition and school choice for families. This could lead to a redistribution of students across schools. If new schools are more attractive or conveniently located, they may draw

students away from existing schools, thus affecting those schools' ability to meet quotas. Subsequently, if the pool of disadvantaged groups is now distributed among a larger number of schools, individual private schools may struggle to enroll enough eligible students to meet the quota.

Additionally, the construction of new private schools could draw students away from government schools. If new private schools are perceived as high-quality, they might attract more students, including those from disadvantaged backgrounds who would otherwise attend government schools. However, if there are many private schools within close proximity, increased school choice could result in some seats remaining unfilled in individual private schools under the reservation policy. On the other hand, if there are only a few private schools nearby competing with existing government schools, there could be oversubscription to free seats under the reservation policy. This could result in many disadvantaged students not getting a free seat under the policy and ending up in government schools.

The opening of new schools also involves resource allocation and infrastructure development. In areas where resources and infrastructure are limited, the opening of new schools could strain these resources further, impacting the quality of education and the ability of schools to meet quotas. Furthermore, economic factors such as the ability of families to afford private school fees or the availability of transportation to schools, also plays a crucial role in determining which schools children attend.

The general equilibrium effects of the construction of new government and private schools on the implementation of quotas is multifaceted and highly dependent on local contexts, including the number and quality of schools, demographic factors, and socioeconomic conditions. This complexity necessitates careful planning by policymakers and continuous monitoring by government authorities to ensure that the RTE Act's reservation policy achieves its intended goals.

1.6 Effect of RTE on the share of disadvantaged groups

Analyzing the post-RTE trends, it becomes evident that private schools, which were previously under the stipulated quota, witnessed a noticeable increase in the enrolment and share of disadvantaged children. However, merely examining these trends does not conclusively establish the RTE Act's role in enhancing primary school enrolment of disadvantaged children.

To get a more robust understanding of RTE's impact, I incorporate a difference-in-

differences model that compares the share of disadvantaged children in schools previously below the 25% quota with those above it, both before and after RTE's implementation. I hypothesise that schools that were already at the 25% quote had no incentive to make free places available, whereas those with lower disadvantaged enrolment were more likely to offer free places to meet the quota.

I first include state fixed effects in the model which accounts for a large number of time-invariant unobservables that are constant within a state. This controls for the variation in the implementation of the RTE Act across states. Then I include school fixed effects, which account for certain time-invariant characteristics specific to schools, making the estimates more consistent and reliable. It also focuses the analysis on within-school changes, offering a clearer picture of RTE's impact.

I further incorporate a triple-difference model comparing changes differentially between schools participating and not participating in the reservation policy. This model offers a more granular perspective, shedding light on whether the increased enrolment in schools previously below the quota was directly influenced by the reservation policy.

1.6.1 A difference-in-differences estimation

To find stronger evidence of the role of the RTE Act in increasing the share of disadvantaged groups, I first use a difference-in-differences strategy. I define the 'treatment' group as private schools that enrolled less than 25% students from disadvantaged groups in all years before 2010 (schools below the quota). The 'control' group includes private schools that enrolled at least 25% students from disadvantaged groups in any year before 2010 (schools above the quota).

As shown in Table 1.4, the average number of students enrolled in grade 1 across both groups is quite close. In fact, there is no significant change in the average enrolment in both groups post-RTE. So, schools that enrolled at least 25% students from disadvantaged groups in the pre-RTE period is a plausible control group. I find that 34% of schools in the sample are in the treatment group and 66% of schools are in the control group.

The baseline characteristics of the treatment and control group are shown in Table 1.5. Schools in the control group were 8 percentage points more likely to be in rural areas compared to treatment schools before RTE. This makes sense as the control group had a higher share of disadvantaged children, many of whom live in rural areas. The average school size, which is measured by the number of students enrolled in grades 1-8, was not very different across both groups. However, the treatment group was more

likely to have upper primary (1-8) and higher secondary grades (1-12). Furthermore, schools in the treatment group were more likely to have pre-primary grades.

Table 1.5. Baseline characteristics of the Treatment and Control groups

	Treatment	Control	Difference
Area			
Rural	0.57	0.66	-0.08
			(0.002)
Average school size	218	211	7
			(0.677)
School category			
Lower primary only	0.41	0.52	-0.12
			(0.002)
Up to Upper primary	0.42	0.37	0.04
			(0.002)
Up to Higher secondary	0.17	0.10	0.07
			(0.001)
Pre-primary grades			
Available	0.43	0.31	0.12
			(0.002)

Notes: Mean values are averaged over 5 years (2005-2009). Results are based on a paired sample t-test. Standard errors of the differences are reported in parentheses.

First, I undertake a simple difference-in-differences estimation to see if the post-RTE share of disadvantaged groups significantly increased for the treatment group. I estimate the following model:

$$SDG_{iy} = \beta_0 + \beta_1 (DG < 25p)_i + \beta_2 Post_y + \beta_3 (DG < 25p)_i \cdot Post_y + \beta_4 X_{iy} + \alpha_i + \varepsilon_{iy} \tag{1.1}$$

SDG_{iy} is the share of disadvantaged groups in grade 1 in private school i and academic year y. $(DG < 25p)_i$ is the treatment dummy that equals 1 for schools that enrol less than 25% students from disadvantaged groups in grade 1 in the pre-RTE period. $Post_y$ is a dummy variable that equals 1 for the post-RTE period. $(DG < 25p)_i \cdot Post_y$ is the interaction dummy, such that the coefficient β_3 captures the difference-in-differences effect. X_{iy} is the vector of control variables, α_i captures the state/school fixed effects and ε_{iy} is the error term.

The results are presented in Table 1.6. Column (1) is the simple difference-in-

differences model that is equivalent to the result in Table 1.4. The increase in the share of disadvantaged groups in the post-RTE period was more in the treatment group by 12 percentage points compared to the control group. Even after including control variables and state dummies (column 3), the DID estimate remains positive and significant, although the magnitude becomes slightly smaller.

In column (4), I estimate a model with school fixed effects where estimates show the variation within private schools over time. Therefore, time invarying factors including the treatment dummy drop out because the treatment status is fixed for each school across the two time periods. The coefficient on the interaction term becomes even smaller but remains positive and highly significant. I find that the increase in the share of disadvantaged groups in the post-RTE period was 6 percentage points more in the treatment group compared to the control group.

Table 1.6. Effect of RTE on the share of disadvantaged groups

	(1)	(2)	(3)	(4)
VARIABLES				
DG<25p	-0.454***	-0.428***	-0.285***	
	(0.002)	0.002)	(0.002)	
Post	0.032***	0.043***	0.026***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
$(DG < 25p) \times Post$	0.116***	0.114***	0.092***	0.061***
	(0.002)	(0.002)	(0.002)	(0.001)
Constant	0.517***	0.515***	0.232***	0.362***
	(0.002)	(0.004)	(0.009)	(0.004)
Observations	952,715	946,199	946,199	946,217
R-squared	0.27	0.30	0.47	0.71
Controls	No	Yes	Yes	Yes
State FE	No	No	Yes	No
School FE	No	No	No	Yes

Notes: Dependent variable is the share of disadvantaged groups in grade 1. Control variables included are dummies for rural/urban, school size, school category (primary, upper primary etc.) and availability of pre-primary grades. Standard errors are clustered at the village level in columns 1-3 and at the school level in column 4. *** p<0.01, ** p<0.05, * p<0.1

1.6.2 A triple difference estimation

While there is evidence to believe that the RTE Act encouraged some schools to offer more places to disadvantaged children, to see if the increase in their share is driven

by the reservation policy, I compare the treatment effect between RTE and non-RTE schools. RTE schools enrol at least 1 student under the reservation policy in any of the years after 2009, whereas non-RTE schools never enrol any student under the policy. Specifically, I estimate a triple difference model of the following form:

$$SDG_{iy} = \beta_0 + \beta_1(DG < 25p)_i + \beta_2 Post_y + \beta_3 RTE_i + \beta_4(DG < 25p)_i \cdot Post_y + \beta_5 RTE_i \cdot Post_y + \beta_6(DG < 25p)_i \cdot RTE_i + \beta_7(DG < 25p)_i \cdot RTE_i \cdot Post_y + \beta_8 X_{iy} + \alpha_i + \varepsilon_{iy} \tag{1.2}$$

The equation is similar to the simple DID model except now I introduce a dummy variable for RTE schools and its interaction with the treatment and time dummy. RTE_i takes the value of 1 for private schools which enrol at least 1 student under the reservation policy in any year after 2009 and 0 for schools which never enrol any student under the policy after 2009. β_4 shows the change in the share of disadvantaged children in non-RTE treatment group relative to non-RTE control group. $RTE_i \cdot Post_y$ is the interaction between the RTE dummy and time dummy, such that β_5 shows how the share of disadvantaged groups changes in RTE schools relative to non-RTE schools, both in the control group.

$(DG < 25p)_i \cdot RTE_i$ is the interaction between the RTE dummy and the treatment dummy. β_6 shows the pre-RTE difference in the share of disadvantaged groups between RTE schools in the treatment group and RTE schools in the control group, relative to the pre-RTE difference between non-RTE schools in the treatment group and non-RTE schools in the control group. Finally, $(DG < 25p)_i \cdot RTE_i \cdot Post_y$ is the interaction between the RTE dummy, the treatment dummy and the time dummy. The coefficient β_7 captures the triple difference effect.

In the treatment group, 50% of schools are RTE schools whereas in the control group, only 43% of schools are RTE schools. This means that schools that were below the 25% quota were more likely to participate in the reservation policy. The results of the triple difference estimation are given in Table 1.7. Firstly, I find that the treatment effect exists for non-RTE schools as well. β_4 in the model is positive and significant. In columns (1) and (2), the increase in the share of disadvantaged groups in the post-RTE period was 12 percentage points more in the non-RTE treatment group compared to the non-RTE control group. Including state fixed effects (column 3) reduces the coefficient to around 10 percentage points but the level of significance does not change.

In the model with school fixed effects (column 4), the coefficient further reduces to 4.8 percentage points but remains significant. Therefore the treatment effect also

persists in schools that did not give free places to disadvantaged children. Nonetheless, in column (4), the triple difference estimate is positive and significant. The increase in the share of disadvantaged groups in the post-RTE period was higher by 2.4 percentage points in RTE treatment schools compared to non-RTE treatment schools. This implies that the treatment effect was higher among RTE schools.

The results show that while non-RTE schools increased the intake of disadvantaged children following the implementation of the policy, they did not offer them free places as the policy required. So, while non-RTE schools below the quota reserved more places for disadvantaged groups after 2009, they did charge some amount of fee from them. Nonetheless, the increase in the number of places was higher in schools that offered some free places under the policy. Therefore, I conclude that the effect of the RTE Act on the enrolment of disadvantaged groups in private schools was largely 'indirect'. The indirect effect was roughly 6 percentage points as shown in Table 1.6 (column 4). However, the 2.4 percentage points higher increase in the share pertaining to RTE schools (column 4 in Table 1.7) was a 'direct' effect of the reservation policy.

Table 1.7. Differential effect of RTE in schools participating in the reservation policy

VARIABLES	(1)	(2)	(3)	(4)
DG<25p	-0.508***	-0.480***	-0.287***	
	(0.003)	(0.003)	(0.003)	
Post	0.049***	0.049***	0.024***	0.021***
	(0.002)	(0.002)	(0.002)	(0.001)
RTE	-0.125***	-0.097***	0.004	
	(0.004)	(0.004)	(0.003)	
$(DG < 25p) \times Post$	0.123***	0.120***	0.099***	0.049***
	(0.004)	(0.004)	(0.003)	(0.002)
$RTE \times Post$	-0.016***	-0.004	0.004	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
$(DG < 25p) \times RTE$	0.140***	0.121***	0.004	
	(0.003)	(0.003)	(0.003)	
$(DG < 25p) \times RTE \times Post$	-0.030***	-0.030***	-0.014***	0.024***
	(0.004)	(0.004)	(0.003)	(0.002)
Constant	0.564***	0.543***	0.230***	0.362***
	(0.003)	(0.005)	(0.009)	(0.004)
Observations	950,359	943,844	943,844	943,861
R-squared	0.29	0.31	0.47	0.71
Controls	No	Yes	Yes	Yes
State FE	No	No	Yes	No
School FE	No	No	No	Yes

Notes: Dependent variable is the share of disadvantaged groups in grade 1. Control variables included are dummies for rural/urban, school size, school category (primary, upper primary etc.) and availability of pre-primary grades. Standard errors are clustered at the village level in columns 1-3 and at the school level in column 4. *** p<0.01, ** p<0.05, * p<0.1

1.6.3 Mechanisms

Results from the previous section indicate that students from disadvantaged groups were being offered more places in private schools after the RTE Act was introduced, especially in schools that were previously below the quota. In Section 1.7 I show that this trend was much less evident before RTE and was predominantly observed in the post-RTE period.

Results also show that the increased share of disadvantaged groups in the post-RTE period was not directly through the reservation policy. This suggests that most private schools were substituting disadvantaged children for RTE children (applying for free seats under the policy) in grade 1. If that is true, RTE enrolment in grade 1 would explain very little variation in the size of disadvantaged groups. To test this, I estimate the following log-log model:

$$LnDGE_{iy} = \beta_0 + \beta_1 LnDGE_{iy-1} + \beta_2 LnERTE_{iy} + \beta_3 X_{iy} + \alpha_i + \delta_y + \varepsilon_{iy} \tag{1.3}$$

$LnDGE_{iy}$ is the log of the number of students from disadvantaged groups enrolled in grade 1 in school i and academic year y. I control for the existing number of disadvantaged children in the school by including a lagged dependent variable. This is because as students move from one grade to the next, the number of students in year y will depend on the number of students in year $y-1$. $LnDGE_{iy-1}$ denotes the log of the number of students from disadvantaged groups enrolled in grade 1 in school i and academic year $y-1$.

$LnERTE_{iy}$ is the log of the number of students enrolled under the reservation policy in grade 1 in school i and academic year y, and is the variable of interest. In DISE, from 2010 to 2012, schools are asked how many students they enrol under the policy in grade 1. Whereas, from 2013, schools are asked how many students they enrol under the policy at the 'entry level'. Even though the entry level is typically grade 1, as per the RTE Act, it could also be a pre-primary grade. However, DISE does not collect enrolment data for pre-primary grades and only asks whether pre-primary grades are available in the school. Using this information, I remove schools where pre-primary grades were available from 2013 to 2017. This makes the independent variable $LnERTE_{iy}$ consistent across all years. X_{iy} is the vector of control variables. α_i captures the state/school fixed effects, δ_y captures the year fixed effects and ε_{iy} is the error term.

The results are presented in Table 1.8. In column (1), a 10% increase in RTE enrolment is associated with a 1.6% increase in the enrolment of disadvantaged groups in grade 1. The coefficient remains the same even when I include school fixed effects

(column 5). The results indicate that the majority of students who were enrolled under the RTE reservation policy did not contribute to the admission of disadvantaged groups, even though all of these disadvantaged children were eligible for free seats. This means that private schools were substituting fee-paying disadvantaged children for disadvantaged children eligible for subsidized education under the reservation policy.

However, as shown in Table 1.7, I also find that RTE schools had a larger increase in the share of disadvantaged children after 2009. This suggests that RTE schools were not substituting fee-paying disadvantaged children for children enrolled under the reservation policy or vice-versa. The higher share in the post-RTE period was due to RTE schools taking up students both directly through the policy and otherwise.

Table 1.8. Effect of RTE enrolment on the enrolment of disadvantaged groups

VARIABLES	(1)	(2)	(3)	(4)	(5)
Lagged log enrolment	0.656***	0.611***	0.608***	0.520***	
	(0.003)	(0.003)	(0.003)	(0.004)	
Log RTE enrolment	0.164***	0.123***	0.128***	0.140***	0.165***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
Constant	0.410***	0.085***	-0.065*	-0.535	0.756***
	(0.008)	(0.033)	(0.035)	(0.336)	(0.070)
Observations	95,927	95,222	95,222	95,222	127,268
R-squared	0.50	0.52	0.52	0.55	0.88
Controls	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	No
School FE	No	No	No	No	Yes

Notes: Dependent variable is the log enrolment of disadvantaged groups in grade 1. Control variables included are dummies for rural/urban, school size, school category (primary, upper primary etc.) and availability of pre-primary grades. Standard errors are clustered at the village level in columns 1-5 and at the school level in column 6. According to Angrist and Pischke (2009), a model with lagged dependent variable is similar to a model with fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

1.7 Robustness checks

The increase in enrolment of disadvantaged groups in private schools is not driven by free admission under the reservation policy. However, it does seem to be indirectly influenced by the RTE Act. To further validate this, I undertake three robustness checks. First, I check if the parallel trends assumption holds both graphically and using a formal test. In particular, I look at the pre-RTE trends across the treatment (schools below the 25% quota) and control (schools above the 25% quota) groups in terms of their share of disadvantaged children. I find that even though the difference in the share of disadvantaged children between treatment and control groups was not zero before RTE, it was much smaller compared to the post-RTE period.

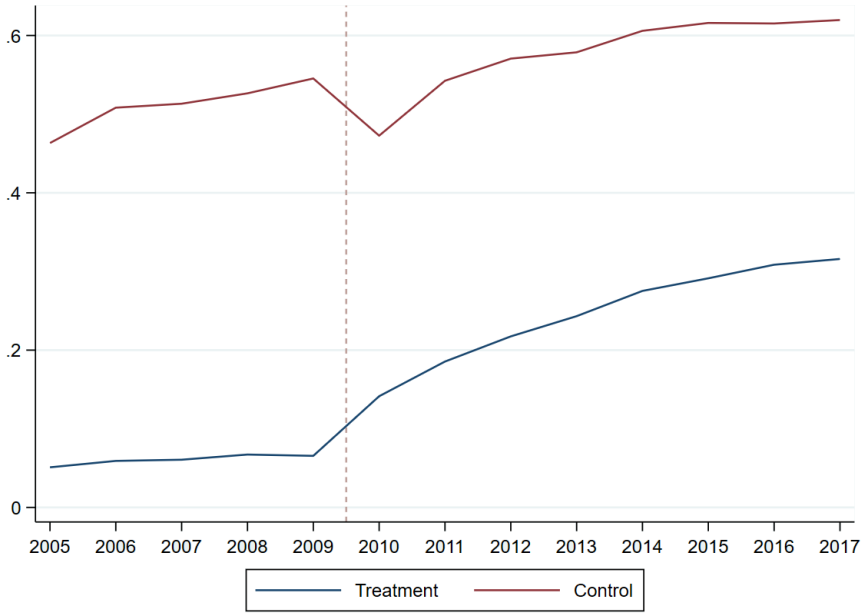
Second, I estimate a triple-difference model, where I compare the treatment and control groups across states with differential treatment. Here I first compare the state of Jammu and Kashmir where the RTE Act was not implemented, with the rest of the states. Then with Jammu and Kashmir, I include states which had few private schools enrolling any students under the reservation policy. I find that the differential effect was larger among states where the RTE Act was implemented and where there was more participation in the reservation policy.

Finally, I show that the differential effect on the share of disadvantaged children between the treatment and control groups is not driven by a differential effect on total enrolment. For this, I estimate a DID model where the dependent variable is total enrolment in grade 1. I do not find that the change in total enrolment was significantly different in treatment schools relative to control schools. This implies that the increase in the share of disadvantaged children was in fact driven by an increase in the their enrolment.

1.7.1 Pre-trends

To check the pre-trends, I plot the share of disadvantaged groups over time for both the treatment and control groups, as shown in Figure 1.15. The trend across the two groups seems to be parallel before the implementation of the RTE Act. An interesting observation is that between 2009 and 2010, the average share of disadvantaged children dropped in the control group, while it sharply increased in the treatment group. This indicates that only private schools previously below the 25% quota offered more places to the new grade 1 disadvantaged students immediately after RTE.

Figure 1.15. Average share of disadvantaged groups in grade 1



I also formally test the identifying assumption by including pre and post-treatment year dummies and their interactions with the treatment dummy in the DID model. For the common trends assumption to hold, there should not be a significant difference in the pre-treatment years between the two groups. I estimate the following model:

$$SDG_{iy} = \beta_0 + \beta_1 (DG < 25p)_i + \sum_{s=-4}^{s=5} \lambda_s \cdot 1(r = s) + \sum_{s=-4}^{s=5} \delta_s ((DG < 25p)_i \cdot 1(r = s)) + \beta_2 X_{iy} + \alpha_i + \varepsilon_{iy} \tag{1.4}$$

I define r as time relative to the year of implementation, such that $r = 0$ if the year is 2009, $r = -4$ if the year is 2005, $r = -3$ if the year is 2006 and so on. Similarly, $r > 0$ for the post-RTE period and $r \leq 0$ for the pre-RTE period. In the specification below, λ_s is the coefficient on the individual time periods, relative to 2009 (r). δ_s is the coefficient on the interaction between the treatment dummy and the year dummies relative to 2009. The dependent variable is the share of disadvantaged groups in grade 1 in private school i and academic year y. X_{iy} is the vector of control variables and α_i are the state/school fixed effects.

Table 1.9 shows the results of the DID estimation with year dummies and their interactions with the treatment variable. I find that even in the years before the RTE Act,

the increase in the share of disadvantaged groups was higher in the treatment group. For instance, between 2005 and 2009, the share of disadvantaged groups in the treatment group increased by 6.7 percentage points more than the control group. This difference drops to 3 percentage points in 2006 and continues on a downward trend. However, after 2009, which was the year RTE was implemented, the coefficient jumps. Between 2009 and 2010, the share of disadvantaged groups increased by almost 15 percentage points in the treatment group relative to the control group.

The jump between 2009 and 2010 persists even when I incorporate a DID model with school fixed effects (column 4). In fact, between 2008 and 2009 the relative difference was only 1.7 percentage points, whereas between 2009 and 2010 it was 12 percentage points. So, even if we allow for differential trends in the pre-treatment period there is still a large treatment effect.

Table 1.9. Effect of RTE on the share of disadvantaged groups across years

VARIABLES	(1)	(2)	(3)	(4)
DG<25p	-0.480***	-0.457***	-0.318***	
	(0.002)	(0.002)	(0.002)	
$(DG < 25p) \times 2005$	0.068***	0.078***	0.098***	0.083***
	(0.003)	(0.003)	(0.003)	(0.002)
$(DG < 25p) \times 2006$	0.030***	0.035***	0.042***	0.046***
	(0.002)	(0.002)	(0.002)	(0.002)
$(DG < 25p) \times 2007$	0.027***	0.029***	0.026***	0.023***
	(0.002)	(0.002)	(0.002)	(0.001)
$(DG < 25p) \times 2008$	0.020***	0.025***	0.025***	0.017***
	(0.002)	(0.002)	(0.002)	(0.001)
$(DG < 25p) \times 2010$	0.148***	0.150***	0.140***	0.122***
	(0.003)	(0.003)	(0.002)	(0.002)
$(DG < 25p) \times 2011$	0.123***	0.124***	0.114***	0.085***
	(0.003)	(0.003)	(0.002)	(0.002)
$(DG < 25p) \times 2012$	0.127***	0.130***	0.112***	0.076***
	(0.003)	(0.003)	(0.002)	(0.002)
$(DG < 25p) \times 2013$	0.144***	0.145***	0.121***	0.077***
	(0.003)	(0.003)	(0.003)	(0.002)
$(DG < 25p) \times 2014$	0.149***	0.152***	0.125***	0.076***
	(0.003)	(0.003)	(0.003)	(0.002)
Constant	0.545***	0.545***	0.260***	0.384***
	(0.002)	(0.004)	(0.009)	(0.004)
Observations	952,715	946,199	946,199	946,217
R-squared	0.28	0.32	0.48	0.72
Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No
School FE	No	No	No	Yes

Notes: Dependent variable is the share of disadvantaged groups in grade 1. Control variables included are dummies for rural/urban, school size, school category (primary, upper primary etc.) and availability of pre-primary grades. Standard errors are clustered at the village level in columns 1-3 and at the school level in column 4. *** p<0.01, ** p<0.05, * p<0.1

1.7.2 States with differential treatment

Jammu and Kashmir is a state located in the northern part of India. Until 2019, the state received special status under Article 370 of the Indian constitution. This allowed Jammu and Kashmir to have a separate constitution and autonomous power over its administrative decisions. Therefore, despite being a national-level policy, the RTE Act was not implemented in the state. I use Jammu and Kashmir as a placebo group and estimate a triple-difference model. The argument is that since the RTE Act was not implemented in the state, there will be a large differential effect compared to the rest of the states. Specifically, the increase in the share of disadvantaged groups post-RTE will be significantly lower in the treatment group in Jammu and Kashmir.

Since there is no official definition of disadvantaged groups in Jammu and Kashmir, I calculate the enrolment of disadvantaged groups as the sum of enrolment of Scheduled Castes (SC) and Scheduled Tribes (ST) in grade 1. I do not include Other Backward Classes (OBC) because, in many states, not all children from OBC are eligible for the reservation. To see if this differential effect between Jammu and Kashmir and other states is significant, I run the following triple difference model:

$$SDG_{iy} = \beta_0 + \beta_1 (DG < 25p)_i + \beta_2 Post_y + \beta_3 JK_i + \beta_4 (DG < 25p)_i \cdot Post_y + \beta_5 JK_i \cdot Post_y + \beta_6 (DG < 25p)_i \cdot JK_i + \beta_7 (DG < 25p)_i \cdot JK_i \cdot Post_y + \beta_8 X_{iy} + \alpha_i + \varepsilon_{iy} \tag{1.5}$$

Here, JK is a dummy variable that equals 1 for Jammu and Kashmir and 0 otherwise. SDG_{iy} is the share of disadvantaged groups in grade 1 in school i and academic year y. $(DG < 25p)_i$ is the treatment dummy and $Post_y$ is the dummy for the post-RTE period. The results are given in Table 1.10. The triple difference estimates are negative and significant. The increase in the share of disadvantaged groups in treatment schools of Jammu and Kashmir was lower by 9 percentage points compared to the treatment schools in the rest of the states (column 1).

The magnitude becomes smaller in the model with school fixed effects but the coefficient remains negative and statistically significant (column 4). In Jammu and Kashmir, schools in the treatment group had 3 percentage points lower share of disadvantaged groups post-RTE than other states. Thus, the rest of the states had a much larger treatment effect compared to Jammu and Kashmir, where the RTE Act was not implemented.

Table 1.10. Differential effect of RTE in Jammu and Kashmir

VARIABLES	(1)	(2)	(3)	(4)
DG<25p	-0.454***	-0.429***	-0.285***	
	(0.002)	(0.002)	(0.002)	
Post	0.032***	0.043***	0.026***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
JK	-0.125***	-0.054***	0.168***	
	(0.009)	(0.009)	(0.012)	
$(DG < 25p) \times Post$	0.116***	0.114***	0.092***	0.061***
	(0.002)	(0.002)	(0.002)	(0.001)
$JK \times Post$	-0.034***	-0.044***	-0.030***	-0.034***
	(0.005)	(0.005)	(0.005)	(0.004)
$(DG < 25p) \times JK$	0.079***	0.054***	-0.087***	
	(0.009)	(0.009)	(0.009)	
$(DG < 25p) \times JK \times Post$	-0.093***	-0.093***	-0.069***	-0.033***
	(0.005)	(0.006)	(0.005)	(0.004)
Constant	0.517***	0.515***	0.233***	0.355***
	(0.002)	(0.004)	(0.009)	(0.004)
Observations	991,086	984,550	984,550	984,570
R-squared	0.28	0.32	0.48	0.72
Controls	No	Yes	Yes	Yes
State FE	No	No	Yes	No
School FE	No	No	No	Yes

Notes: Dependent variable is the share of disadvantaged groups in grade 1. Control variables included are dummies for rural/urban, school size, school category (primary, upper primary etc.) and availability of pre-primary grades. Standard errors are clustered at the village level in columns 1-3 and at the school level in column 4. *** p<0.01, ** p<0.05, * p<0.1

As an additional robustness check, I club together states where few private schools participated in the reservation policy. So, with Jammu and Kashmir, I include Andhra Pradesh and Uttar Pradesh, where more than 90% of private schools did not offer any free places to disadvantaged children after 2009 (see Figure 1.5). I estimate a triple difference model similar to Equation (1.5).

Results are reported in Table 1.11, where the triple difference estimates are negative and statistically significant. As per column (1), in states with few RTE schools, the share of disadvantaged groups in treatment schools was 1 percentage point lower than the treatment schools in other states. In the model with school fixed effects (column 4), the share was lower by 7 percentage points. This implies that in these states, treatment schools offered relatively fewer places to disadvantaged groups after 2009 than such schools in the other states. So, states that had a larger proportion of private schools participating in the reservation policy experienced a relatively larger treatment effect.

Table 1.11. Differential effect of RTE in states with little participation in the reservation policy

VARIABLES	(1)	(2)	(3)	(4)
DG<25p	-0.375***	-0.373***	-0.314***	
	(0.002)	(0.003)	(0.002)	
Post	0.021***	0.029***	0.008***	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)
State	0.178***	0.140***	0.424***	
	(0.004)	(0.004)	(0.009)	
$(DG < 25p) \times Post$	0.112***	0.111***	0.110***	0.084***
	(0.002)	(0.002)	(0.002)	(0.001)
$State \times Post$	0.032***	0.025***	0.039***	0.037***
	(0.003)	(0.003)	(0.002)	(0.002)
$(DG < 25p) \times State$	-0.179***	-0.149***	0.091***	
	(0.004)	(0.004)	(0.004)	
$(DG < 25p) \times State \times Post$	-0.012**	-0.017***	-0.067***	-0.075***
	(0.005)	(0.005)	(0.003)	(0.002)
Constant	0.434***	0.450***	0.263***	0.354***
	(0.002)	(0.005)	(0.009)	(0.004)
Observations	991,086	984,550	984,550	984,570
R-squared	0.33	0.34	0.48	0.72
Controls	No	Yes	Yes	Yes
State FE	No	No	Yes	No
School FE	No	No	No	Yes

Notes: Dependent variable is the share of disadvantaged groups in grade 1. State is a dummy variable which equals 1 for Andhra Pradesh, Uttar Pradesh, and Jammu and Kashmir. Control variables included are dummies for rural/urban, school size, school category (primary, upper primary etc.) and availability of pre-primary grades. Standard errors are clustered at the village level in columns 1-3 and at the school level in column 4. *** p<0.01, ** p<0.05, * p<0.1

1.7.3 Effect on total enrolment

The share of disadvantaged groups is the ratio of the enrolment of disadvantaged groups to total enrolment. Therefore, it seems possible that the share of disadvantaged groups increased significantly in the treatment group after 2009, because *total enrolment* declined sharply relative to the control group in the same period. To check this, I estimate a DID model similar to Equation (1.4) with year dummies and their interaction with the treatment dummy. I replace the dependent variable with the log of total enrolment in grade 1.

Results are shown in Table 1.12. Even though the change in total enrolment was significantly lower in the treatment group between 2009 and 2010 (column 2), the magnitude is smaller compared to 2008. Moreover, when I include state fixed effects and then school fixed effects (columns 3 and 4 respectively), I find that the decrease in total enrolment in the treatment group in 2010 becomes insignificant. This means the change in total enrolment in grade 1 after 2009 was the same across both groups. The jump in the share of disadvantaged groups in treatment schools in 2010 was therefore entirely due to a relatively higher increase in their enrolment.

Table 1.12. Effect of RTE on total enrolment in grade 1

VARIABLES	(1)	(2)	(3)	(4)
DG<25p	-0.008	0.072***	0.082***	
	(0.008)	(0.004)	(0.004)	
$(DG < 25p) \times 2005$	-0.046***	-0.083***	-0.059***	-0.048***
	(0.018)	(0.007)	(0.007)	(0.006)
$(DG < 25p) \times 2006$	-0.005	-0.011*	-0.002	-0.014***
	(0.009)	(0.006)	(0.006)	(0.005)
$(DG < 25p) \times 2007$	0.014*	-0.003	0.007	0.001
	(0.008)	(0.005)	(0.005)	(0.005)
$(DG < 25p) \times 2008$	0.017***	-0.028***	-0.015***	-0.016***
	(0.006)	(0.005)	(0.005)	(0.004)
$(DG < 25p) \times 2010$	0.004	-0.011***	-0.004	-0.002
	(0.006)	(0.004)	(0.004)	(0.004)
$(DG < 25p) \times 2011$	0.005	-0.036***	-0.027***	-0.025***
	(0.007)	(0.005)	(0.005)	(0.004)
$(DG < 25p) \times 2012$	-0.032***	-0.044***	-0.032***	-0.027***
	(0.007)	(0.005)	(0.005)	(0.005)
$(DG < 25p) \times 2013$	-0.001	-0.033***	-0.023***	-0.016***
	(0.007)	(0.005)	(0.005)	(0.005)
$(DG < 25p) \times 2014$	0.007	-0.017***	-0.006	0.009*
	(0.009)	(0.005)	(0.005)	(0.005)
Constant	3.416***	1.518***	1.438***	1.731***
	(0.004)	(0.007)	(0.078)	(0.008)
Observations	952,715	946,199	946,199	946,217
R-squared	0.001	0.54	0.56	0.76
Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No
School FE	No	No	No	Yes

Notes: Dependent variable is the log of total enrolment in grade 1. Control variables included are dummies for rural/urban, school size, school category (primary, upper primary etc.) and availability of pre-primary grades. Standard errors are clustered at the village level in columns 1-3 and at the school level in column 4. *** p<0.01, ** p<0.05, * p<0.1

1.8 Conclusion

This chapter provides evidence on the role of India's RTE Act in increasing the enrolment of socially disadvantaged children in private schools. The RTE Act mandated all private schools to reserve at least 25% of their places in grade 1 for these children. I find that following the implementation of this policy, the enrolment of disadvantaged children increased significantly in private schools. This was accompanied by a decline in their enrolment in government schools. The increase in private school enrolment of disadvantaged children further led to an increase in their share in grade 1.

However, the increase in the enrolment and share of disadvantaged children is not just driven by an increase in the supply of private schools. I find that these effects persist within the private sector even after excluding new schools. Schools that existed before 2010 also significantly increased their share after RTE. These are mostly schools that had a low share (less than the stipulated 25%) of disadvantaged children before the policy. However, I find that this effect is not directly driven by the reservation policy, where disadvantaged children receive free places. Using a difference-in-differences strategy I find that even schools that had no take-up under the reservation policy experienced an increase in the share of disadvantaged children after RTE. Nonetheless, there was still a positive differential effect on schools that had some take-up under the policy.

Exploring the mechanisms, I find that private schools were mainly substituting fee-paying disadvantaged children for disadvantaged children who would receive free admission under the reservation policy. The enrolment under the reservation policy explains very little variation in the enrolment of disadvantaged children in the same year. However, this seems to be largely true for schools that did not participate in the policy. This is because schools that participated had a relatively higher share of disadvantaged children post-RTE. This implies that they offered more places to disadvantaged children both through the policy and by charging fees.

The findings are robust when I look at the change in the share of disadvantaged groups over time. I find that there was only a small increase in the share of disadvantaged children in all years before the policy. In fact, the increase was lowest between 2008 and 2009. However, between 2009 and 2010, when the RTE Act was implemented, there was a sudden increase in their share. This increase was around 10 percentage points more compared to the increase between 2008 and 2009. Between 2009 and 2010, the RTE Act was the only education policy implemented in India. Therefore, the huge jump in the year 2010 indicates that the RTE Act did play a role in increasing the share of disadvantaged groups.

The findings are also robust to using placebo states where the RTE Act was not implemented and where there was little participation under the reservation policy. This includes the states of Jammu and Kashmir, Andhra Pradesh, and Uttar Pradesh. Both sets of results show that in these states the increase in the share of disadvantaged children was much lower. This again indicates that the RTE Act contributed to a higher enrolment of disadvantaged children in private schools. In particular, it was the schools that were enrolling a relatively lower share of disadvantaged children before RTE that offered them more places.

I also find that the lower the pre-RTE share of disadvantaged groups in private schools the higher the post-RTE increase in their share. This monotonic negative relationship did not exist between 2005 and 2007 or 2007 and 2009. Additionally, I find that the positive effect on the share of disadvantaged children is driven by an increase in their enrolment and not by a decrease in total enrolment. The change in total enrolment after RTE was not significantly different between schools that had a lower and a higher share of disadvantaged children before RTE.

The results from this chapter imply that the majority of the disadvantaged children enrolled in private schools after RTE were not enrolled through the reservation policy. While private schools that previously had fewer disadvantaged students did see an increase in such admissions after RTE, it was mainly because these students were paying tuition fees. Therefore, private schools seem to be filling potential free spots available under the policy with these fee-paying disadvantaged students instead. This explains why the effect of the RTE Act was indirect.

Finally, the chapter suggests that the general equilibrium effects of the policy largely depends on the availability of schools. The construction of new government and private schools increases competition and choice for families, and plays a crucial role in shaping enrolment patterns. In Chapter 2, Section 2.9.3, I show an increase in overall enrolment rates of disadvantaged children post-RTE and a large shift towards private schools across all primary-school going age groups. With increased competition, existing private schools with a higher initial share of disadvantaged students might have struggled to expand places for them. On the other hand, schools with a lower initial share of disadvantaged students likely had more "space" to absorb an increased pool of students. Furthermore, oversubscription and undersubscription to quotas under the reservation policy is also influenced by local school availability. Given the absence of school building data at a more local level, I assume that the effects cancel out at the aggregate level.

References

Akyeampong, K. (2009). "Public–private partnership in the provision of basic education in Ghana: challenges and choices". In: *Compare* 39.2, pp. 135–149.

Amjad, R. and Macleod, G. (2014). "Academic effectiveness of private, public and private–public partnership schools in Pakistan". In: *International Journal of Educational Development* 37, pp. 22–31.

Angrist, J., Bettinger, E., and Kremer, M. (2006). "Long-term educational consequences of secondary school vouchers: Evidence from administrative records in Colombia". In: *American economic review* 96.3, pp. 847–862.

Angrist, J. and Pischke, JS. (2009). "Mostly harmless econometrics: An empiricistVs companion". In: *Princeton Univ Pr*.

Ansari, A. (2020). "Cream skimming? Evaluating the access to Punjab's public-private partnership programs in education". In: *International Journal of Educational Development* 72.

Azam, M. and Saing, C.H. (2017). "Assessing the impact of district primary education program in India". In: *Review of Development Economics* 21.4, pp. 1113–1131.

Bhattacharjee, S. (2019). "Ten years of RTE act: revisiting achievements and examining gaps". In: *ORF Issue Brief* 304.

De, A., Majumdar, M., Samson, M., and Noronha, C. (2002). "Private schools and universal elementary education". In: *India education report: a profile of basic education*, pp. 131–150.

Dixon, P., Egalite, A., Humble, S., and Wolf, P. (2019). "Experimental results from a four-year targeted education voucherprogram in the slums of Delhi, India". In: *World Development* 124.

Dongre, A. and Kapur, A. (2016). "Trends in public expenditure on elementary education in India". In: *Economic and Political Weekly* 39.

French, R. and Kingdon, G. (2010). "The relative effectiveness of private and government schools in Rural India: Evidence from ASER data". In: *London: Institute of Education* 11.

Härmä, J. (2009). "Can choice promote Education for All? Evidence from growth in private primary schooling in India". In: *Compare* 39.2, pp. 151–165.

— (2011). "Low cost private schooling in India: Is it pro poor and equitable?" In: *International journal of educational development* 31.4, pp. 350–356.

Hill, E., Samson, M., and Dasgupta, S. (2011). "Expanding the school market in India: Parental choice and the reproduction of social inequality". In: *Economic and political weekly*, pp. 98–105.

Jalan, J. and Glinskaya, E. (2002). “Small bang for big bucks? An evaluation of a primary school intervention in India”. In: *with Elena Glinskaya), mimeo, the World Bank*.

Khanna, G. (2023). “Large-scale education reform in general equilibrium: Regression discontinuity evidence from india”. In: *Journal of Political Economy* 131.2, pp. 549–591.

Kingdon, G. (2020). “The Private Schooling Phenomenon in India: A Review”. In: *The Journal of Development Studies* 56.10, pp. 1795–1817.

Krishna, A.H., Sekhar, M.R., K.R., Teja, and S.M., Reddy (2017). “Enrolment in Elementary Education with Reference to Right to Education Act 2009: An Empirical Analysis of Selected States of India during 2004-05 to 2015-16”. In: *IOSR Journal Of Humanities And Social Science (IOSR-JHSS)* 22.11, pp. 43–51.

Malakar, R. and Mahato, A. (2015). “Implementation Status of Right to Education (RTE) Act 2009 in Tripura: A Critical Analysis”. In: *MGIRED Journal* 2.1, pp. 90–100.

Mehrotra, S. (2012). “The cost and financing of the right to education in India: Can we fill the financing gap?” In: *International Journal of Educational Development* 32.1, pp. 65–71.

Mfum-Mensah, O. (2003). “Fostering educational participation in pastoral communities through non-formal education: The Ghanaian perspective”. In: *International Journal of Educational Development* 23, pp. 661–677.

Muralidharan, K. and Sundaraman, V. (2015). “The aggregate effect of school choice: Evidence from a two-stage experiment in India”. In: *Quarterly Journal of Economics* 130.3, pp. 1011–1066.

Ojha, S. (2013). “Implementing right to education: Issues and challenges”. In: *Research Journal of Educational Sciences* 2321, p. 0508.

Sarin, A., Kuhn, S., Singh, B.D., Khanghta, P., Dongre, A., Joshi, E., Sengupta, A., and Rahman, F. (2015). “State of the Nation: RTE Section 12 (1)(c)”. In: *Available at SSRN 2637817*.

Shah, M. and Steinberg, B. (2019). “The right to education act: Trends in enrollment, test scores, and school quality”. In: *AEA Papers and Proceedings*. Vol. 109. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, pp. 232–238.

Singh, V. (2016). “Status of implementation of the Right to Education Act, 2009 in Himachal Pradesh”. In: *International Journal of Scientific Engineering and Applied Science, 2 (1)*, pp. 491–505.

Tooley, J. and Dixon, P. (2003). “Private Schools for the Poor: A Case Study from India”. In: *Centre for British Teachers Research and Development*.

— (2006). “‘De facto’ privatisation of education and the poor: implications of a study from sub-Saharan Africa and India”. In: *Compare* 36.4, pp. 443–462.

Tooley, J., Dixon, P., Shamsan, Y., and Schagen, I. (2010). “The relative quality and cost-effectiveness of private and public schools for low-income families: A case study in a developing country”. In: *School Effectiveness and School Improvement* 21.2, pp. 117–144.

Appendices

1.A.1 Figures

Figure 1.A.1. Average enrolment of disadvantaged groups in grade 1

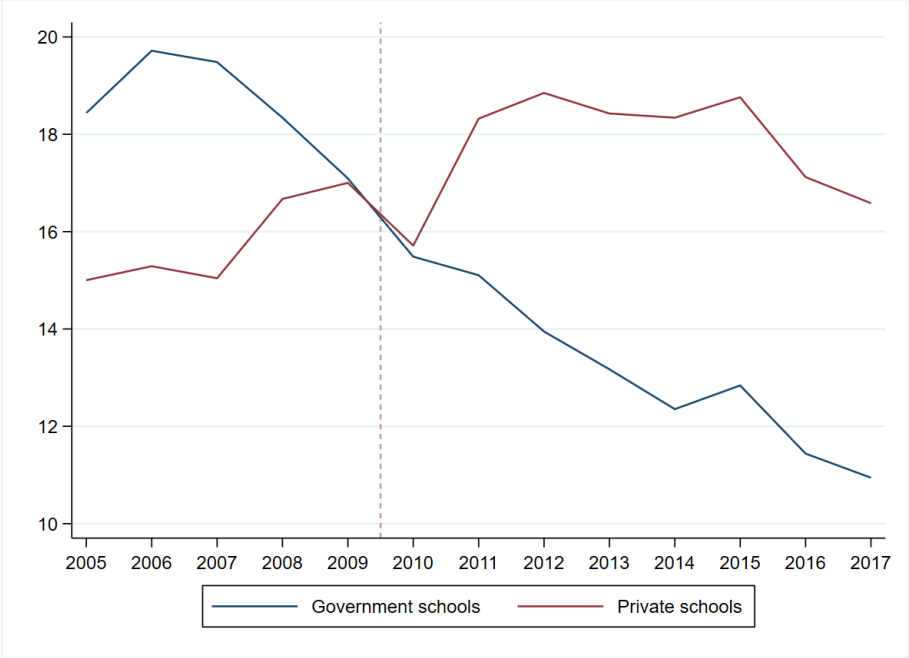


Figure 1.A.2. SC and ST children aged 6 as a percentage of the total SC-ST population

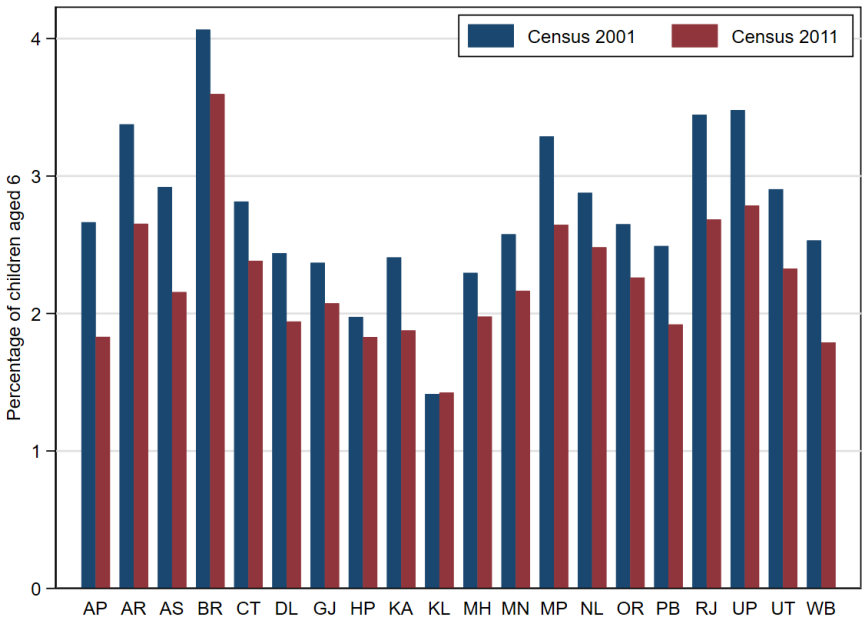


Figure 1.A.3. Enrolment of SC and ST children aged 6 as a percentage of their population

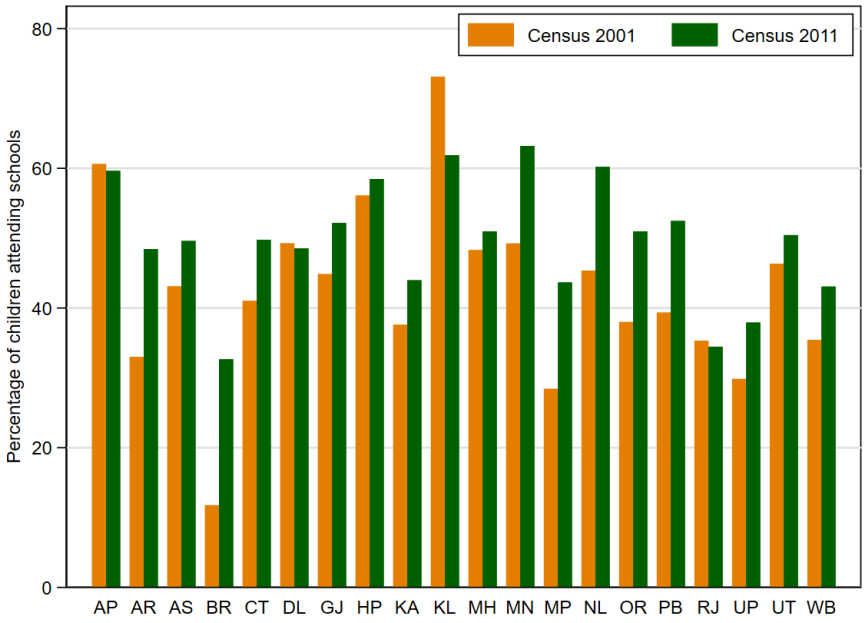
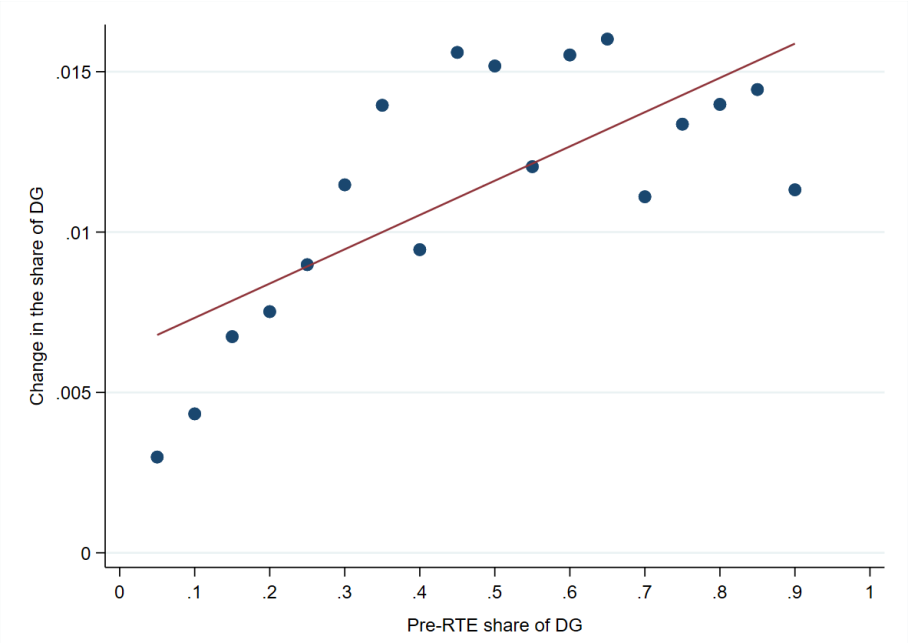


Figure 1.A.4. Change in the share of disadvantaged groups between 2007 and 2009



Notes: The x-axis denotes the average share of disadvantaged groups in schools from 2005 to 2009. The y-axis denotes the average change in the share from 2007 to 2009.

1.A.2 Tables

Table 1.A.1. Enrolment in grade 1 in all RTE and non-RTE schools

	Pre-RTE	Post-RTE
RTE schools		
Average enrolment	36.81	35.74
Average enrolment of disadvantaged groups	12.33	12.89
Average share of disadvantaged groups	0.32	0.36
Observations	176,433	382,941
Non-RTE schools		
Average enrolment	41.78	45.37
Average enrolment of disadvantaged groups	17.61	22.85
Average share of disadvantaged groups	0.41	0.50
Observations	362,178	407,377

Notes: Haryana, Mizoram, Tamil Nadu do not enrol SC, ST, OBC or children with special needs under RTE. Jharkhand, Meghalaya and Tripura only include SC and ST from BPL families. No official definition of disadvantaged groups is available for Sikkim. Schools from these states are therefore, excluded.

Table 1.A.2. Average enrolment of disadvantaged groups in grade 1 in RTE and non-RTE schools

	Non-RTE schools			RTE schools		
State	Pre-RTE	Post-RTE	Difference	Pre-RTE	Post-RTE	Difference
Uttar Pradesh	35 (N=117,062)	38 (N=177,694)	3.54	39 (N=12,051)	41 (N=20,452)	1.91
Rajasthan	7 (N= 38,136)	7 (N=17,917)	-0.14	8 (N=59,775)	8 (N=122,430)	-0.31
Madhya Pradesh	6 (N=33,065)	7 (N=21,677)	0.76	7 (N=45,027)	7 (N=92,695)	0.33
Andhra Pradesh	7 (N=51,041)	7 (N=66,618)	0.59	7 (N=3,355)	8 (N=4,625)	0.59
Karnataka	23 (N=20,557)	21 (N=17,412)	-1.61	24 (N=15,916)	25 (N=36,553)	0.80
Maharashtra	8 (N=12,790)	7 (N=18,129)	-0.99	8 (N=5,392)	9 (N=17,512)	0.97
West Bengal	6 (N=28,222)	8 (N=21,422)	1.52	8 (N=4,018)	10 (N=10,403)	2.13
Gujarat	18 (N=10,979)	19 (N=15,422)	1.07	23 (N=8,555)	26 (N=18,852)	2.37
Chhattisgarh	8 (N=6,508)	8 (N=6,121)	0.19	9 (N=6,159)	9 (14,470)	0.70
Uttarakhand	16 (N=4,165)	17 (N=4,378)	1.33	12 (N=6,480)	13 (N=15,226)	1.62
Assam	5 (N=12,709)	8 (N=6,547)	2.87	5 (N=1,343)	7 (N=4,825)	1.34
Punjab	8 (N=5,907)	9 (N=8,645)	1.27	9 (N=1,240)	9 (N=4,632)	0.17
Odisha	15 (N=4,436)	21 (N=5,578)	6.22	16 (N=1,157)	24 (N=2,941)	7.50
Himachal Pradesh	5 (N=6,908)	7 (N=7,711)	1.98	6 (N=2,563)	7 (N=3,822)	1.84
Kerala	39 (N=732)	38 (N=6,781)	-1.19	39 (N=378)	42 (N=2,867)	2.19
Delhi	5 (N=2,864)	3 (N=1,830)	-1.50	5 (N=1,001)	7 (N=3,742)	1.24
Bihar	34 (N=731)	35 (N=1,186)	0.95	38 (N=8)	34 (N=2,264)	-3.95
Manipur	15 (N=1,861)	15 (N=2,077)	0.20	20 (N=691)	21 (N=1,367)	0.83
Nagland	46 (N=2,509)	37 (N=2,256)	-9.07	45 (N=543)	36 (N=1,109)	-9.36
Arunachal Pradesh	23 (N=335)	24 (N=989)	1.59	24 (N=126)	24 (N=515)	0.08

Notes: The difference in non-RTE schools is significant in all states except Rajasthan, Kerala, Chhattisgarh, Manipur, Bihar and Arunachal Pradesh. The difference in RTE schools is significant in all states except Punjab, Kerala, Manipur, Bihar and Arunachal Pradesh. Haryana, Mizoram and Tamil Nadu only enrol economically weaker sections under RTE. Jharkhand, Meghalaya and Tripura only include SC and ST from BPL families. No official definition of disadvantaged groups is available for Sikkim.

Table 1.A.3. Average share of disadvantaged groups in grade 1 in RTE and non-RTE schools

	Non-RTE schools			RTE schools		
State	Pre-RTE	Post-RTE	Difference	Pre-RTE	Post-RTE	Difference
Uttar Pradesh	0.67	0.73	0.07	0.73	0.79	0.06
	(N=117,062)	(N=177,694)		(N=12,051)	(N=20,452)	
Rajasthan	0.25	0.29	0.03	0.24	0.27	0.03
	(N= 38,136)	(N=17,917)		(N=59,775)	(N=122,430)	
Madhya Pradesh	0.19	0.26	0.07	0.20	0.26	0.06
	(N=33,065)	(N=21,677)		(N=45,027)	(N=92,695)	
Andhra Pradesh	0.17	0.19	0.02	0.16	0.18	0.02
	(N=51,041)	(N=66,618)		(N=3,355)	(N=4,625)	
Karnataka	0.62	0.59	-0.03	0.65	0.64	-0.01
	(N=20,557)	(N=17,412)		(N=15,916)	(N=36,553)	
Maharashtra	0.16	0.14	-0.02	0.18	0.18	-0.01
	(N=12,790)	(N=18,129)		(N=5,392)	(N=17,512)	
West Bengal	0.21	0.25	0.04	0.23	0.30	0.06
	(N=28,222)	(N=21,422)		(N=4,018)	(N=10,403)	
Gujarat	0.50	0.54	0.04	0.49	0.57	0.08
	(N=10,979)	(N=15,422)		(N=8,555)	(N=18,852)	
Chhattisgarh	0.34	0.32	-0.02	0.29	0.30	0.02
	(N=6,508)	(N=6,121)		(N=6,159)	(14,470)	
Uttarakhand	0.43	0.50	0.07	0.35	0.41	0.06
	(N=4,165)	(N=4,378)		(N=6,480)	(N=15,226)	
Assam	0.29	0.29	-0.00	0.22	0.23	0.01
	(N=12,709)	(N=6,547)		(N=1,343)	(N=4,825)	
Punjab	0.31	0.30	-0.00	0.27	0.29	0.02
	(N=5,907)	(N=8,645)		(N=1,240)	(N=4,632)	
Odisha	0.52	0.57	0.05	0.54	0.62	0.08
	(N=4,436)	(N=5,578)		(N=1,157)	(N=2,941)	
Himachal Pradesh	0.30	0.36	0.06	0.32	0.39	0.07
	(N=6,908)	(N=7,711)		(N=2,563)	(N=3,822)	
Kerala	0.55	0.64	0.10	0.56	0.65	0.09
	(N=732)	(N=6,781)		(N=378)	(N=2,867)	
Delhi	0.10	0.07	-0.03	0.11	0.11	0.01
	(N=2,864)	(N=1,830)		(N=1,001)	(N=3,742)	
Bihar	0.61	0.68	0.07	0.70	0.68	-0.02
	(N=731)	(N=1,186)		(N=8)	(N=2,264)	
Manipur	0.45	0.43	-0.03	0.55	0.60	0.05
	(N=1,861)	(N=2,077)		(N=691)	(N=1,367)	
Nagland	0.95	0.93	-0.02	0.90	0.85	-0.06
	(N=2,509)	(N=2,256)		(N=543)	(N=1,109)	
Arunachal Pradesh	0.79	0.79	-0.00	0.79	0.86	0.07
	(N=335)	(N=989)		(N=126)	(N=515)	

Notes: The difference in non-RTE schools is significant in all states except Punjab, Assam and Arunachal Pradesh. The difference in RTE schools is significant in all states except Karnataka, Assam, Delhi and Bihar. Haryana, Mizoram and Tamil Nadu only enrol economically weaker sections under RTE. Jharkhand, Meghalaya and Tripura only include SC and ST from BPL families. No official definition of disadvantaged groups is available for Sikkim.

Chapter 2

The effect of reservation in private schools on the education expenditure by disadvantaged groups

2.1 Introduction

Like many developing countries of the world, India faces the problem of under-education and low literacy rates. Despite the expansion of schools in the last two decades, millions of children are not enrolled and dropout rates are high. Given that almost 80% of India's population is poor and socially disadvantaged, the issue of low school enrolment is almost entirely concentrated among lower social categories.[1] The National Sample Survey (NSS) of India found that in 2014, more than 75% of children aged 6-14 not enrolled in schools belonged to lower social categories. Furthermore, only 15% of children from low-income families are found to attend private schools in India (Alcott and Rose, 2015).

To address these issues, the government of India introduced the Right to Education (RTE) Act in August 2009. One of the main provisions of the Act was subsidizing private education for the poor and socially disadvantaged through a reservation policy. It required private schools to reserve 25% primary school places for children from lower socio-economic backgrounds. The RTE Act's reservation policy is the first national-level policy in private education aimed at the social integration of primary-school-age children. It is one of the world's largest policies in education with the potential to benefit

[1] These typically include the Scheduled Caste (SC), Scheduled Tribe (ST) and Other Backward Classes (OBC).

the lives of millions of children from lower social backgrounds.

The reservation policy should, in theory, increase private school enrolment and lower school fees through subsidized education. However, according to the Ministry of Education (MoE), even by 2019-20, less than 5% of all eligible children in India were enrolled under the policy. One reason for low enrolment is that not all states of India have systematically implemented the policy. The second reason is that even within states that have implemented the policy, many private schools have not filled all the available seats under the policy. The poor implementation in many states is mainly due to a lack of proper incentives for the schools, unclear rules regarding the admission procedure, and parents being charged non-tuition fees (Sarin, Dongre, and Wad, 2017).

As a result, nationally, only a small fraction of eligible children are studying in private schools free of cost. However, despite the low take-up, the policy could have some spillovers on the market for private schools by affecting the demand and supply conditions (Ferreira, Lozano-Gómez, and Stathopoulos, 2021) or by influencing behaviour through 'signaling' (see Spence (1978), Weiss (1995), and Lang and Manove (2011)). If the policy had an indirect effect on the demand and supply of private schools, it could have also led to changes in the price of private schooling.

In Chapter 1, I showed that the RTE Act led to a significant rise in private school enrolment among lower social categories, but not primarily through the free seats reserved under the policy. In this chapter, I investigate whether the reservation policy had a spillover effect on price, that is the tuition fees in private schools. To identify the effect of the policy on fees, I exploit an exogenous variation in the age of starting school due to the timing of the policy. I use repeated cross-sectional household survey data and a difference-in-differences strategy to compare the fees of two age cohorts from lower social categories across two time periods– before and after the policy.

Due to large district-level variations in the takeup under the policy, I also incorporate a continuous measure of program intensity in the model, which makes the measure of treatment stronger. The intensity of the program is proxied using the rate of enrolment under the policy, which I calculate from administrative school-level data. Apart from district fixed effects, I also use household fixed effects and compare the outcome between siblings. This allows me to control for a large set of unobserved characteristics that are constant within a household, thus strengthening the identification.

I find that the reservation policy reduced annual private school fees by ₹223 ($p<0.1$).[2] The reduction in fees was larger among households with higher demand for private education (₹844, $p<0.05$). This includes households that were economically better off within lower social categories and were living in states where there was a more systematic implementation of the policy. The decrease in fees for these households was equivalent to around 2.5% of their monthly consumption expenditure. I also find that a 5 percentage points increase in the enrolment rate under the policy in a district reduced annual private school fees by ₹240 ($p<0.1$). Among economically better-off households in the states with better implementation of the policy, this was associated with a reduction in annual private school fees of ₹470 ($p<0.1$).

The main effect of the policy is, however, indirect. It is not directly driven by children studying in private schools for free but rather an increase in the supply of private schools in India. Five years after the policy, there were 79% more private schools that could, in principle, provide subsidized education to the less privileged. I find that these new private schools charged a much lower fee than the existing schools and therefore, had a higher take-up of children from lower social categories. Furthermore, the entry of new low-fee schools was strongly and positively correlated with the program intensity at the district level. Moreover, the new low-fee schools also had a relatively higher enrolment rate under the policy. The district-level variation in the enrolment rate under the policy therefore seems to be driven by the district-level variation in the entry of new schools.

The increase in the number of private schools seems to be a supply-side response to an increased demand for private education. In India, there has been a growing demand for private education, which is well established in the literature (see Krishna et al. (2017), Bhattacharjee (2019), and Kingdon (2020)). With the implementation of the policy, this increasing demand seems to have amplified, as now, children from lower social categories have the opportunity to attend private schools for free, especially in states that formally implemented the policy (Noronha and Srivastava, 2013). This increased demand could have incentivized new private schools to enter. As these new schools were low-fee, it encouraged children from lower social categories to enrol in these schools.

A potential threat to identification is if there are other factors or other aspects of the RTE Act that led to a reduction in private school fees. The RTE Act also mandated free primary education in government-run schools as well as the establishment of these schools in areas where no such school existed. If the existence of new government-

[2] 1 USD is roughly equal to ₹83.

run free schools shifted the demand towards low-fee private schools that are deemed better, it could have resulted in lower fees. Another important aspect of the RTE Act is that it became mandatory for private schools to be recognized by the government. The growth of recognized private schools could have added to the increased supply of private schools, which could have direct implications on fees.

However, my findings are robust to the inclusion of a placebo group that was not eligible under the reservation policy but could have been affected by other provisions of the RTE Act. This includes children from higher social categories. Moreover, the reservation policy was the only policy at the time that was aimed at private education of lower social categories. As an additional robustness check, I estimate the model in states without formal implementation of the reservation policy but that may have seen a growth in recognized private schools. While the increase in low-fee private schools also seems to be prevalent in these states, there is no significant differential impact on fees for the cohort targeted by the reservation policy. This suggests that although other provisions of the RTE Act could have increased the demand for private education and led to the growth of low-fee private schools, they do not seem to have a direct correlation with reduced fee structures for the intended beneficiaries of the reservation policy.

The rest of the chapter is organized as follows. Section 2.2 provides details of the RTE reservation policy. Section 2.3 discusses the related literature. Section 2.4 describes the datasets used in the chapter. Section 2.5 explains the treatment and shows some descriptive evidence. Sections 2.6 and 2.7 present the DID models and report the main findings. Section 2.8 investigates the mechanisms that explain the results. Section 2.9 examines the robustness of the results and Section 2.10 concludes.

2.2 Institutional details: The reservation policy

The Right to Education Act implemented a reservation policy that mandates all private unaided[3] schools to reserve at least 25% of their seats at entry-level (a pre-primary grade or grade 1), for **economically weaker sections** and **disadvantaged groups**. Economically weaker sections include children whose parents earn an annual income that is below a certain threshold determined by the state government. Disadvantaged groups typically include three main social categories in India- Scheduled Caste (SC), Scheduled Tribe (ST) and Other Backward Classes (OBC). However, the formal definition of disadvantaged groups varies across states.[4]

The admission process is consistent throughout the country but the timeline varies by state. In the application stage, parents of eligible children are required to choose 3-5 preferred schools from a list of private schools in the neighbourhood. Upon verification of all necessary documents, the system matches each child with their preferred school. In case there is oversubscription to schools, seats are allotted through a lottery system. All children admitted under the policy then receive free education till they complete grade 8 and for each child admitted, private schools receive reimbursement from the state government. The amount of reimbursement is equal to the per-child expenditure of the government or the actual per-child fee charged by the private school, whichever is lower.

Despite the reservation policy being one of the most important educational policies in India, its implementation has been sporadic. For instance, in states such as Tamil Nadu, Rajasthan, and Chhattisgarh, the policy has been implemented more systematically, whereas, in Andhra Pradesh, the policy has still not been formally administered. Subsequently, there has been very little enrolment under the policy overall. According to the Ministry of Education, in 2014-15, less than 2% of children in the eligible age group were studying under the policy in India. By 2019-20, this increased to around 4.6%.

Apart from poor implementation, there are several other issues that might explain the low takeup of children under the policy. These have been extensively discussed in a report by Sarin, Dongre, and Wad (2017). For instance, with many states switching to online portals for admission, the application procedure has become more complex as it

[3]These schools are managed by an autonomous private body and do not receive any maintenance grants or funds from the government. Private unaided schools are referred to as simply private schools in the chapter unless mentioned otherwise.

[4]Definitions of disadvantaged groups are given in the official notices of state governments: https://www.education.gov.in/en/rte_dws.

now requires the knowledge of computers and technology. It also requires a good internet connection which many poor families might not have access to. There is also a lack of clarity on the rules among parents, and as a result, they are subjected to bureaucracy by government officials and schools.

On the supply side, there are no clear incentives for private schools to offer free places to students, especially if they charge a high fee, as the reimbursement received would be lower than the actual fee charged by the school. Moreover, the reimbursement amount is set to match the government's per child expenditure, which is often underreported than the actual expenditure incurred (Kingdon and Muzammil, 2015; Dongre and Kapur, 2016). As a result, private schools receive a reimbursement even lower than the stipulated amount. According to Sarin, Dongre, and Wad (2017), in many states, private schools do not receive timely reimbursements from the government.

Sarin, Dongre, and Wad (2017) also found that the admission timelines under the policy did not sync with regular admissions in some states. This led to delays in admissions, resulting in parents paying high tuition fees to secure places. Private schools also subjected parents to heavy non-tuition fees.

In the city of Bangalore, Karnataka, parents raised complaints against 31 private schools that demanded non-tuition fees (books, uniform, transport) from students enrolled under the policy (Economic Times). Similar cases where parents were charged fees in the name of 'other charges' were also reported in the state of Gujarat (The Indian Express). In 2018, the Uttarakhand Commission for Protection of Child Rights (UCPCR) received over 70 complaints against private schools for demanding fees from students enrolled under the policy (Hindustan Times). In Chennai, Tamil Nadu, some private schools charged tuition fees from these students in 2019, due to delays in reimbursement from the state government in the previous year. In one of the schools, parents were asked to pay first, with the promise of reimbursement later, when the school received money from the government (Times of India).

Although the reservation policy has failed to achieve its full potential in terms of enrolment, given its scale, it could still have indirect implications on the market through spillovers. Furthermore, despite the policy's failure to reach all potential beneficiaries, in 2019-20, the central government spent a total of ₹14.6 billion on reimbursements[5], which was 2.6% of the total funds[6] allocated to school education. The reservation policy is therefore, an important policy to study, and its effects are worth investigating.

[5]Based on the information from the Ministry of Education, sought under the Right to Information Act, 2005.

[6]According to the Indian Economic Survey 2019-20, the central government allocated ₹565.37 billion to school education.

2.3 Related literature

2.3.1 Supply-side interventions

The RTE reservation policy is a large supply-side intervention that is aimed at increasing the number of places in private schools for poor and disadvantaged children. Another important supply-side intervention in education is the construction of new schools nearby, such that it increases the supply of places and also reduces the cost of the commute. The seminal paper by Duflo (2001) investigates the impact of a school construction program in Indonesia on years of education and wages. Using data from the Intercensal Population Survey of Indonesia (SUPAS) and a difference-in-differences framework, the paper found that each primary school constructed per 1,000 children led to an average increase of 0.12 to 0.19 years of education. Duflo (2001) used variation in the year of birth and region of birth to identify the effect of the program. The DID estimates were calculated using an interaction between a measure of program intensity at the district level (the number of new schools) and the cohort dummy.

A similar empirical strategy was used by Handa (2002) to evaluate the effect of a school construction program in Mozambique. The study used a difference-in-differences methodology by comparing the outcomes across cohorts of children in regions with differential program intensity. Handa (2002) employed two measures of program intensity separately: a continuous measure of the number of new schools in the region, and a dummy variable that divided regions into 'high' exposure (number of new schools above median) and 'low' exposure (number of new schools below median). The household survey data was merged with school administrative data from the Mozambique Ministry of Education (MINED) for information on the number of primary schools. Estimating the effect using a probit model, Handa (2002) found that building new schools was associated with a higher probability of being enrolled for the younger cohort.

A village-level school construction experiment in Afghanistan also led to an increase in the enrolment of children in schools (Burde and Linden, 2013). Using a randomized controlled trial, Burde and Linden (2013) assigned new schools to randomly selected villages in rural Afghanistan. Villages that received a new school formed the treatment group, while villages that did not receive a new school formed the control group. They found that the presence of a school in the treatment village increased the enrolment of children by 42 percentage points. The program also reduced gender disparity as school enrolment of girls was around 17 percentage points higher than that of boys.

A 'girl-friendly' primary school construction program in Burkina Faso also led to a higher increase in the enrolment of girls (Kazianga et al., 2013). Using a regression discontinuity design, Kazianga et al. (2013) found that enrolment of primary school-aged children increased by 19% after the implementation of the program. Further, the increase was 5% more for girls than boys. Under the program, the Ministry of Education assigned a score to each village and ranked them based on the number of children to be served. The top half of the villages received a 'girl-friendly' school. Kazianga et al. (2013) defined discontinuity point as half of the difference between the lowest score of each village that received a school and the highest score of each village that did not. They also found that the provision of 'girl-friendly' schools with amenities like sex-specific latrines, increased enrolment by 13% more than regular schools.

In the education literature, most studies have evaluated the effect of public-private partnership (PPP) programs on enrolment and learning outcomes in Pakistan. Essentially, India's reservation policy which is funded by the state is also a PPP program. The paper by Kim, Alderman, and Orazem (1999) was the first of its kind to look at the effect of a PPP program in Pakistan on enrolment. Under the program, new private schools for girls were built in randomly assigned neighborhoods of Balochistan. These schools received a per-child subsidy to cover the fees of girl children. Kim, Alderman, and Orazem (1999) found that the program resulted in an increase in the enrolment of girls by 33 percentage points. As the PPP schools were not exclusive to girls, the program also increased the enrolment rate of boys.

Other studies that have used randomized controlled trials have also found positive effects of PPP programs in Pakistan on enrolment, as well as learning outcomes (Andrabi et al., 2020; Barrera-Osorio et al., 2022). In the paper by Andrabi et al. (2020), where treatment schools were split into 'low' and 'high' treatment, low treatment schools saw 12% more enrolment. However, test scores were only higher in high treatment schools relative to control schools by 0.16 SD. Barrera-Osorio et al. (2022) found that a PPP program in Sindh increased the enrolment of younger children and older children by 31.5 percentage points and 11 percentage points respectively. But despite treatment schools receiving an additional subsidy for girls, there was no differential effect on enrolment by gender. They also found that treatment schools scored 0.17 SD higher on tests than government schools, while there was no difference with other private schools.

In the context of PPP programs in Pakistan, there are also studies that have used quasi-experimental methods (Barrera-Osorio and Raju, 2015; Crawfurd, 2018). Barrera-Osorio and Raju (2015) used a regression discontinuity design to investigate the impact of a PPP program, where private schools received a subsidy upon achieving a cut-off

pass rate on the Quality Assurance Test. They found that within 17 months, the program led to a 47% increase in enrolment, a 46% increase in the number of teachers, and a 14% reduction in the student-classroom ratio. Using a difference-in-differences approach, Crawfurd (2018) compared outcomes across early and late converters in a PPP program, under which poorly performing public schools were converted to free private schools and were offered a per-child subsidy. The study found that while the program led to 60% more enrolment, the average test scores in treatment schools were slightly lower. This was potentially due to treatment schools having a higher number of exam candidates, which could include a higher number of weaker students.

There are other studies that are not causal but have investigated the relationship between PPP programs and learning outcomes (Amjad and MacLeod, 2014) and have looked at the factors determining the type of school attended (Ansari, 2020). Using household survey data and employing a logistic regression, Amjad and MacLeod (2014) found that students in PPP schools of Pakistan outperform students in government schools only due to private tuition. Moreover, while students in low-fee private schools outperform students in government schools, higher fees are not strongly related to better performance within the private sector. The study by Ansari (2020) estimated Poisson regressions using administrative and survey data on schools in Punjab, Pakistan. Ansari (2020) found that PPP schools were built in districts with relatively higher shares of out-of-school children. Furthermore, PPP students were 35% more likely to be female than students in government schools but were similar to students in other (non-PPP) private schools.

Studies on school construction programs have shown how exogenous variation in birth and regional variation in intensity can be exploited for causal inference by comparing cohorts differentially affected (Duflo, 2001; Handa, 2002). This chapter uses a similar approach but is the first to do it in the context of the RTE reservation policy. Similarly, PPP programs in Pakistan have been widely studied using both quasi-experimental methods and randomized controlled trials. To the best of my knowledge, this chapter is the first to use a quasi-experimental approach to evaluate the causal effect of the reservation policy, which is the longest-running PPP program in education in India.

2.3.2 School choice programs

This chapter also contributes to the literature on school choice. One of the earliest empirical studies in the literature found that a private school voucher program in Chile

immediately resulted in middle-income families shifting to private schools (Hsieh and Urquiola, 2006). Using panel data on municipalities, Hsieh and Urquiola (2006) evaluated the effect of the program on learning outcomes by comparing communities differentially affected by the program. They found no effect of the policy on educational outcomes. However, it still led to more than 1,000 private schools entering the educational market and an increase in the private enrolment rate by 20 percentage points. They also found that the increase in the enrolment rate was higher in communities where demand for private education was higher (urban, wealthier communities). The study proposes that the private sector is more responsive in systems where there is more importance placed on private schools.

Another study found that Brazil's conditional cash transfer program led to the entry of new private schools as a result of increased skill dispersion in the public sector (Menezes-Filho, Moita, and Andrade, 2012). Menezes-Filho, Moita, and Andrade (2012) used the share of CCT recipients in a municipality as an instrumental variable for test-scores dispersion. They found that municipalities, where skill distribution widened, were more likely to have new private schools entering. They argue that this results in increased socioeconomic stratification and the persistence of inequality.

Similarly, Böhlmark and Lindahl (2015) found that a voucher reform in Sweden that gave free choice between public and private schools resulted in increased competition between the two sectors. This further led to an increase in the number of independent private schools and improved learning outcomes. Using data on individuals completing compulsory schooling (9th grade), Böhlmark and Lindahl (2015) calculated the share of 9th-grade students living in a municipality, who attended an independent school, which did not exist before the voucher reform. They estimated the effect on achievement as the difference between the average performance of the last post-reform cohort and the last pre-reform cohort. Average educational performance was found to increase both in the short run and the long run.

A recent study by Dinerstein and Smith (2021) argues that due to smaller average size and high tuition costs, the supply of private schools is more elastic. They found that a public school funding policy in the city of New York led to a decline in private school supply. Further, the exit of private schools was more prominent among low-enrolment and low-value-added schools. Dinerstein and Smith (2021) used a difference-in-differences approach with a continuous measure of the funding received by public schools (in $1,000 per student). Among other outcomes, they studied the effect of the funding policy on public school enrolment and private school closure rates. They compared private schools that were and were not close substitutes of public schools that

received more funding. Dinerstein and Smith (2021) found that for every projected $1,000 rise in funding per student, the enrolment in a public school grew by 32 students. It further resulted in a decline in the number of private schools nearby by 6%.

With respect to other school choice programs in India, existing studies have exploited randomized controlled trials to investigate the effect of vouchers on learning outcomes (Muralidharan and Sundaraman, 2017; Dixon et al., 2019). While Muralidharan and Sundaraman (2017) studied the impact of a school choice program in Andhra Pradesh, Dixon et al. (2019) looked at the effect of a similar program that targeted children living in the slums of Delhi, who were below the poverty line. In both studies, children were offered vouchers through a lottery that enabled them to attend their preferred private school. However, the studies found mixed results. In Andhra Pradesh, after four years, lottery winners scored 0.55 SD higher on test scores in Hindi, while there was a very small positive effect on test scores in English (0.12 SD). In Delhi, the effect of the program was positive for English (0.31 SD) but negative for Hindi (0.20 SD).

The relationship between government-run school choice policies and the supply of private schools is well established in the literature. This chapter corroborates the finding that increased demand for private education results in an increase in the supply of private schools. It is the first study to provide empirical evidence on the relation between the RTE reservation policy's school choice and the entry of new private schools in India.

2.3.3 Affirmative action in India

There exists a limited number of studies evaluating the causal effect of affirmative action in primary education in India. In recent years, two studies have used natural experiments to investigate the impact of reservations on educational attainment (Cassan, 2019; Rao, 2019). Using data from the National Family Health Survey (NFHS) 1998-99, Cassan (2019) explored variation in the 'SC' (Scheduled Caste) status that was given to 2.5 million people in India in 1976. The study used a difference-in-differences methodology to compare the outcomes across groups that received the SC status during independence and after 1976. Cassan (2019) found that this natural exogenous variation resulted in a 10 percentage points increase in literacy and a 7 percentage points increase in attainment in secondary education. However, there was no effect on higher education.

Rao (2019) studied the effect of affirmative action on social behaviour and learning outcomes of rich children with poor classmates (low social categories) in private schools of Delhi. Using a field experiment based on a charity event, the study found

that the share of volunteering increased by 13 percentage points for students with poor classmates, and 15 percentage points for students with poor study partners. Similarly, by incorporating a dictator game in a lab setting, it was found that rich students with poor classmates shared more money with a poor student (0.43 SD). Finally, using data on test scores and a difference-in-differences strategy, Rao (2019) found that students with poor classmates scored marginally lower in English.

A similar study by Joshi (2020) analyzed the relationship between the reservation policy and social integration in a classroom in urban areas of Karnataka and Maharashtra. In particular, the study looked at how likely RTE students were to be friends with their non-RTE classmates using a friendship survey. Joshi (2020) also collected data on test scores to analyze the difference in learning outcomes between RTE and non-RTE students in a classroom. Using Anova tests, the study found that RTE students were more likely to be friends with other RTE students, and non-RTE students were more likely to be friends with other non-RTE students. RTE students scored significantly lower on tests than their non-RTE classmates but there was a positive relationship between the share of non-RTE friends and the test scores of RTE students. On the other hand, the share of RTE friends had a negative effect on the test scores of non-RTE students.

Only a few studies have estimated the causal effect of the reservation policy in India. Using randomization in the lottery system to oversubscribed schools, Damera (2017), Dongre, Sarin, and Singhal (2018) and Romero and Singh (2023) studied the causal effect of the policy on the outcomes of lottery winners. The papers found similar results. Firstly, lottery winners were more likely to attend private schools. These private schools were largely English-medium and charged marginally higher fees on average. In Karnataka, the probability of attending private schools for lottery-winning boys and girls increased by 5 percentage points and 7 percentage points respectively (Damera, 2017). In Chhattisgarh, lottery winners were 24 percentage points more likely to attend private schools and 11 percentage points more likely to attend English-medium private schools (Romero and Singh, 2023). In Ahmedabad, Gujarat, the fraction of children attending English-medium private schools was higher among lottery winners by 7.5% (Dongre, Sarin, and Singhal, 2018).

Secondly, a majority of the lottery losers also ended up attending private schools. 88% of lottery losers in Chhattisgarh (Romero and Singh, 2023) and 60% of lottery losers in Ahmedabad (Dongre, Sarin, and Singhal, 2018) attended private schools. Finally, all three studies found that children from economically better-off households and those with more educated parents were more likely to apply for free seats under the

policy. Damera (2017) and Romero and Singh (2023) also evaluated the effect of the policy on learning outcomes. Damera (2017) found that in Karnataka, the policy increased test scores only for lottery-winning girls by 0.11 SD. According to Romero and Singh (2023), the policy increased test scores by 0.19 SD for lottery winners in Chhattisgarh during COVID-19.

Given the poor implementation of the policy, the lottery winners in Karnataka, Chhattisgarh and Ahmedabad account for a very small fraction of eligible children, who could potentially benefit from affirmative action. While winning the lottery and getting a free seat in a private school could have positive implications, as found in the literature, the aim of the policy was the social integration of 'all poor and disadvantaged' children in India. This chapter fills the gap by focusing on all children who were eligible to apply for free seats under the policy due to their social category. It also looks at the effects of the policy on the expenditure on private education, which has not been explored yet.

2.4 Data

2.4.1 National Sample Survey

The primary source of data for this chapter is the National Sample Survey (NSS) of India, which allows me to study the effect of the RTE reservation policy on education expenditure from the demand side. NSS is a nationally-representative survey of households, sampled from all Census districts of India. I use the 64th and 71st rounds of NSS, which collected detailed information on education. The 64th round of the survey was carried out from July 2007 to June 2008, while the 71st round was carried out from January to June 2014. This allows for a comparison of outcomes before and after the reservation policy was implemented. However, NSS data is cross-sectional, so the households interviewed in both rounds are different.

In the 64th and 71st rounds, NSS collects schooling information of all children in the household above the age of 5. For all individuals aged 5-29, it records the status of current enrolment and attendance in an educational institute. For all children above the age of 5, who are at least attending a primary grade (grade 1 or above), the survey records the type of school attended, which can be either government, private aided, or private unaided.[7] In the data, those who attend private unaided schools are further asked

[7]Government schools in India are public schools run by the central, state or local government. Private aided schools are partly funded by the government and partly managed by a private committee of individuals.

if the schools are *recognized*[8] by the government. NSS also collects information on the amount of fees paid towards the course, uniform, books, transport, and private coaching for each child attending a primary grade or above.

The RTE Act's reservation policy was implemented only in recognized private unaided schools. For the remainder of this chapter, I refer to recognized private unaided schools as simply private schools, unless mentioned otherwise. The sample of interest in the chapter is the disadvantaged groups, who are eligible under the policy due to their lower social category.[9]

2.4.2 District Information System for Education

To further exploit the intensity of the policy, I link the NSS data with the District Information System for Education (DISE) at the district level. DISE is a nationwide database of roughly 2 million recognized[10] schools in India and is available from 2005-06 to 2017-18 (18 million observations). From 2010-11 onward, DISE collects information on the number of students enrolled under the reservation policy at entry-level (typically grade 1) in private schools. Total enrolment under the policy by 2014 – corresponding to round 71 in NSS – is, therefore, the sum of the number of children enrolled under the policy at the entry level from 2010-11 to 2014-15.

Although the reservation policy was introduced nationally, only 16 out of 33 states have formally implemented the policy according to the Ministry of Education (MoE).[11] Figure 2.1 shows the total enrolment under the policy as a percentage of the population of primary-school-going children (aged 5-9) in the largest 20 states of India. The enrolment data reported by schools in DISE is plotted against the enrolment data reported by the states to the MoE.[12]

States such as Madhya Pradesh, Rajasthan, Karnataka, Uttarakhand, and Chhattisgarh have the highest enrolment under the policy. However, there is a discrepancy in

[8] Private unaided schools are recognized by the government upon fulfillment of certain standards and requirements in terms of infrastructure, enrolment, and expenditure.

[9] States such as Haryana, Mizoram, and Tamil Nadu do not enroll disadvantaged groups under the policy. Jharkhand, Meghalaya, and Tripura only include SC and ST from families below the poverty line. In Goa, only disabled children are eligible under the policy. No official definition of disadvantaged groups is available for Sikkim, and Dadra and Nagar Haveli. These states are, therefore, excluded from the sample.

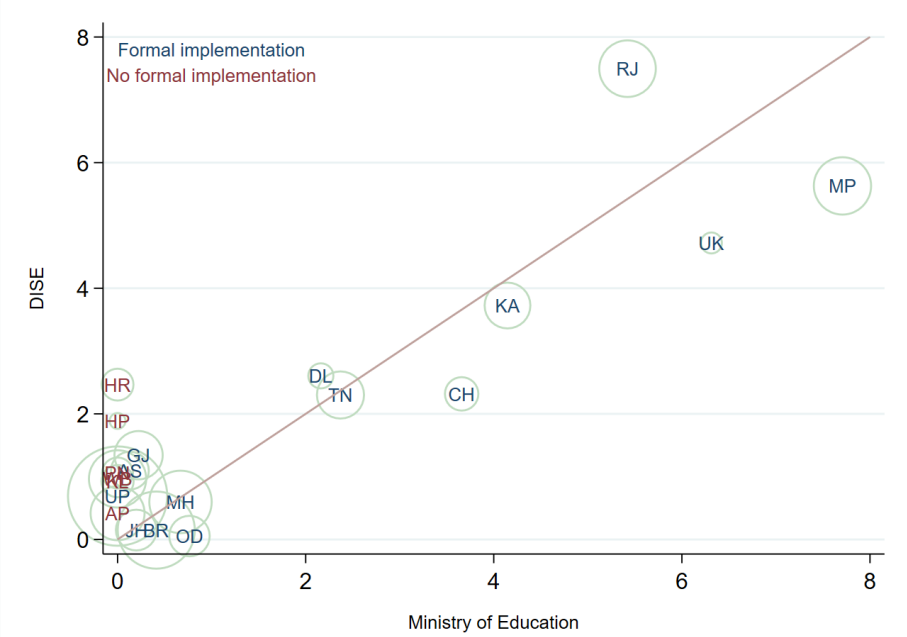
[10] All recognized private schools are included but unrecognized private schools are not.

[11] These include Madhya Pradesh, Rajasthan, Karnataka, Tamil Nadu, Chhattisgarh, Uttarakhand, Maharashtra, Bihar, Delhi, Odisha, Gujarat, Jharkhand, Assam, Chandigarh, Andaman and Nicobar Islands, and Uttar Pradesh.

[12] The enrolment numbers from the MoE are based on the information sought under the Right to Information Act, 2005.

the enrolment calculated from DISE for these states and the enrolment reported by the MoE. In all states that did not formally implement the policy, and therefore report no data to the MoE, the calculated enrolment from DISE is 1% or less. Anomalies include Haryana and Himachal Pradesh. In Haryana, the enrolment calculated from DISE is almost 3%, while in Himachal Pradesh, it is around 2%. Nonetheless, there is a high positive correlation of 0.90 (in the 16 states) and 0.60 (in all 33 states) between the percentage of enrolment calculated using data from the MoE and DISE.

Figure 2.1. Percentage of children enrolled under the reservation policy in the largest 20 states by 2014-15



Note: States are weighted by the population of children aged 5-9. States with formal implementation of the policy are Madhya Pradesh, Rajasthan, Uttarakhand, Karnataka, Chhattisgarh, Tamil Nadu, Delhi, Maharashtra, Odisha, Bihar, Jharkhand, Uttar Pradesh, Assam and Gujarat. States with no formal implementation of the policy are Andhra Prdaesh, Kerala, West Bengal, Punjab, Haryana, and Himachal Pradesh.

2.5 Identification strategy

To examine the impact of the policy, I focus on the effects of 'exposure' rather than 'enrolment' within the policy framework. The reason for this is that the actual enrolment of disadvantaged children under the policy was low. Additionally, as found in Chapter 1, the direct effect of the policy on enrolment was limited. Yet, a significant indirect effect was evident on disadvantaged children entering grade 1 post the RTE Act. This pattern suggests that the sheer presence and awareness of the policy may have had broader implications for eligible children, influencing decisions and outcomes even if they were not directly enrolled under the policy's provisions.

Section 2.5.1 explains how I define 'exposure' to the policy. Essentially, I leverage the exogenous variation in eligibility to receive free seats under the policy. Using data on social category and age at which schooling starts from the NSS, I identify the cohort aged 5-9 from disadvantaged groups (SC/ST/OBC) as children exposed to the policy.

If the reservation policy is effective, it would lead to higher enrolment in private schools among children who are eligible and thus exposed to the policy. Furthermore, it would lead to higher overall enrolment among these children in schools if there is no substitution from government to private schools. On the other hand, if the effects of the policy have been largely indirect as found in Chapter 1, the increased private school enrolment could be due to reduced private school fees. To explore these effects, I first look at the descriptive evidence from the NSS data in Section 2.5.2.

2.5.1 Defining exposure to the policy

As the RTE Act was introduced in August 2009, the policy is expected to have an effect on outcomes from the school year 2010-11[13] onwards. At the same time, free places under the policy were only made available to new entrants in school (pre-primary or grade 1). Therefore, children who were already attending schools (grade 2 or above) in 2010-11 were not exposed to the policy. In other words, children who are potentially exposed to the reservation policy are those who started school after August 2009.

To define exposure, I use the two cross-sectional surveys from NSS– round 64 and round 71. Interviews in round 64 took place between July 2007 and June 2008, and interviews in round 71 took place between January and June 2014. Children interviewed between July 2007 and March 2008 therefore, correspond to the school year 2007-08, while those interviewed between April and June 2008 correspond to the school year

[13] A school year in India typically starts in April and ends in March next year.

2008-09. Similarly, in round 71, those interviewed between January and March 2014 correspond to the school year 2013-14 and those interviewed between April and June 2014 correspond to the school year 2014-15.

For all children attending schools, the present age and the age at which they entered grade 1 are reported in the data. Using these and the date of the survey, I calculate the school year in which all disadvantaged children in round 71 started school. I define a disadvantaged child in round 71 as 'exposed' if she started school after 2009, that is, any school year from 2010-11 onwards. She is 'not exposed' if she started school any time before 2010-11. I observe that 91% of children who started school after 2009 are aged 5-9, and 94% of children who started school before 2010 are aged 10-14 in round 71. Therefore, disadvantaged children aged 5-9 in round 71 form the treatment group, and older children, aged 10-14 form the control group.

A simple comparison of the treatment and control groups would result in biased estimates if the outcomes are different for younger and older children due to their age, or due to other differences which are correlated with age. Therefore, I also construct the same treatment and control groups from the round 64 interviews, which took place before the policy was introduced. The 'treated' are disadvantaged children who are aged 5-9 and the 'controls' are those aged 10-14 at the time of the round 64 interviews. The difference in the outcome variable between these two groups serves as the pre-treatment difference, such that the difference-in-differences remove any age effects. If Y is the outcome, the DID estimate can be represented as:

$$[\mathrm{Y}(\text{5-9 in round 71}) - \mathrm{Y}(\text{10-14 in round 71})] - [\mathrm{Y}(\text{5-9 in round 64 }) - \mathrm{Y}(\text{10-14 in round 64})] \quad (2.1)$$

2.5.2 Descriptive evidence

I begin my analysis by simply comparing the schooling outcomes of disadvantaged children in both rounds of NSS. In Table 2.1, the younger cohort aged 5-9 form the treatment group, while the older cohort aged 10-14 form the control group. By round 71, there is a significant increase in the share of disadvantaged children attending schools. Surprisingly, the increase in the share is around 3 percentage points higher for the older cohort (control group). There is also an increase in the share of disadvantaged children attending private schools. This is consistent with India's trend of rising enrolment in private schools. However, for both treatment and control groups, the increase has been the same (around 8 percentage points).

For the treatment group, the increase in private school enrolment seems to be almost entirely offset by a decrease in government school enrolment, whereas for the control group, there was no change in government school enrolment. This means that among the younger cohort, there was a shift away from government to private schools. Children who would have otherwise gone to government schools chose to go to private schools after the policy. Among the older cohort, the increase in private school enrolment is almost entirely driven by the fact that there was a higher proportion of these children attending schools by round 71. This suggests that compared to round 64, the older cohort in round 71 had better access to education perhaps due to more availability of private school places.

Table 2.1. Proportion of disadvantaged children in school

	Round 64 Mean	**Round 71** Mean	**Difference**	**Std. error**
Treatment group				
Attends school	0.78	0.87	0.09	0.005
Attends government school	0.58	0.52	-0.06	0.006
Attends recognized private school	0.09	0.17	0.08	0.004
Attends unrecognized private school	0.02	0.03	0.01	0.002
Observations	19,080	11,843		
Control group				
Attends school	0.80	0.92	0.12	0.004
Attends government school	0.61	0.61	0.00	0.005
Attends recognized private school	0.07	0.15	0.08	0.003
Attends unrecognized private school	0.01	0.02	0.01	0.001
Observations	19,345	14,099		

Source: National Sample Survey
Notes: Remaining children attend private aided schools. Disadvantaged children who do not know if their private school is recognized or unrecognized are dropped (less than 5%). The differences and standard errors of differences are based on a paired sample t-test.

Table 2.2 shows the average fees of disadvantaged children attending recognized private schools. I observe that by round 71, the fees for both groups in private schools significantly increased, even in real terms. However, compared to the control group, the increase in real fees of the treatment group was much lower. This is despite an equal increase in their share attending private schools as seen in Table 2.1. In other words, younger disadvantaged children in round 71 were paying a 25% lower fee than their older counterparts in private schools, compared to younger disadvantaged children in round 64.

Next, I restrict the sample to only richer disadvantaged households that were more likely to apply for free seats under the reservation policy. Studies such as Romero and Singh (2023), Dongre, Sarin, and Singhal (2018) and Damera (2017) have found that within the eligible groups, the majority of the applicants of the reservation policy belong to economically better-off households. This is largely because of low awareness about the policy among the poor, lack of access to technology, and a complicated application process. I define a 'richer' disadvantaged household as one that has an annual real consumption expenditure higher than the median consumption expenditure of all disadvantaged households in the round in which the household is surveyed.

Then I restrict the sample to states that had a better implementation of the reservation policy and subsequently a higher enrolment under the same. As per the data from the Ministry of Education and DISE, these states include Rajasthan, Madhya Pradesh, Karnataka, Chhattisgarh, and Uttarakhand. I find that in both cases, the difference consistently increases in magnitude. When I further restrict the sample to richer disadvantaged households in the top RTE states, who were most likely to participate in the policy, the increase in fees of the treatment group was even lower than that of the control group, by more than ₹1,000. However, this estimate is imprecise and not significant at conventional levels.

Table 2.2. Average annual fees of disadvantaged children in private schools

	Round 64		Round 71		Difference	DID
	Obs.	Mean	Obs.	Mean		
	(1)	(2)	(3)	(4)	(5)	(6)
Whole sample						
Treatment group	1,598	2,746	2,009	3,857	1,111***	
Control group	1,303	2,638	1,975	4,112	1,474***	-363*
Richer households						
Treatment group	1,229	3,145	1,289	4,756	1,611***	
Control group	949	3,098	1,333	5,026	1,928***	-317
Top RTE states						
Treatment group	356	2,864	329	4,765	1,901***	
Control group	260	2,659	324	5,331	2,672***	-771
Richer households in top RTE states						
Treatment group	301	3,137	234	5,379	2,242***	
Control group	221	2,889	228	6,185	3,296***	-1,054

Source: National Sample Survey

Notes: Fee includes tuition fee, examination fee and other compulsory payments. Reported fee is in real terms, deflated by the Consumer Price Index (2010=100). All values in columns (2), (4), (5) and (6) are in Indian rupees (1 USD= ₹83). Results in column (5) are based on a paired sample t-test. Results in column (6) are the relative differences in the change in fees of younger and older children reported in column (5). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

To check if the lower increase in fees of the younger cohort was driven by free places under the reservation policy, I use other expenditure-related information in the data reported in Table 2.A.1. For each child in school, NSS collects information on whether education is free. Education is considered free if it applies to the whole institution and not to the student's specific situation. It is still defined as free if there is no tuition fee in a school but a fixed amount of money is charged in the form of development fee, library fee, etc. Education in government schools in most states is free.[14] Students whose education is not free in both rounds are asked if their tuition fee was waived (fully/partly/not) due to special circumstances. The reason for waiver is also recorded which includes the disadvantaged categories (ST, SC, OBC), disability, merit, financially weak, or others.

If fees were waived for children enrolled under the reservation policy in private schools – that are otherwise not free – this would reflect in the household's response to the question of whether the tuition fee was waived due to special circumstances. Furthermore, for disadvantaged children, who are eligible on the basis of caste (social category), the reason recorded would be SC, ST or OBC. Table 2.A.1 shows that only a very small proportion of children in the treatment group had their tuition fees waived in private schools, even after the reservation policy was implemented. Moreover, the proportion of children in private schools who had their fees waived is not different between the treatment and control groups. Therefore, any effect on fees seen in Table 2.2 cannot be driven by fee waivers.

I find that there is a notable shift from government to private schools for disadvantaged groups following the introduction of the RTE Act. However, there is no differential increase for the younger disadvantaged cohort as one would expect if the reservation policy increased access to children who started school after the policy was implemented. Nonetheless, descriptive evidence shows that after RTE, the younger disadvantaged cohort's private school fees grew almost 25% more slowly. Furthermore, among those more likely to apply for free seats under the policy, the difference in fee growth was an added 7%. However, using additional information on education expenditures from the data, I find that very few of the disadvantaged children were studying in private schools for free or had their fees waived. This implies that the slower growth in their private school fees cannot be attributed to free seats provided under the reservation policy.

[14]The Right to Education Act made education in government schools free and compulsory in primary grades (1-8).

2.6 Effect of exposure on fees

Descriptive evidence shows that enrolment directly under the reservation policy could not have driven the reduction in fees for the younger disadvantaged cohort after RTE. To see if reservation policy indirectly influenced the changes in fees, I conduct a more robust investigation of its effects.

To establish a causal relationship between the reservation policy and fees, it is not sufficient to show that the relative increase in fees was lower for the treatment group (column 6 in Table 2.2). There could be individual-level and household-level confounding factors such as gender or household income that could determine exposure to the policy while also being correlated with fees. To account for these factors, I estimate a difference-in-differences (DID) model controlling for a series of pre-determined characteristics. I also incorporate district fixed effects and household fixed effects that leads to comparisons within a district and within a household respectively. Refining the model by adding controls and fixed effects also improves the precision of the estimates.

2.6.1 Basic DID model

I begin by estimating a standard DID equation. The outcome variable is the 'annual course fees of a child attending a private school'. Course fees include tuition fees, examination fees, and other compulsory payments such as lab fees and library charges. I estimate the following model:

$$Fee_i = \beta_0 + \beta_1 Young_i + \beta_2 Post_i + \beta_3 Young_i \cdot Post_i + \gamma_0 X_i + \alpha_d + \varepsilon_i \qquad (2.2)$$

Fee_i is the real[15] annual school fee of a disadvantaged child i currently attending a private school. $Young_i$ is a dummy variable that indicates whether child i belongs to the treatment group. $Young = 1$ if the child is aged 5-9 and 0 if the child is aged 10-14. $Post_i$ is the post-treatment time dummy. $Post = 1$ if the child is interviewed in round 71 and 0 if interviewed in round 64. $Young_i \cdot Post_i$ is the interaction of treatment and time dummy, such that β_3 captures the DID effect. X_i is a vector of individual and household-level observable characteristics[16]. α_d controls for district fixed-effects and ε_i

[15]It is the nominal fees reported in the data deflated by the Consumer Price Index (2010=100). CPI data is obtained from World Bank for the years 2007, 2008, 2013 and 2014. This is because data reported by India is based on the fiscal year, which begins in April (same as the school year).

[16]Individual and household-level characteristics include the log of household size, and dummies for rural area, female, religion, medium of instruction in school, private coaching and distance to child's school. These are based on a paper by Mukherjee and Sengupta (2021) that analyzes the factors affecting private education expenditure in India using NSS data.

is the unobserved error term.

Exposure to the policy reduces school fees if the difference in the fees of the younger cohort in private schools is significantly lower in round 71. The DID estimates rest on the assumption that in the absence of the policy, the fees for the two age groups would have changed in the same manner. One way to check this is by estimating Equation (2.2) for groups that were not exposed to the reservation policy even after August 2009. These include non-disadvantaged households and those living in areas where there was no formal implementation of the policy (see Section 2.9).

Another strategy is to estimate the model within disadvantaged households, which would compare the fees of younger and older siblings. A within-household model is useful because it will control for unobservables that are fixed within a disadvantaged family. So, I estimate the same model for siblings within disadvantaged households as the trends in fees are more likely to be parallel in the absence of the policy. I do this by restricting the sample to disadvantaged households that each has at least 1 child in the treatment group (aged 5-9) and 1 child in the control group (aged 10-14). I then undertake a within-household estimation of the following form:

$$Fee_{ih} = \beta_0 + \beta_1 Young_{ih} + \beta_2 Post_{ih} + \beta_3 Young_{ih} \cdot Post_{ih} + \gamma_0 X_{ih} + \mu_h + \varepsilon_{ih} \qquad (2.3)$$

where the dependent variable Fee_{ih} is the real annual school fee of disadvantaged child i in household h, currently attending a private school. $Young = 1$ if child i in household h is aged 5-9 and 0 if the child is aged 10-14. $Post = 1$ if child i in household h corresponds to round 71 and 0 if the child corresponds to round 64. However, since the households in both rounds are different, with household-fixed effects, outcomes within the same household cannot be observed over time. As a result, β_2 drops out of the model. β_3 still captures the DID effect, which is the relative difference in fees between siblings in round 71 and siblings in round 64. I also control for gender, medium of instruction, private coaching and distance to school. μ_h controls for household fixed effects.

I first estimate Equations (2.2) and (2.3) for the whole sample, which includes all disadvantaged children aged 5-14. Then I restrict the sample to disadvantaged children aged 5-14 from 'richer' disadvantaged households and states that had a better implementation of the policy. These samples were more likely to apply for free seats under the policy and therefore would reflect a higher demand for private education. As per the data from the Ministry of Education and DISE, the states with the highest enrolment under the policy include Rajasthan, Madhya Pradesh, Karnataka, Chhattisgarh, and Uttarakhand. Finally, I estimate both equations for a sample of children from 'richer' disadvantaged households in these five states.

2.6.2 Results

Table 2.3 presents the results from the basic difference-in-differences model, where exposure only varies by time. It is similar to Table 2.2 but includes control variables and district fixed effects. It also reports results from the within-household estimation. I find that before the policy (round 64), fees of younger disadvantaged children in private schools were lower than that of older children within districts (columns 1-4), as well as within households (columns 5-8). After the policy (round 71), fees increased for both groups, but the increase was relatively lower for younger children. However, the difference is not statistically significant with district fixed effects as the standard errors are high (columns 1-4).

In the specifications with household fixed effects (columns 5-8), I find that within disadvantaged households in round 71, the fees of younger children were significantly lower than that of their older siblings relative to round 64. Additionally, the magnitude of the effect is larger within households that were more likely to apply for free seats under the reservation policy.

In the states with the best implementation of the policy (column 7), the annual fees of younger children were lower than that of their older siblings by almost ₹650 compared to round 64. Within richer disadvantaged households in these states (column 8), which were even more likely to apply for free seats under the policy, annual fees of younger children were lower by ₹844 after RTE. This means that given a monthly consumption expenditure of ₹2,784 (Table 2.A.2), disadvantaged households with only younger children saved about 2.5% of their expenditure after the policy.

Table 2.3. Effect of exposure to RTE on school fees

	Whole sample				Sibling sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Young	-0.355***	-0.326**	-0.256	-0.150	-0.342***	-0.386***	-0.222**	-0.156
	(0.114)	(0.145)	(0.258)	(0.289)	(0.070)	(0.085)	(0.104)	(0.115)
Post	0.902***	1.293***	1.601***	1.813***				
	(0.159)	(0.225)	(0.346)	(0.497)				
Young x Post	-0.251	-0.346	-0.502	-0.428	-0.223*	-0.329**	-0.649**	-0.844**
	(0.166)	(0.213)	(0.399)	(0.472)	(0.117)	(0.161)	(0.322)	(0.390)
Constant	1.983***	3.090***	3.405***	4.022***	1.988***	2.379***	1.712**	1.864**
	(0.255)	(0.379)	(0.825)	(1.361)	(0.301)	(0.390)	(0.692)	(0.781)
Observations	6,885	4,800	1,269	984	3,233	2,214	554	426
R-squared	0.46	0.47	0.44	0.46	0.96	0.96	0.96	0.96
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	No	No	No	No
Household FE	No	No	No	No	Yes	Yes	Yes	Yes

Notes: Dependent variable is the real annual fee in private school (in thousand rupees). Fee includes tuition fee, examination fee and other compulsory payments. Columns (1) and (5) correspond to all households. Columns (2) and (6) correspond to a sample of children from richer households, that have a real consumption expenditure higher than the median consumption in the round in which they are surveyed. Columns (3) and (7) correspond to a sample of top RTE states- Rajasthan, Madhya Pradesh, Chhattisgarh, Karnataka, and Uttarakhand. Columns (4) and (8) correspond to a sample of richer households in the top RTE states. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Results from the basic DID model are consistent with the descriptive evidence in Table 2.2. Post RTE, there was a lower increase in the fees of younger disadvantaged children, who were exposed to the reservation policy compared to the older disadvantaged children, who were not. Among samples that exhibit a higher likelihood to apply for free seats under the policy, the increase in the fees of younger disadvantaged children was even lower. The DID estimates with household fixed effects have a lower standard error and therefore, generate more precise estimates.

2.7 Effect of district-variation in exposure on fees

In the basic DID model, the 'treatment', which is the exposure to the reservation policy, is simply based on eligibility as a result of age and disadvantaged status. Many children in the treatment group are less exposed to the policy if, for instance, they live in regions where only a few places were offered under the policy in private schools. Despite being a national-level policy, its implementation has not been consistent across states, with states such as Madhya Pradesh and Rajasthan implementing the policy well, and states such as Andhra Pradesh not implementing the policy even after five years. Columns (3) and (7) in Table 2.3 suggest that the extent of exposure at the state level matters. This provides a rationale for a model in which local 'exposure' matters for the size of the

treatment effect.

Descriptive evidence from the administrative school data shows that enrolment under the reservation policy varies not only across states but also within states. In Figure 2.A.1, I map the enrolment rate under the reservation policy at the district level for all of India using data from DISE. As seen in the map, even within states, some districts had a higher take-up under the policy. District-level variation in enrolment under the policy could arise because of variation in the availability of private schools or variation in the proportion of disadvantaged children in the district.

The district-level variation can strengthen the identification as exposure to the policy varies based on the district in which a disadvantaged child resides. I use the enrolment rate under the policy as a proxy measure of exposure/program intensity. It is calculated as the percentage of children aged 5-9 enrolled under the reservation policy in each district.[17] I also formally check the district-level variation by first regressing the percentage of RTE enrolment in a district on state dummies and then including district dummies. When I include only state dummies, the adjusted R^2 is 0.21. However, when I include district dummies, the adjusted R^2 increases to 0.34. It means that 13% more variation in RTE enrolment is explained by districts within the states.

Moreover, even within states that had a systematic implementation, some districts had higher exposure to the policy than others (Figure 2.A.2). If the effect on fees is driven by the policy albeit indirectly, districts with higher exposure would have a larger effect on fees.

2.7.1 DID model with regional variation

To estimate the effect of district-level exposure to the policy, I exploit this regional variation[18] in the intensity of the policy to estimate the effect on the fees of 'treated' children in private schools. I use the enrolment under the reservation policy at the district level as a continuous proxy measure of program intensity. Specifically, using data from DISE and Census 2011, I calculate the percentage of children aged 5-9 enrolled under the reservation policy in private schools in each district. This is given by:

[17] Population data is used from Census 2011. Out of 640 districts in the Census, 625 matched with DISE.

[18] Other studies that have used a similar strategy to investigate the effect of supply-side interventions in education include Duflo (2001), Handa (2002) and Lucas and Mbiti (2012). Duflo (2001) and Handa (2002) explore regional variation in new schools in the context of a school construction program in Indonesia and Mozambique respectively. Lucas and Mbiti (2012) use variation in the number of new test-takers to study the effect of a free primary education program in Kenya.

$$RTE_{dt} = \frac{\text{Total enrolment under RTE at the primary level in district } d \text{ and round } t}{\text{Population of children aged 5-9 in district } d} \times 100$$

where total enrolment under RTE at the primary level (grades 1-5) in district d in round 71 is the sum of enrolment under the reservation policy at the entry level in district d in the post-RTE period. This is calculated from school years 2010-11 to 2014-15, as school years after 2014 are not relevant to round 71. Since the policy did not exist in round 64, RTE_{dt} is 0 in round 64 for all d.

Then I match this district-level measure with the household data, such that for each child, I know the percentage of children that were enrolled under the policy in the child's district of residence. Using this measure of program intensity, I estimate the following equation:

$$Fee_i = \beta_0 + \beta_1 Young_i + \beta_2 RTE_{dt} + \beta_3 Young_i \cdot RTE_{dt} + \gamma_0 X_i + \alpha_d + \varepsilon_i \tag{2.4}$$

The specification is similar to Equation (2.2) except here, RTE_{dt} denotes the enrolment rate under the policy in district d and round t. β_2 measures the change in the real annual fees of older children in private schools associated with a 1 percentage point increase in the policy enrolment in a district. The variable of interest is $Young_i \cdot RTE_{dt}$, such that β_3 captures the DID effect. It measures the change in the fees of younger children relative to older children when the rate of enrolment under the policy in a district increases by 1 percentage point. All other variables remain the same.

I also estimate the program intensity model for siblings within disadvantaged households, similar to Equation (2.3):

$$Fee_{ih} = \beta_0 + \beta_1 Young_{ih} + \beta_2 RTE_{dt} + \beta_3 Young_{ih} \cdot RTE_{dt} + \gamma_0 X_{ih} + \mu_h + \varepsilon_{ih} \tag{2.5}$$

With household-fixed effects, β_2 drops out as the same household cannot be observed in both rounds. As in the basic model, Equations (2.4) and (2.5) are estimated for the whole sample, a sample of children from 'richer' disadvantaged households, a sample of children from the top RTE states, and a sample of children from 'richer' disadvantaged households in the top RTE states.

Exposure to the reservation policy has a positive effect on fees if the difference in the fees of younger children was significantly lower than that of older children when policy enrolment increased in a district by 1 percentage point. Consequently, the difference would be larger in districts that had a higher enrolment under the policy. Furthermore, the magnitude of the effect would be larger among samples that had a higher demand for private education.

2.7.2 Results

Table 2.4 reports the results from the model with district-level variation in exposure, where the effect on fees is estimated not only over time but also by the rate of enrolment under the policy in a district. When there was no enrolment under the policy in a district, that is in round 64, younger disadvantaged children paid a lower fee than older children in private schools. This is consistent with the basic model. Similarly, an increase in the enrolment rate under the policy in a district – that captures a change in time – was associated with a higher fee for both groups. I find that within districts (columns 1-4), an increase in the RTE enrolment rate resulted in lower fees for younger children.

The results from the within-household estimation (columns 5-8) are however more precise. For instance in column (5), when the RTE enrolment rate in a district increased by 1 percentage point, the annual private school fees of younger children were significantly lower than that of their older siblings by ₹48. If the enrolment rate increased by 5 percentage points in a district, younger children paid ₹240 less than their older siblings (column 5).

Similar to the basic DID model, the difference is larger in samples that were more likely to apply for free seats under the policy and had a higher demand for private schools. In the top RTE states (column 7), a 5 percentage point increase implies that annual fees paid by younger children were lower than that of their older siblings by ₹380. In richer disadvantaged households in these states (column 8), it implies that younger children's annual fees were lower by ₹470 compared to their older siblings.

Although the results from columns (1)-(4) are insignificant, the estimated effects are quite consistent with those from columns (5)-(8). Moreover, the estimates in each column of Table 2.4 are consistent with the corresponding estimates in Table 2.3. For instance, in both models, the effect among the richer disadvantaged households in the top RTE states (column 4) is lower than that among all disadvantaged households in these states (column 3). But when I include household fixed effects in both models, the effect becomes largest among the richer disadvantaged households in the top RTE states (column 8). However, the size of estimates in Table 2.4 is much smaller due to the fact that the overall enrolment under the policy was less than 5% of all eligible children. If the policy had been successful, it would have had a much higher enrolment rate overall which would presumably have had a much larger effect on fees.

Table 2.4. Effect of district-level variation in RTE places on school fees

	Whole sample				Sibling sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Young	-0.465***	-0.505***	-0.302	-0.215	-0.423***	-0.501***	-0.340**	-0.332**
	(0.097)	(0.130)	(0.245)	(0.305)	(0.071)	(0.094)	(0.138)	(0.164)
RTE enrolment rate	0.154***	0.206***	0.159***	0.177***				
	(0.045)	(0.070)	(0.042)	(0.058)				
Young x RTE enrolment rate	-0.040	-0.027	-0.086*	-0.066	-0.048*	-0.069	-0.076*	-0.094*
	(0.031)	(0.051)	(0.049)	(0.061)	(0.027)	(0.046)	(0.040)	(0.056)
Constant	2.255***	3.324***	3.693***	4.296***	1.983***	2.377***	1.707**	1.874**
	(0.257)	(0.383)	(0.847)	(1.417)	(0.301)	(0.388)	(0.690)	(0.775)
Observations	6,885	4,800	1,269	984	3,233	2,214	554	426
R-squared	0.46	0.46	0.43	0.46	0.96	0.96	0.96	0.96
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	No	No	No	No
Household FE	No	No	No	No	Yes	Yes	Yes	Yes

Notes: Dependent variable is the real annual fee in private school (in thousand rupees). Fee includes tuition fee, examination fee and other compulsory payments. Columns (1) and (5) correspond to all households. Columns (2) and (6) correspond to a sample of children from richer households, that have a real consumption expenditure higher than the median consumption in the round in which they are surveyed. Columns (3) and (7) correspond to a sample of top RTE states- Rajasthan, Madhya Pradesh, Chhattisgarh, Karnataka, and Uttarakhand. Columns (4) and (8) correspond to a sample of richer households in the top RTE states. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

2.8 Mechanisms

Results from the difference-in-differences model show that exposure to the reservation policy reduced private education expenditure. Younger disadvantaged children paid a lower fee than older children in private schools after the policy, especially in districts where enrolment under the policy was higher. Additionally, the effect was stronger for children who were more likely to have applied for free seats under the policy. However, from Table 2.A.1, it is evident that the effect was not directly driven by free places offered under the reservation policy.

A potential mechanism driving the effect could be the increase in the entry of new low-fee private schools after the reservation policy was implemented. If the policy encouraged many new private schools to enter and if these schools were low-cost or low-fee, it could explain why younger children paid a lower fee in the post-RTE round. This is because new schools are most likely to enroll new entrants, that is children who newly start school, as opposed to older children who already attend existing schools.

Existing studies in the literature find evidence of the responsiveness of private school supply to school choice policies that increase the demand for private education and subsequently the enrolment in these schools. The reservation policy gave school choice to children who in principle, could not afford private education. The increased school choice could have, in theory, led to an increase in the demand for private education among these children despite a low takeup directly under the policy. Due to the limited

availability of seats under the policy, the prevailing high demand for private education could have been amplified.

According to Noronha and Srivastava (2013), parents of children who were eligible for free seats under the RTE reservation policy were enthusiastic about the opportunity and put in significant efforts to secure a spot. They often applied to multiple local schools and were prepared to try again the next year if they did not succeed. This increased demand could have encouraged more private schools to enter the market.

Subsequently, the new schools would have had a higher take-up of these children, especially in places where demand for private education was higher. This would explain why the effect of exposure was stronger and more significant for disadvantaged children from better-off families, particularly in the states with the best implementation of the policy. To test this hypothesis, I study the trends in the growth of private schools using data from DISE in Section 2.8.1. I find that following the implementation of the RTE Act, there was a surge in the number of private schools in India.

In Section 2.8.2, I show that all the new private schools that entered after RTE in fact charged a lower fee than existing schools on average. Thus, lower private school fee for the younger disadvantaged cohort after RTE is driven by these new low-fee private schools.

2.8.1 Entry of new schools

First, I check whether the reservation policy increased the entry of new private schools. Table 2.5 shows the total stock of private schools in India and the change in the stock over time. These are reported from the raw DISE data. I find that the net change in the number of private schools was 79% higher in the post-RTE period (2010-2014). Moreover, one year after the policy became effective, that is between 2010 and 2011, the total number of private schools in DISE increased by 31,700, which was much higher than the increase in any of the preceding years.

It is possible that the increase in the supply of private schools was driven by previously unrecognized schools becoming recognized due to the mandatory requirement of the RTE Act. The RTE Act made it compulsory for all private schools to be recognized by the government. If schools failed to get recognized, they were to be shut down. Therefore, many schools that were established before 2010 but entered DISE after 2010 might have been previously unrecognized. These schools might have started reporting data under DISE only after getting formal recognition, as DISE does not collect information from unrecognized private schools. Private schools now had an incentive

to become recognized to avoid being closed down. Furthermore, only recognized private schools could offer free seats under the reservation policy. So there could be a correlation between recognition and reservation.

To see if the period following RTE also saw an increase in the number of schools constructed, I study the trends in the growth of 'newly built schools'. Using the information on the 'year of establishment' – reported by each school – I exclude schools that were established before RTE but enter DISE only after RTE. Similarly, out of the schools that enter in the pre-RTE period (2006-2009), I exclude schools that were established before 2006. As a result, the remaining schools in the pre-RTE and post-RTE periods are certainly 'newly built'. These are reported in the last column of Table 2.5. The period following the implementation of the reservation policy also saw a big increase of 42,432 newly built recognized private schools in India, which was 10% higher than the pre-RTE period.

Table 2.5. Total private in India as reported in DISE

School year	No. of schools	Change in stock	New schools
2005-06	124,270		
2006-07	143,982	19,712	14,081
2007-08	156,118	12,136	9,684
2008-09	155,631	-487	7,816
2009-10	168,768	13,137	6,853
Total		**44,498**	**38,434**
2010-11	178,404	9,636	5,437
2011-12	210,104	31,700	11,078
2012-13	222,080	11,976	8,639
2013-14	233,337	11,257	7,059
2014-15	248,638	15,301	10,219
Total		**79,870**	**42,432**

Notes: The 'change in stock' is the total number of schools in year t - the total number of schools in year $t-1$. 'New schools' are the actual newly built schools each year.

Additionally, the RTE Act made education in government schools free. This might have resulted in more children from low-income families and poorer socio-economic backgrounds enrolling in government schools and private schools cream-skimming children from better-off families. This could result in higher post-entry profits for private schools and more private schools entering, as predicted by Menezes-Filho, Moita, and Andrade (2012). Free government education along with the reservation policy in private schools could have indirectly signaled to socially disadvantaged groups that private schools in fact provide better quality education. It could have also signaled to entrepreneurs that setting up private schools is profitable. Therefore, an increase in school choice could have resulted in an increase in the demand for private education and subsequently led to private schools either becoming recognized or newly constructed.

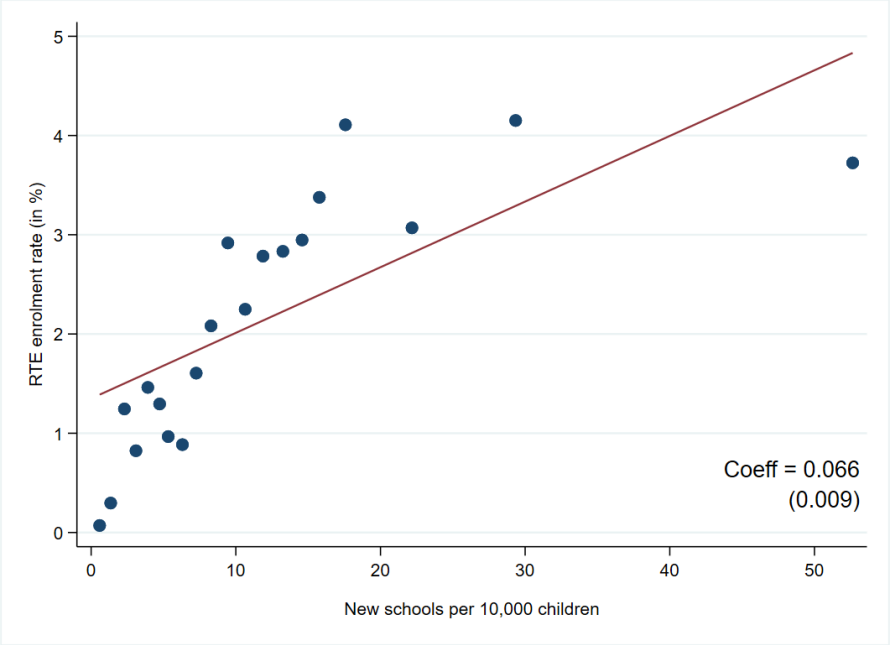
Results from the program intensity model show that exposure to the policy in a district also had an effect on fees. Therefore, I investigate the relationship between the entry of new schools and the enrolment rate under the policy at the district level. I use a scaled measure of 'new places': the number of new schools per 10,000 children (aged 5-9). This is based on a few similar studies in the literature.[19]

Figure 2.2 shows that there exists a very strong and positive relationship between new schools entering after RTE and the enrolment rate under the policy in a district. In Figure 2.2a, 10 new schools per 10,000 children (1 new school per 1,000 children) in a district is roughly associated with a 0.7 percentage points increase in the enrolment rate under the policy. Only looking at the newly built schools (Figure 2.2b), this correlation is even stronger. 10 new schools per 10,000 children in a district is associated with a 1.9 percentage points increase in the enrolment rate under the policy. Both figures show that districts that had a higher number of new private schools also had a higher enrolment under the policy.

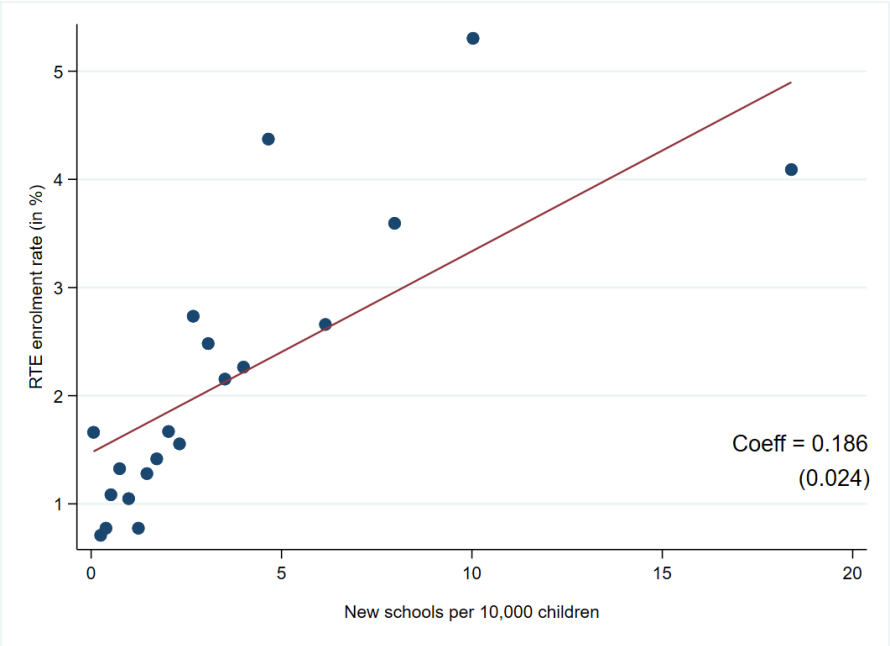
A higher number of new private schools in a district would in principle drive up the stock of private schools in the district. This would mechanically imply a higher enrolment rate under the reservation policy. However, I also find that these new schools themselves had a higher enrolment rate under the policy, as shown in Figure 2.3. If a district had 10 new schools per 10,000 children, it was associated with an additional 0.1 percentage points enrolment under the policy in the new school (Figure 2.3a). Newly built schools had approximately 0.2 percentage points more enrolment under the policy (Figure 2.3b).

[19] For example, Duflo (2001) uses new schools built per 1000 children in the region of birth as a measure of program intensity to investigate the impact of a school construction program in Indonesia.

Figure 2.2. Correlation between new schools and RTE enrolment at the district level



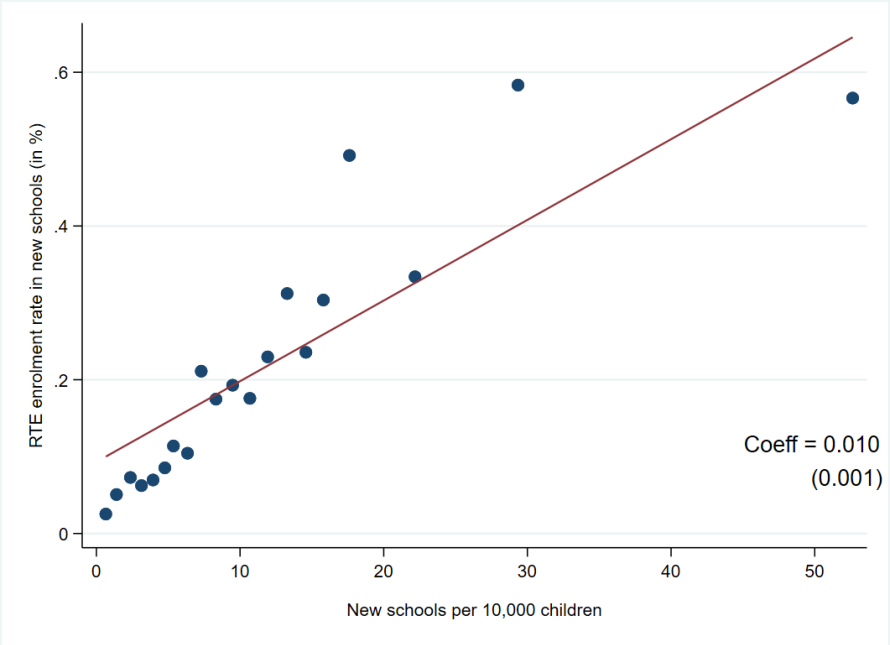
(a) All new recognized private schools



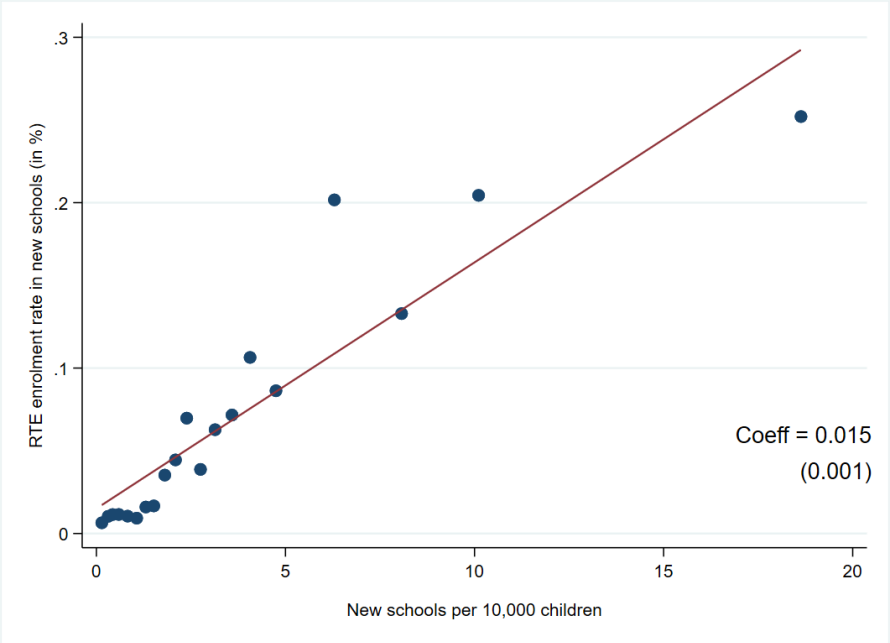
(b) Newly built recognized private schools

In Figure 2.2a, the number of new schools is calculated as the total number of new recognized private schools in the post-RTE period, that is from 2010 to 2014. These include private schools that were newly built and schools that might have been previously unrecognized. Figure 2.2b includes only those schools that were newly built after the policy.

Figure 2.3. Correlation between new schools and RTE enrolment in new schools at the district level



(a) All new recognized private schools



(b) Newly built recognized private schools

In Figure 2.3a, the number of new schools is calculated as the total number of new recognized private schools in the post-RTE period, that is from 2010 to 2014. These include private schools that were newly built and schools that might have been previously unrecognized. Figure 2.3b includes only those schools that were newly built after the policy. In both figures, the enrolment rate under RTE is calculated only in the new schools.

The growth of private schools after the RTE Act could be driven by the reservation policy, compulsory recognition of private schools, or free government education. It could also be a combined effect of all three aspects. Furthermore, the district-level variation in the number of new private schools seems to be driving the district-level variation in enrolment under the reservation policy. Evidence shows that the new private schools are also filling more places under the policy. Moreover, the variation in policy enrolment had a higher correlation with the variation in private schools newly built after the policy. This suggests that private schools constructed after the policy were at least in part associated with an increased demand for such schools due to the reservation policy.

2.8.2 'Low-fee' new schools

The high number of new schools entering after the reservation policy only explains the effect on fees if these new schools charged a lower fee than the existing schools. A limitation of DISE is that it does not collect data on school fees. However, it does collect information on infrastructure and facilities that are indicative of the quality of a school and the costs incurred by the school. DISE also includes data on the number of qualified teachers in a school, which enables me to calculate the pupil-teacher ratio for each school. The pupil-teacher ratio is also a good indicator of quality, and a higher ratio implies lower access for students to qualified teachers.

Using these measures of quality, I compare new and existing recognized private schools after RTE. Table 2.6 shows that new schools which entered in the post-RTE period (2010-2014), were on average lower in quality than existing schools. They had a higher pupil-teacher ratio and fewer facilities. New schools had around 42 students per teacher while existing schools had around 33 students per teacher. They were more likely to have only primary grades. New schools were also less likely to have computers, playgrounds, libraries, and tap water for drinking than existing schools. They were also less likely to conduct medical checkups for students. I find similar differences when I compare only the newly built private schools with the existing schools (Table 2.7).

I find strong evidence that after RTE, new private schools had fewer facilities than existing schools. Fewer facilities and resources in schools may lead to reduced operational costs. As a result, these schools may need to charge students a lower fee to attract enrolment, especially when competing with existing schools that offer better amenities. The lower fee can also reflect the reduced quality of education provided. So, if parents are paying less, they might be getting less in terms of educational standards, facilities, or resources.

Table 2.6. Characteristics of new and existing recognized private schools after RTE

	Existing	New	Difference	Std. error
Pupil-teacher ratio	33.00	42.00	9.00	0.121
Primary grades only	0.36	0.39	0.03	0.001
Facilities				
Computers available	0.49	0.46	-0.03	0.001
Playground available	0.84	0.71	-0.13	0.001
Library available	0.68	0.59	-0.09	0.001
Girls toilet available	0.90	0.90	-0.00	0.001
Source of drinking water: taps	0.44	0.36	-0.08	0.001
Medical check-ups conducted	0.58	0.51	-0.07	0.001

Source: DISE raw data
Notes: The differences and standard errors of differences are based on a paired sample t-test. All differences are significant at the 1% level.

Table 2.7. Characteristics of newly built and existing recognized private schools after RTE

	Existing	New	Difference	Std. error
Pupil-teacher ratio	35.00	38.00	3.00	0.193
Primary grades only	0.37	0.43	0.06	0.002
Facilities				
Computers available	0.49	0.44	-0.05	0.002
Playground available	0.81	0.70	-0.11	0.001
Library available	0.66	0.56	-0.10	0.002
Girls toilet available	0.90	0.90	-0.00	0.001
Source of drinking water: taps	0.42	0.36	-0.06	0.002
Medical check-ups conducted	0.57	0.50	-0.07	0.002

Source: DISE raw data
Notes: The differences and standard errors of differences are based on a paired sample t-test. All differences are significant at the 1% level.

On comparing new and existing schools in the pre-RTE period (2006-2009), I find that new schools before RTE also had fewer facilities than existing schools (Table 2.A.3). This suggests that new private schools in India, in general, are lower in cost and quality than existing schools, which implies that they also charge a lower fee. When new schools enter, they have fewer facilities but over time, they improve in quality. This difference in new and existing schools did not change after RTE except for the pupil-teacher ratio. However, for the mechanism to work, this is not a necessary condition. The main channel driving the effect on fees is the increased supply of such low-fee

schools.

Not only did the number of new private schools increase after RTE, but in districts where there was a higher number of new schools, there was also a higher enrolment under the policy. Since the new schools were low-cost or low-fee compared to the existing schools, they had a higher take-up of children from disadvantaged families. Further, as these new schools were smaller and less likely to have upper primary grades, it was the younger cohort that enrolled in these low-fee schools. As a result, children exposed to the policy in private schools (disadvantaged and aged 5-9) paid a lower fee than children not exposed (disadvantaged and aged 10-14).

However, considering that mandatory private school recognition or free government education could have also contributed to the growth of low-fee private schools, it is possible that the fee reduction for the younger cohort was not due to the reservation policy. I address these concerns in Section 2.9, where I show that aspects other than the reservation policy do not seem to be correlated with fee changes for the younger disadvantaged cohort.

2.9 Robustness checks

2.9.1 Placebo group

The DID estimates rely on the assumption that private school fees for the treatment and the control groups would have changed in the same way over time in the absence of the reservation policy. One way I check this is by estimating the DID model for a group that was not exposed to the reservation policy even after August 2009. This includes children from non-disadvantaged households, who do not belong to the lower social categories and thus are not eligible to apply for free seats under the policy.

The results from the basic DID model and the DID model with program intensity for non-disadvantaged groups are reported in Table 2.8. I only report the within-household estimates as it produces lower standard errors. The results are somewhat similar to those in Table 2.3. There was a lower increase in the fees of the younger non-disadvantaged children compared to their older siblings in round 71 (columns 1 and 2). However, unlike disadvantaged groups, the magnitude of the effect for non-disadvantaged groups is smaller in the top RTE states and richer non-disadvantaged households in these states (columns 3 and 4). Moreover, these differences are not statistically significant.

Columns (5)-(8) show the results from the program intensity model for non-disadvantaged groups. Similar to disadvantaged groups, the younger non-disadvantaged children paid lower fees than their older siblings in private schools, when there was no RTE enrolment in a district. However, when RTE enrolment in a district increased by 1 percentage point, the fees of younger and older siblings within non-disadvantaged households were not significantly different, unlike disadvantaged households as seen in Table 2.4.

Table 2.8. Effect of exposure to RTE on school fees of non-disadvantaged children

	Simple DID				Program intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
Young	-0.665***	-0.745***	-0.672***	-0.788***	-0.857***	-0.960***	-0.693***	-0.761***
	(0.099)	(0.141)	(0.085)	(0.124)	(0.148)	(0.206)	(0.098)	(0.135)
Young x Post	-0.449**	-0.529*	-0.252	-0.172				
	(0.209)	(0.310)	(0.173)	(0.268)				
Young x RTE enrolment rate					-0.023	-0.034	-0.032	-0.036
					(0.027)	(0.036)	(0.020)	(0.026)
Constant	4.195***	5.128***	3.238***	3.948***	4.203***	5.144***	3.240***	3.949***
	(0.577)	(0.751)	(0.178)	(0.199)	(0.582)	(0.761)	(0.180)	(0.203)
Observations	4,578	2,978	1,767	1,150	4,578	2,978	1,767	1,150
R-squared	0.94	0.94	0.96	0.96	0.94	0.94	0.96	0.96
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the real annual fee in private school (in thousand rupees). Fee includes tuition fee, examination fee and other compulsory payments. Columns (1) and (5) correspond to all households. Columns (2) and (6) correspond to a sample of children from richer households, that have a real consumption expenditure higher than the median consumption in the round in which they are surveyed. Columns (3) and (7) correspond to a sample of top RTE states- Rajasthan, Madhya Pradesh, Chhattisgarh, Karnataka, and Uttarakhand. Columns (4) and (8) correspond to a sample of richer households in the top RTE states. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1

Comparing the fees for younger and older 'non-disadvantaged' groups, who were not eligible under the policy, I observe a slower growth in the fees for the younger cohort relative to the older cohort. This is similar to the trends for disadvantaged groups. However, in places with greater demand for private education and higher enrolment under the policy, the difference between the fees of younger and older non-disadvantaged groups is lower and insignificant whereas, for disadvantaged groups, the difference is higher and significant.

The results confirm that while the policy had no direct effect on fee waivers, it had an indirect effect on the fees of children exposed to the policy. This is through the entry of new low-fee schools. While these new schools also took up non-disadvantaged children, they catered more to disadvantaged children at least in states where the policy was implemented well. As a result, it was predominantly the younger disadvantaged cohort that enrolled in the new low-fee private schools. This again suggests that increased school choice for the disadvantaged did result in the increased availability of cheaper schools.

2.9.2 Placebo states

If other aspects of the RTE Act— such as free government education or compulsory recognition of private schools which also led to the entry of new schools— directly affected younger disadvantaged children more than older disadvantaged children then the identifying assumption would not hold. To check this I estimate the DID model for states that had no formal implementation of the policy even by 2014-15. These include Andhra Pradesh, Himachal Pradesh, Kerala, Punjab and West Bengal (see Figure 2.1).

Columns (1) and (2) in Table 2.9 show the within-household estimates from the simple DID model. I find that after the policy, the increase in fees was lower for younger disadvantaged children in private schools than for their older siblings even in these states. The magnitude is high although the estimates are not statistically significant. Comparing it to the estimates from the main DID model (see columns 5-6 in Table 2.3), I find that the effect size is similar but the standard errors are much lower in the model with all states. This could be due to a larger sample size. However, in the top RTE states and richer households in these states, the size of the effect is much larger and highly significant. This is despite a sample size that is smaller and closer to the sample size with the placebo states (see columns 7-8 in Table 2.4).

The results from the program intensity model are also similar. Despite the placebo states having no formal implementation, they report some (albeit very little) enrolment under the reservation policy in DISE. This enables me to calculate the rate of RTE enrolment at the district level in these states. In columns (3) and (4), I find that a 1 percentage point increase in RTE enrolment is not associated with a significant difference in the fees between younger and older disadvantaged siblings. Even though the magnitude of the estimates is higher compared to the estimates in Table 2.4, the standard errors are also much higher.

Results from Table 2.9 imply that even in states with no formal implementation of the reservation policy, the younger disadvantaged children did pay a lower fee, which was also potentially due to the entry of new low-fee schools. However, the difference between the fees of younger and older children was not statistically significant. This suggests that the supply of new schools in these states did not increase the enrolment of the younger disadvantaged in the new low-fee private schools as much as it did in the states with a formal implementation of the policy. If any other aspect of the RTE Act resulted in the entry of low-fee private schools, it also seems to be correlated with the reservation policy. Therefore, the reduction in the fees for disadvantaged children does seem to be an effect of the policy.

Table 2.9. Effect of exposure on fees in states with no formal implementation

	Simple DID		Program intensity	
	(1)	(2)	(3)	(4)
VARIABLES				
Young	-0.820***	-0.875***	-0.954***	-1.024***
	(0.221)	(0.225)	(0.255)	(0.285)
Young x Post	-0.387	-0.436		
	(0.457)	(0.530)		
Young x RTE enrolment rate			-0.144	-0.142
			(0.311)	(0.368)
Constant	3.727***	3.844***	3.793***	3.906***
	(1.226)	(1.422)	(1.220)	(1.417)
Observations	465	378	465	378
R-squared	0.95	0.95	0.95	0.95
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Notes: Columns (1)-(4) present results from the within-household estimation for the states of Andhra Pradesh, Himachal Pradesh, Punjab, Kerala and West Bengal. The dependent variable is the real annual fee in private school (in thousand rupees). Fee includes tuition fee, examination fee and other compulsory payments. Columns (1) and (3) correspond to all households. Columns (2) and (4) correspond to a sample of children from richer households, that have a real consumption expenditure higher than the median consumption in the round in which they are surveyed. Standard errors are clustered at the district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

2.9.3 All disadvantaged children

The RTE Act could have spillover effects on all disadvantaged children in the eligible age group, and not just children in private schools. There could be a concern that focusing only on the private sector misses what happens to disadvantaged children in general. In principle, free government education, the reservation policy and the growth of both government and private schools could have an effect on the enrolment trends of all disadvantaged children, as well as their cost of schooling.

Therefore, I estimate the simple DID model in Equation (2.2) on the sample of all disadvantaged children aged 5-14. The treatment group is still the younger cohort (aged 5-9) and the control group is the older cohort (aged 10-14). I incorporate only the within-household estimation as it produces more precise estimates. The results are reported in Table 2.10. Columns (1) and (2) show that post-policy increase in fees was significantly lower for younger disadvantaged children relative to their older siblings. The effect is larger in magnitude among the richer disadvantaged households (column 2). This is similar to the results in Table 2.3, where I estimate the effect on fees within the private sector. This implies that all younger disadvantaged children benefited from a lower fee and not just those attending private schools.

Columns (3) and (4) report the estimates from the top RTE states. I find that while the younger disadvantaged cohort pays a lower fee overall than the older cohort post-policy, the difference is not statistically significant. Even though the magnitude is higher among the richer disadvantaged households (column 4), the estimate is still insiginificant. Therefore, in the states where the reservation policy was implemented more effectively, only younger disadvantaged children in private schools benefited from a lower fee (as shown in Table 2.3).

Table 2.10. Effect of exposure on fees of all disadvantaged children

VARIABLES	(1)	(2)	(3)	(4)
Young	-0.068***	-0.099***	-0.082***	-0.121***
	(0.017)	(0.030)	(0.023)	(0.040)
Young x Post	-0.117**	-0.256***	-0.108	-0.301
	(0.046)	(0.092)	(0.107)	(0.190)
Constant	0.427***	0.733***	0.465***	0.839***
	(0.039)	(0.075)	(0.061)	(0.115)
Observations	25,520	12,019	4,627	2,176
R-squared	0.90	0.90	0.94	0.95
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is the real annual fee in school of all disadvantaged children (in thousand rupees). Fee includes tuition fee, examination fee and other compulsory payments. Columns (1) corresponds to all households. Column (2) correspond to a sample of children from richer households, that have a real consumption expenditure higher than the median consumption in the round in which they are surveyed. Column (3) corresponds to a sample of top RTE states- Rajasthan, Madhya Pradesh, Chhattisgarh, Karnataka, and Uttarakhand. Column (4) corresponds to a sample of richer households in the top RTE states. Standard errors are clustered at the district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

To understand the mechanisms, it is useful to study the trends in enrolment. Table 2.1 shows that overall there was an increase in private school enrolment of disadvantaged children. However, for the younger cohort it was accompanied by a decline in government school enrolment, while for the older cohort there was no such decline. RTE Act made government education free up to age 14, which means even the older cohort in government schools in round 71 were studying for free. Despite the same proportion of older cohort studying in government schools (for free post-policy) and a decline in government school enrolment for the younger cohort, Table 2.10 shows a lower average fee for the younger cohort post-policy.

The decline in government school enrollment for the younger cohort indicates a stronger preference towards private schools. The shift towards private schools among the younger cohort could have led to increased competition among private schools, resulting in more competitive fee structures. This competition might be more pronounced for the younger cohort, who were newly entering the education system and whose parents were making fresh enrolment decisions. In section 2.8, I also showed that there was an increase in the growth of low-fee private schools after the RTE Act.

On the other hand, for the older cohort, the increase in private school enrolment was not accompanied by a departure from government schools. In fact, the increase is driven by overall higher school attendance rates rather than a shift in preferences. As a result, private schools might not have felt the same pressure to adjust fees competitively for this cohort. Additionally, as the older cohort attending private schools in round 71 are essentially children who would not have otherwise gone to school, the average fees of the cohort is higher post policy.

In the top RTE states, I find that there was a shift from government to private schools for both younger and older cohorts of disadvantaged children (Table 2.11). There seems to be a strong preference for private schools among both younger and older children in these states. The increase in private school enrolment is equal for both cohorts although the accompanying decrease in government school enrolment is 3 percentage points larger for the younger cohort.

Essentially, those who would have gone to government schools are attending private schools in round 71 among both cohorts. However, a larger decline in government school enrolment among the younger cohort implies a relatively larger share of older children in government schools paying no fees. This could offset the difference in fees between the cohorts in the private sector and could explain why there is no difference in fees overall. Moreover, private schools might not need to reduce fees drastically to attract students if there are other compelling reasons for families to choose private

education over free government education, such as the reservation policy which was much more systematically implemented in these states.

To summarize, post-RTE, the younger disadvantaged cohort paid significantly lower fees in general than their older counterparts. However, in states where the demand for private education was larger due to better implementation of the reservation policy, only the younger disadvantaged cohort attending private schools paid relatively lower fees. This lends credibility to the idea that the impact on private school fees is largely tied to the reservation policy.

Table 2.11. Proportion of disadvantaged children in school in the top RTE states

	Round 64 Mean	**Round 71** Mean	**Difference**	**Std. error**
Treatment group				
Attends school	0.82	0.88	0.06	0.010
Attends government school	0.62	0.56	-0.06	0.014
Attends recognized private school	0.10	0.16	0.06	0.009
Attends unrecognized private school	0.01	0.01	0.00	0.002
Observations	3,437	2,052		
Control group				
Attends school	0.81	0.90	0.10	0.009
Attends government school	0.66	0.63	-0.03	0.012
Attends recognized private school	0.07	0.13	0.06	0.008
Attends unrecognized private school	0.00	0.01	0.01	0.002
Observations	3,566	2,562		

Source: National Sample Survey
Notes: Remaining children attend private aided schools. Disadvantaged children who do not know if their private school is recognized or unrecognized are dropped (less than 5%). The differences and standard errors of differences are based on a paired sample t-test.

2.10 Conclusion

This chapter finds an indirect effect of the reservation policy of the RTE Act on the expenditure on private education of disadvantaged children in India. It uses a difference-in-differences methodology to estimate the effect of the policy by exploring time and regional variation in exposure. This chapter compares the outcome across two age cohorts of disadvantaged groups, starting school at different times, that is before and after the policy was introduced. Regional variation in exposure is proxied with a measure of enrolment rate under the policy, calculated at the district level.

I find that the growth in the annual fees for younger disadvantaged children in private schools was slower than their older counterparts after the policy. There was a consistently larger effect among households with a higher demand for private education. These were the richer disadvantaged households, households in the states that adhered more to the reservation policy, and richer disadvantaged households in these states.

This chapter finds that following the implementation of the RTE Act, there was a large increase in the number of private schools in India. In addition, these new private schools were found to be low-cost or low-fee compared to the existing schools, which led to a higher enrolment of younger disadvantaged children in the new schools. There was also a district-level variation in the enrolment under the policy, which was strongly associated with the entry of new schools. Therefore, in districts that had a higher enrolment under the policy, younger disadvantaged children paid a relatively lower fee in private schools.

The findings imply that although few disadvantaged children were admitted directly under the policy in private schools, after RTE, there was a higher proportion of disadvantaged children in private schools which were largely low-fee. The results are robust to the inclusion of non-eligible groups like non-disadvantaged children, states with no formal implementation of the policy and all disadvantaged children as counterfactuals. New low-fee schools were not exclusive to disadvantaged groups, but disadvantaged households with a higher demand for private education were more likely to enroll children in these new schools. This implies that they were willing to pay a lower fee to secure a place in a private school even if they did not receive a free place under the policy.

However, the exact channel that resulted in an increased supply of private schools after the RTE Act is unclear. It could have been due to an increase in the stock of 'recognized' private schools, as after RTE, it was compulsory for private schools to be recognized by the government. It could also have been due to an increased prefer-

ence for private education as a result of free primary education in government schools. Nonetheless, in states that formally implemented the policy, increased school choice due to subsidized private education does seem to have also increased the supply of low-fee private schools. As a result in these states, the reservation policy increased the enrolment of disadvantaged children in these schools. School choice was greater among the better-off disadvantaged families who were even more likely to send their children to these schools and therefore benefited from paying a lower fee.

Descriptive evidence from the household survey data shows that disadvantaged children were more likely to attend private schools after RTE. While the younger cohort shifts from government to private schools, the older cohort does not. However, the older cohort is 3 percentage points more likely to be in school after RTE. The DID results show that the younger cohort pays a significantly lower fee in private schools after RTE. This indicates that within the private sector, the younger cohort was enrolled in the new low-fee schools. On the other hand, the older cohort seems to be attending the existing higher-fee private schools. In the household data, I only have information on whether a child attends a recognized private school. I do not know whether the child attends a private school recognized after 2010 (new) or before (existing). As a result, I cannot accurately see if the older cohort was more likely to attend existing, higher-fee private schools using the household data.

The reservation policy to some extent is counter-intuitive as private schools mostly accommodated fee-paying disadvantaged children, especially from better-off families, who could afford private education. Due to its weak implementation, the poorest of the poor are still left out and are forced to attend government schools. If government schools mostly include children from low-income backgrounds, the reservation policy could have negative implications on the quality of government education. Similarly, as the policy resulted in exposed children attending low-fee, and therefore, low-quality private schools, there could be a negative effect on their learning outcomes. These are two aspects that future research can explore.

References

Alcott, B. and Rose, P. (2015). "Schools and learning in rural India and Pakistan: Who goes where, and how much are they learning?" In: *Prospects* 45.3, pp. 345–363.

Amjad, R. and MacLeod, G. (2014). "Academic effectiveness of private, public and private–public partnership schools in Pakistan". In: *International Journal of Educational Development* 37, pp. 22–31.

Andrabi, T., Das, J., Khwaja, A.I., Ozyurt, S., and Singh, N. (2020). "Upping the ante: The equilibrium effects of unconditional grants to private schools". In: *American Economic Review* 110.10, pp. 3315–49.

Ansari, A.H. (2020). "Cream skimming? Evaluating the access to Punjab's public-private partnership programs in education". In: *International Journal of Educational Development* 72, p. 102126.

Barrera-Osorio, F., Blakeslee, D.S., Hoover, M., Linden, L., Raju, D., and Ryan, S.P. (2022). "Delivering education to the underserved through a public-private partnership program in Pakistan". In: *Review of Economics and Statistics* 104.3, pp. 399–416.

Barrera-Osorio, F. and Raju, D. (2015). "Evaluating the impact of public student subsidies on low-cost private schools in Pakistan". In: *The Journal of Development Studies* 51.7, pp. 808–825.

Bhattacharjee, S. (2019). "Ten Years of RTE Act: Revisiting Achievements and Examining Gaps". In: *ORF Research Brief* 39.

Böhlmark, A. and Lindahl, M. (2015). "Independent schools and long-run educational outcomes: Evidence from Sweden's large-scale voucher reform". In: *Economica* 82.327, pp. 508–551.

Burde, D. and Linden, L.L. (2013). "The effect of village-based schools: Evidence from a randomized controlled trial in Afghanistan." In: *American Economic Journal: Applied Economics* 5, pp. 27–40.

Cassan, G. (2019). "Affirmative action, education and gender: Evidence from India". In: *Journal of Development Economics* 136, pp. 51–70.

Crawfurd, L. (2018). *Contracting out schools at scale: Evidence from Pakistan*. Tech. rep. RISE-WP-18/022, Research on Improving Systems of Education (RISE).

Damera, V. K. (2017). "Choice for the poor or poor choice? Experimental evidence from implementation of India's school choice policy". Blavatnik School of Economics, University of Oxford.

Dinerstein, M. and Smith, T.D. (2021). "Quantifying the supply response of private schools to public policies". In: *American Economic Review* 111.10, pp. 3376–3417.

Dixon, P, Egalite, A.J., Humble, S., and Wolf, P.J. (2019). "Experimental results from a four-year targeted education voucher program in the slums of Delhi, India". In: *World Development* 124, p. 104644.

Dongre, A. and Kapur, A. (2016). "Trends in public expenditure on elementary education in India". In: *Economic and Political Weekly* 39.

Dongre, A., Sarin, A., and Singhal, K. (2018). "Can a mandate for inclusion change school choices for disadvantaged parents? – Evidence from Urban India". Indian Institute of Management, Ahmedabad.

Duflo, E. (2001). "Schooling and labor market consequences of school construction in Indonesia: Evidence from an unusual policy experiment". In: *American Economic Review* 91.4, pp. 795–813.

Economic Times (June 7, 2018). "Six Years of RTE but Schools Still Seek Excess Fee [Namma Bengaluru]: Parents say 31 private schools demanding fees anywhere between ₹6k and ₹22k". In: *The Economic Times*. URL: https://www.proquest.com/docview/2054037549/94610EF32B2641C8PQ/1?accountid=8018.

Ferreira, P.G., Lozano-Gómez, J.D., and Stathopoulos, A. (2021). "Electric vehicle adoption and the battery market: A market equilibrium model with spillover effects". In: *Transportation Research Part D: Transport and Environment* 91, p. 102664.

Handa, S. (2002). "Raising primary school enrolment in developing countries: The relative importance of supply and demand". In: *Journal of Development Economics* 69, pp. 103–128.

Hindustan Times (Sept. 14, 2018). "Over 70 complaints against private schools in Uttarakhand for alleged violation of RTE Act". In: *The Hindustan Times*. URL: https://www.proquest.com/docview/2103382529/94610EF32B2641C8PQ/8?accountid=8018.

Hsieh, C.T. and Urquiola, M. (2006). "The effects of generalized school choice on achievement and stratification: Evidence from Chile's voucher program". In: *Journal of Public Economics* 90.8-9, pp. 1477–1503.

Joshi, R. (2020). "Can social integration in schools be mandated: Evidence from the Right to Education Act in India". In: *International Journal of Educational Development* 77, p. 102228.

Kazianga, H., Levy, D., Linden, L.L., and Sloan, M. (2013). "The Effects of "Girl-Friendly" Schools: Evidence from the BRIGHT School Construction Program in Burkina Faso". In: *American Economic Journal: Applied Economics* 5.3, pp. 41–62.

Kim, J., Alderman, H., and Orazem, P.F. (1999). “Can private school subsidies increase enrollment for the poor? The Quetta Urban Fellowship Program”. In: *The World Bank Economic Review* 13.3, pp. 443–465.

Kingdon, G. (2020). “The private schooling phenomenon in India: A review”. In: *The Journal of Development Studies* 56.10, pp. 1795–1817.

Kingdon, G. and Muzammil, M. (2015). “Government per pupil expenditure in Uttar Pradesh: Implications for the reimbursement of private schools under the RTE Act”. In.

Krishna, A.H., Sekhar, M.R., K.R., Teja, and S.M., Reddy (2017). “Enrolment in Elementary Education with Reference to Right to Education Act 2009: An Empirical Analysis of Selected States of India during 2004-05 to 2015-16”. In: *IOSR Journal Of Humanities And Social Science (IOSR-JHSS)* 22.11, pp. 43–51.

Lang, K. and Manove, M. (2011). “Education and labor market discrimination”. In: *American Economic Review* 101.4, pp. 1467–1496.

Lucas, M. and Mbiti, I.M. (2012). “Access, sorting, and achievement: The short-run effects of free primary education in Kenya”. In: *American Economic Journal: Applied Economics* 4.4, pp. 226–253.

Menezes-Filho, N., Moita, R., and Andrade, E. (2012). *Entry in School Markets: Theory and Evidence from Brazilian Municipalities*. Tech. rep. Insper Working Paper, Insper Instituto de Ensino e Pesquisa.

Mukherjee, A. and Sengupta, S. (2021). “An Analysis of Factors Affecting Private Expenditure on Education in India”. In: *Arthaniti: Journal of Economic Theory and Practice*.

Muralidharan, K. and Sundaraman, V. (2017). “The aggregate effect of school choice: Evidence from a two-stage experiment in India”. In: *The Quarterly Journal of Economics* 130.3, pp. 1011–1066.

Noronha, C. and Srivastava, P. (2013). “India’s right to education act: Household experiences and private school responses”. In: *Education Support Program Working Paper Series* 53.

Rao, G. (2019). “Familiarity does not breed contempt: Generosity, discrimination, and diversity in Delhi schools”. In: *American Economic Review* 109.3, pp. 774–809.

Romero, M. and Singh, A. (2023). “The incidence of affirmative action: Evidence from quotas in private schools in India”.

Sarin, A., Dongre, A., and Wad, S. (2017). *State of the Nation: RTE Section 12 (1)(c) 2017*.

Spence, M. (1978). “Job market signaling”. In: *Uncertainty in economics*. Elsevier, pp. 281–306.

The Indian Express (May 31, 2018). “Gujarat: On last day of admissions, trail of woes for parents; schools ‘overcharge’, discrepancies in online forms”. In: *Indian Express*. URL: https://www.proquest.com/docview/2047313032/94610EF32B2641C8PQ/5?accountid=8018.

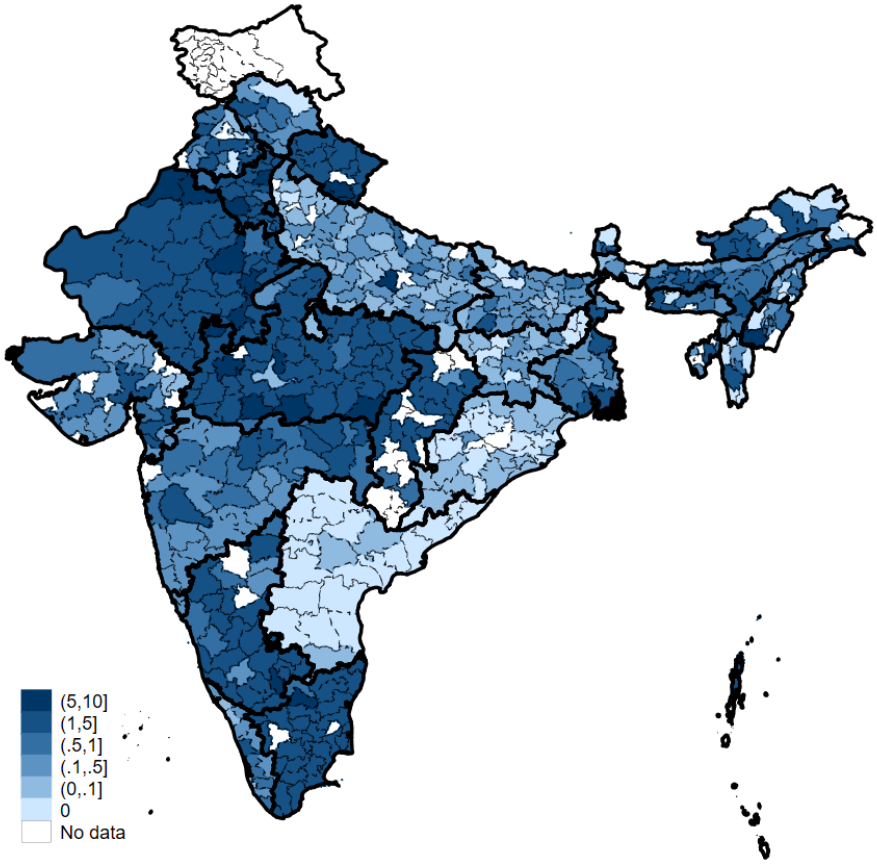
Times of India (May 28, 2019). “Govt defaults payment, schools demand fee from ‘RTE students’ [Chennai]”. In: *The Times of India*. URL: https://www.proquest.com/docview/2230364137/94610EF32B2641C8PQ/6?accountid=8018.

Weiss, A. (1995). “Human capital vs. signalling explanations of wages”. In: *Journal of Economic perspectives* 9.4, pp. 133–154.

Appendices

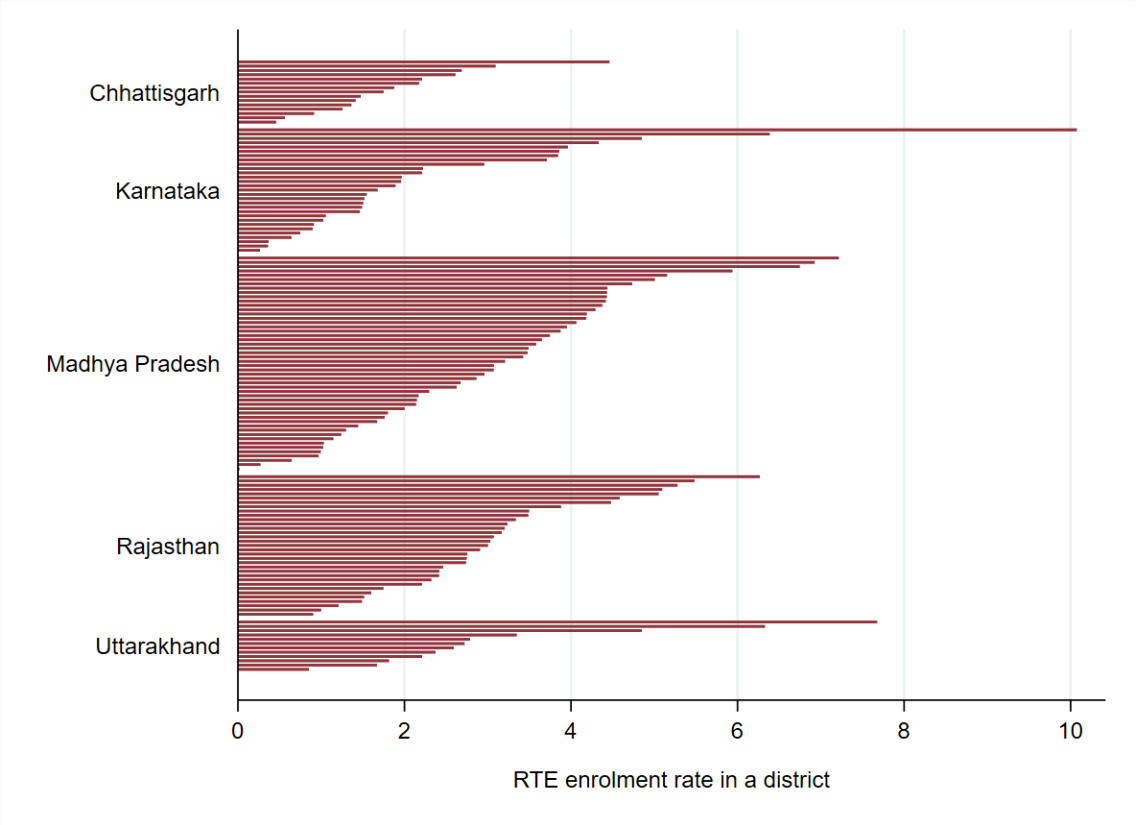
2.A.1 Figures

Figure 2.A.1. Percentage of children enrolled under the reservation policy by 2014-15 (district-level)



Data source: RTE enrolment from DISE data, Population data from Census 2011 and GIS coordinates of districts from GADM data.

Figure 2.A.2. Percentage of children enrolled under the reservation policy in the top RTE states



Top RTE states correspond to the top 5 states that had the highest enrolment rate under the reservation policy. The enrolment rate reported here is the average enrolment rate from 2010-11 to 2014-15. Each bar represents a district within the state.

2.A.2 Tables

Table 2.A.1. Free and subsidized education of disadvantaged children in private schools

	Round 64		**Round 71**		**Difference**	**Std. error**
	Obs.	Mean	Obs.	Mean		
Treatment group						
Education						
Free	105	0.07	48	0.02	-0.05	0.007
Not free	1,497	0.93	1,961	0.98	0.007	
Total	**1,602**		**2,009**			
Tuition fee waived						
Fully	34	0.02	26	0.01	-0.01	0.004
Partly	17	0.01	17	0.01	-0.00	0.003
Not waived	1,446	0.97	1,918	0.98	0.01	0.006
Total	**1,497**		**1,961**			
Control group						
Education						
Free	90	0.07	54	0.03	-0.04	0.007
Not free	1,216	0.93	1,921	0.97	0.04	0.007
Total	**1,306**		**1,975**			
Tuition fee waived						
Fully	17	0.01	14	0.01	-0.01	0.004
Partly	20	0.02	28	0.01	-0.00	0.004
No waiver	1,179	0.97	1,879	0.98	0.01	0.006
Total	**1,216**		**1,921**			

Source: National Sample Survey
Notes: The differences and standard errors of differences are based on a paired sample t-test.

Table 2.A.2. Average monthly consumption expenditure of disadvantaged households with children in private schools

	Round 64 (₹)	**Round 71** (₹)	**Difference** (₹)
Whole sample	2,281	2,300	19
Richer households	2,532	2,683	151***
Top RTE states	2,356	2,195	-161***
Richer households in top RTE states	2,756	2,784	28

Source: National Sample Survey
Notes: Consumption expenditure per adults is in real terms, deflated by the Consumer Price Index (2010=100). Results in column (5) are based on a paired sample t-test. *** p<0.01, ** p<0.05, * p<0.1

Table 2.A.3. Characteristics of new and existing private schools before RTE

	Existing	**New**	**Difference**	**Std. error**
Pupil-teacher ratio	37.00	34.00	3.00	0.244
Facilities				
Computers available	0.37	0.32	-0.05	0.002
Playground available	0.81	0.71	-0.10	0.002
Library available	0.61	0.45	-0.16	0.002
Girls toilet available	0.94	0.91	-0.03	0.001
Source of drinking water: taps	0.43	0.37	-0.04	0.002
Medical check-ups conducted	0.55	0.46	-0.11	0.002

Source: DISE raw data
Notes: The differences and standard errors of differences are based on a paired sample t-test. All differences are significant at the 1% level.

Chapter 3

Elected representative characteristics and economic development: Causal evidence from reserved constituencies

3.1 Introduction

Political representation is the cornerstone of every democracy. Political representatives are accountable to the people who vote for them by actively engaging in policymaking. At times, they also stand for the interests of a particular group of people or geographical area that they represent. Empirical evidence shows that political representatives and their characteristics can have profound effects on overall socio-economic development (Ferreira and Gyourko, 2009; Besley, Montalvo, and Reynal-Querol, 2011; Acemoglu, Egorov, and Sonin, 2013; Kim et al., 2021) as well as resource allocation towards their interest groups (Chattopadhyay and Duflo, 2004; Gilens, 2005; Burgess et al., 2015; Kramon and Posner, 2016).

India, the largest democratic country in the world, is a particularly interesting case study. Given its vast size, the scale of its governance extends over three layers– central, state, and local. Elections are contested at all three levels and moreover, there is a political reservation for minority groups. This includes seats being reserved for socially disadvantaged communities such as Scheduled Castes (SCs) and Scheduled Tribes (STs) at all three levels, and for women at the local level. This policy of affirmative action or 'quotas' in electoral seats has been in existence since the 1950s. While the impact of local (village-level) representatives in India has been widely studied, there is a limited understanding of the role of state-level representatives and their characteristics.

In this chapter, I investigate the effect of having a Scheduled Caste (SC) state-level representative on economic development in India. It is typically believed that SC representatives are less effective (Jensenius, 2015), perhaps due to having lower human capital or less bargaining power. As a result, they might have negative effects on development outcomes. On the contrary, they might have positive effects on the redistribution of resources towards SC communities. Although a few studies have investigated the effect of state-level SC representatives on state-level outcomes, their role in influencing policies at the assembly constituency level is understudied.

Within each state, some assembly constituencies are reserved for SC communities. Only candidates who belong to such communities can be nominated and elected in a constituency reserved for them. However, to study the causal effect of SC representatives, we cannot simply compare reserved and unreserved constituencies. This is because the selection of reserved constituencies is not random and therefore there might be some confounding factors that could explain different levels of development across these constituencies. Nonetheless, the selection of reserved constituencies first depends on the proportion of SC population in a district and then on the proportion of SC population in the constituencies themselves. This allows me to incorporate a regression discontinuity design (RDD) where I exploit a discontinuity in the marginal constituency within a district.

I build on the findings of Jensenius (2015), which is the only other paper to have studied the constituency-level effects of SC representatives. I make five new contributions. First, I use outcomes from Census 2011, which allows me to study the effects 10 years after representatives started receiving development funds. These funds are allocated by the state governments to the state representatives in order to undertake development works in their constituency. Jensenius (2015) found no effect of SC representatives on development outcomes in 2001, which could be because state representatives in general did not affect constituency-level development. However, with the receipt of development funds, they would be able to initiate development projects in their constituency, which could have differential outcomes depending on the representative's caste.

Second, I exploit a discontinuity in the reservation of constituencies for SCs. Unlike Jensenius (2015), who uses a matching method and just compares the two marginal constituencies, I am able to utilize the distribution of constituencies. As a result, I am able to retain a relatively higher number of constituencies and get smaller standard errors. To match pairs of constituencies, Jensenius (2015) uses information on the reservation status and population proportions of SC in a constituency, which in fact results in a

simplified regression discontinuity design. While this reduces bias by ensuring that compared constituencies are similar on the running variable, discarding unmatched observations might increase variance. With a standard RD model, I am able to minimize this bias-variance trade-off using a non-parametric method that generates an optimal bandwidth (see Calonico, Cattaneo, and Titiunik (2014)).

Third, in addition to census outcomes, I use nightlight luminosity as a proxy measure of development. There are several studies that have established nightlights as a good proxy for development.[1] In the context of India, Dhillon et al. (2016) found a strong correlation of 0.6 between wealth and nightlights, which was higher than the correlation of 0.4 between wealth and education. To the best of my knowledge, Prakash, Rockmore, and Uppal (2019) is the only other study to have looked at the effect of state-level representatives' characteristics on economic activity using data on nightlight luminosity. While Prakash, Rockmore, and Uppal (2019) focuses on criminally accused representatives in India, this chapter focuses on representatives from SC communities. However, unlike Prakash, Rockmore, and Uppal (2019), I get imprecise estimates when I use the same nightlights data at the constituency level. My findings suggest that the nightlights data used by Prakash, Rockmore, and Uppal (2019) (and also many other researchers) may be too imprecise to reliably measure economic development at the constituency level.

Fourth, I provide new evidence on other characteristics of representatives that are affected by reservation. I show that constituency reservation has a causal effect on representative gender, age and political affiliation. Representatives in SC constituencies are more likely to be female, younger, and affiliated with political parties. Further, the voter turnout percentage is also significantly lower. This implies that in constituencies reserved for SCs, fewer people cast their votes. My finding that female representatives are mostly SC is consistent with Jensenius (2016), who shows that representation of female candidates increased over time mostly in constituencies reserved for SC. Jensenius (2016) finds this intersection of caste and gender in the context of national elections, while I show that it also exists in state elections. I also show that representatives' caste is linked with other factors besides gender such as age (experience), political affiliation and bias against marginal communities.

Fifth, motivated by my findings in the previous chapter, I investigate the effect of SC representation on the implementation of the RTE Act. I found that the implementation of the RTE Act and particularly its reservation policy varied widely, even within states, and so I test whether SC representation is a factor in explaining this variation. For this,

[1] See Gibson, Olivia, and Boe-Gibson (2020) for a detailed review of some of these contributions.

I use administrative data on all schools in India. The RTE Act, introduced in 2010, made primary education compulsory in India. It also mandated private schools to offer free education to children from poor families and minority groups (SC/ST) by reserving 25% of their primary school places. SC representatives could have differential effects on schooling outcomes post the introduction of the RTE Act. They could also have influenced the schooling outcomes of minority groups, especially in the context of the reservation policy in private schools.

My first set of results reinforces the findings from Jensenius (2015). There is no significant difference in effectiveness between SC and non-SC representatives on overall development. The estimated differences are close to 0 and precise. The use of nightlights as a proxy for development also produces insignificant results. However, my estimates with nightlights are noisy potentially due to some measurement errors in the data. However, I do find evidence that SC representatives positively affected the expansion of private education, especially for SC children. SC representatives increased private school enrolment by 1.6 percentage points for all children and by 0.8 percentage points for SC children. SC representatives also increased the overall share of private schools by 1.3 percentage points. The positive effect on private school enrolment and supply could be potentially associated with the RTE Act or the higher share of female representatives.

The rest of the chapter is arranged as follows. Section 3.2 provides a review of the current literature and my contribution. Section 3.3 describes the rules of reservation and my identification strategy. Section 3.4 gives details about the datasets I use and provides some descriptives from the data. Section 3.5 shows my main results and Section 3.6 concludes.

3.2 Related Literature

3.2.1 Effect of representatives in state assemblies

Similar to national (central) elections, India has assembly elections at the state level every 5 years. Each state has assembly constituencies that elect a representative known as the Member of Legislative Assembly (MLA). The MLAs together form the state assembly and enjoy certain executive, legislative and financial powers. There are a few empirical studies that have investigated the effect of MLAs and their characteristics on socio-economic outcomes in India. The majority of these studies are in the context of political reservation for disadvantaged minorities such as the Scheduled Castes (SC) and Scheduled Tribes (ST). However, in contrast to this chapter, most of these studies have focused on outcomes at the state level.

The study by Pande (2003) is one of the earliest in the literature to look at the effect of reservation for SC and ST groups in state legislative assemblies on policies targeted towards these groups. Using data on government spending and job quotas in states from 1960 to 1992, and a fixed effects regression model, Pande (2003) found that SC and ST reservation resulted in an increase in the allocation of resources to these communities. After controlling for the respective population proportion of the two minority groups, a 1% increase in the reservation of seats for SC was found to increase job quotas by 0.6%. However, it had no effect on targeted spending. On the other hand, a 1% increase in the reservation of seats for ST increased welfare spending towards ST by 0.8 percentage points but had no effect on job quotas.

Using the same identification strategy as Pande (2003), Chin and Prakash (2011) and Kaletski and Prakash (2016) studied the effect of political reservations for ST and SC on state-level poverty and child labour respectively. Chin and Prakash (2011) used the headcount ratio, poverty gap index and squared poverty gap index as measures of poverty for nineteen major states in India for years 1960-2000. While reservation for SCs in state assemblies had no effect on poverty, reservation for STs led to a reduction in poverty. Chin and Prakash (2011) found that the effect was larger on rural poverty, which indicates larger benefits for ST communities, as they tend to be concentrated in rural areas.

Reservation of seats for STs in state assemblies was also found to have significantly reduced child labour, while there was no effect of SC reservation (Kaletski and Prakash, 2016). Using household survey data from 1982 and 1999, Kaletski and Prakash (2016) measured child labour as the number of children aged 5-14 engaged in a paid activity

in a state. Kaletski and Prakash (2016) also found that ST reservation had a large, positive effect on child labour among SC/ST households, whereas SC reservation led to an increase in child labour among these households. Kaletski and Prakash (2016) argue that the latter effect was potentially due to a transfer of resources towards economic activities with a higher demand for labour, including child labour.

Apart from caste, the gender of the MLAs could also have a differential effect on policy decisions. Using panel data on 16 states from 1967 to 2000, Clots-Figueras (2011) found that female MLAs from SC/ST communities invested more in health, primary education and land reforms, and were more in favour of laws promoting gender equality. On the other hand, female MLAs from non-SC/ST communities invested more in higher education, opposed land reforms, and had no effect on laws promoting gender equality. Clots-Figueras (2011) used a variation of the regression discontinuity design at the state-level, whereby the share of female MLAs was instrumented by close election results between men and women.

Pande (2003) argues that when looking at the effect of MLAs, a state-level analysis is appropriate as important decisions are made collectively at the state level. As a result, MLAs might make no difference at the assembly constituency level. However, there is evidence that MLAs use their political and business connections to lobby projects in their constituency (Chopra, 1996; Bussell, 2012; Jensenius, 2015). They also facilitate job assignments and job transfers (Iyer and Mani, 2012; Sukhtankar and Vaishnav, 2015; Kapur, Mehta, and Vaishnav, 2018), and act as mediators between the government and private sectors (Prakash, Rockmore, and Uppal, 2019).

Since 2001, MLAs in India have been receiving Local Area Development (MLALAD) funds. The aim of these funds is to identify and bridge gaps in the infrastructure of a constituency through works including street lights, roads, schools, hospitals, sewage, public parks and toilets. While the funds are transferred to the local authorities, MLAs can recommend works in their constituency which is then approved by the civil servant operating in a district. Therefore, political representatives of a state can not only influence state-level decisions but also affect the economic development policy of their own constituency, at least in theory.

So far, there are two conflicting pieces of empirical evidence on the role of MLAs in assembly constituencies. Jensenius (2015) found that MLAs from socially disadvantaged backgrounds had no effect on overall development or redistribution to disadvantaged communities even after 30 years of reservation. On the other hand, Prakash, Rockmore, and Uppal (2019) found that criminally accused MLAs had large negative effects on GDP growth in a constituency between 2004 and 2008.

Jensenius (2015) used a series of outcomes from the Census 2001 as indicators of development. Then using a matching method, Jensenius (2015) studied the effect of SC reservation in state assembly elections from 1971 to 2001 on economic development in the constituency. Meanwhile, Prakash, Rockmore, and Uppal (2019) used the luminosity of nightlights as a proxy for development, particularly GDP growth. Using data also on candidate characteristics, they exploited a discontinuity in close elections between winning and losing candidates. The negative effect on GDP was larger among representatives with multiple, serious charges and less education. The effect also largely persisted in less developed states of India, where corruption is more prevalent.

3.2.2 Effect of representatives in villages

Political reservation of seats for SCs and STs also takes place in village (*Gram Panchayat*) elections based on the population proportions of these communities. The head of the village, known as the *Sarpanch* is the representative. However, unlike the state elections, where reserved constituencies are fixed, reservation at the village level is rotational. This implies that a village that has very little SC/ST population will also end up getting an SC/ST Sarpanch in some rotation. Conversely, a village with a significant SC/ST population might sometimes not be reserved for an SC/ST Sarpanch due to this rotation. If a village is not set aside for an SC/ST Sarpanch but has a large SC/ST population, an SC/ST candidate might still win the leadership position. In such cases, the SC/ST Sarpanch in the unreserved village may have a stronger influence on village policies, given the substantial community support. Therefore, estimating the effect of SC/ST village heads using evidence from reserved villages might not be straightforward.

One of the first studies to investigate the effect of SC/ST reservation for the post of village head was by Besley et al. (2004). Using survey data from states in the South of India and a fixed-effects model, Besley et al. (2004) looked at the effects on the provision of public goods under welfare schemes. Also controlling for the population proportion of SCs/STs, Besley et al. (2004) found that SC/ST households were more likely to receive public goods under the schemes, especially in reserved villages. They also found small, positive spillovers across villages in terms of goods such as roads and bridges.

A study by Bardhan, Mookherjee, and Parra Torrado (2010) also used fixed-effects regression to look at the effect of reservation of the post of village head for SCs/STs in the state of West Bengal. Bardhan, Mookherjee, and Parra Torrado (2010) found that between 1998 and 2004, reserved villages received more benefits in terms of drinking

water, housing, toilets, employment, roads, BPL cards, and credit schemes. Reservation also had a larger, positive effect on female-headed and landless households within these villages.

Dunning and Nilekani (2013) found no effect of reservation of the post of village head for SCs/STs on benefits or targeted spending towards SC/ST communities. Using survey data from Karnataka, Rajasthan, and Bihar, Dunning and Nilekani (2013) considered benefits as jobs attained in the village or through government schemes as well as fiscal outcomes such as expenditure towards employment and infrastructure. Dunning and Nilekani (2013) employed a variation of the regression discontinuity design and compared pairs of villages close to the threshold of reservation, only differing in the reservation status.

In 1996, the Panchayat Extension to Scheduled Areas (PESA) Act was implemented which led to the demarcation of areas for the ST community. As a result, villages in these areas began to be headed by ST representatives. A recent study by Gulzar, Haas, and Pasquale (2020) incorporated a geographical regression discontinuity design to investigate the effect of ST representatives following the enactment of the PESA Act. Villages that are close in distance but are in non-scheduled areas might or might not have an ST representative, depending on the population proportion of STs. Gulzar, Haas, and Pasquale (2020) found that villages in scheduled areas received more employment benefits, better roads under the road construction program, and more public goods such as education, communication and water supply. The effects only persisted after the PESA Act was implemented, which suggests that these are driven by ST representatives.

There is also extensive literature exploring the effects of female village heads in India. While there is no political reservation for women in state assemblies, 1/3rd of seats for the post of village heads are reserved for women on a randomized, rotational basis.

The study by Chattopadhyay and Duflo (2004) was one of the first to investigate the effect of political reservation for women in villages in the state of Rajasthan and West Bengal. Using the natural experiment caused by the randomization of seats, Chattopadhyay and Duflo (2004) looked at the impact of female village heads on women's political participation, public good provision, and the type of issues raised by men and women. Having a female village head was found to increase the percentage of female voters only in West Bengal. In both states, investments in villages reserved for women were more aligned with the preferences of women rather than men. Chattopadhyay and Duflo (2004) argue that these investments also reflected the female village head's own preferences.

However, a similar study conducted by Ban and Rao (2008) in the South of India found no difference in public goods provision between villages reserved and unreserved for women. They found no evidence of female village heads prioritizing women's preferences over men's. Exploring the role of tokenism in the selection of female village heads, Ban and Rao (2008) found that female heads in reserved villages were younger, less educated, and less experienced than female heads in unreserved villages.

Besides SC/ST village heads, Bardhan, Mookherjee, and Parra Torrado (2010) also studied the effect of female village heads on targeted benefits in West Bengal. They used a similar fixed-effects model but without controlling for the population proportion as villages reserved for women were randomly allocated. Bardhan, Mookherjee, and Parra Torrado (2010) found no effect of female village heads on targeted spending towards villages reserved for women. However, within these villages, there was a negative and significant effect on benefits for SC/ST households.

In the state of Andhra Pradesh, female village heads were found to have a positive effect on children's learning outcomes (Pathak and Macours, 2017). Using data from the Young Lives Survey, Pathak and Macours (2017) exploited the randomized rotations for reservation in 3 election years (1995, 2001, and 2006). The empirical specification captured the differential effect of reservation in 1995 and 2001 compared to 2006. Pathak and Macours (2017) found that 8-year-old children in reserved villages in 1995 received higher test scores in math and language compared to their counterparts in unreserved villages. However, there was no difference in learning outcomes between 8-year-olds in reserved and unreserved villages in 2001. This was largely due to the short time period between the 2001 reservation and the survey. Additionally, there was no differential effect on test scores between girls and boys.

Similar to Chattopadhyay and Duflo (2004), a study by Priebe (2017) found positive effects of female village heads on political participation and empowerment among women in the context of Maharashtra. However, the effect entirely pertained to women from SC/ST communities. Further, women in villages with female heads had higher political participation than women in villages with male heads even when the head was from a different caste. This indicated that caste affiliations were less relevant in female-headed villages.

3.2.3 Contribution to the literature

Looking at the literature on representative characteristics, MLAs from SC communities seem to have had a positive effect only on job quotas at the state level. They had no

effect on the overall economic development of a constituency, which is consistent with the findings in this chapter. In terms of targeted spending, SC MLAs had no effect either at the state level or the assembly constituency level. At the village level, the evidence varies across states. SC village heads had a positive effect on targeted spending towards SC households and SC villages only in some states of India.

To the best of my knowledge, Jensenius (2015) is the only other paper that has explored the impact of SC/ST MLAs on socio-economic outcomes at the assembly constituency level. While Jensenius (2015) only used outcomes from the Census 2001, I also use outcomes from the Census 2011. Since the MLA-LAD funds were sanctioned only after 2001, MLAs could have had some effect on development by 2011. However, my results for 2011 are in line with Jensenius (2015). There was no differential effect of SC MLAs on economic development in a constituency.

It is possible that while socially disadvantaged MLAs make no difference, criminals do (Prakash, Rockmore, and Uppal, 2019). It is however also possible that the use of more detailed nightlights data might enable a more accurate estimation of development than census outcomes. Therefore, in addition to census outcomes, this chapter uses nightlights to investigate the effect of MLAs in a constituency. It adds to the limited literature that uses nightlight luminosity to study the constituency-level impact of political representatives.

Female representatives in state assemblies were also found to have a positive effect on targeted spending towards SC/ST communities at the state level. This could be because female MLAs are more likely to be from SC/ST communities. This chapter finds that constituencies reserved for SCs in state elections also had a significantly higher share of female MLAs.

The evidence of the impact of female village heads on the overall economic development in a village and targeted spending towards women is mixed. Nonetheless, Pathak and Macours (2017) found a positive effect of female village heads on children's learning outcomes. This chapter also finds that reserved constituencies– where the share of female MLAs was higher– performed better in terms of private education. These representatives, who were also mostly from SC communities, were on average younger. This is consistent with Ban and Rao (2008) who found that female village heads in South India were younger and less educated.

3.3 Methodology

3.3.1 Reservation of constituencies

Reservation of seats for SCs in state assemblies is based on the population proportion of the SC group. It began in the 1950s and initially, it was decided that the area of reserved constituencies would change every ten years based on the most recent census. However, after the 1971 census, the government of India decided to freeze the boundaries of the constituencies. As a result, the political boundaries as well as reserved constituencies remained fixed from 1974 to 2007. After 2007, the Delimitation Commission[2] redrew the boundaries of assembly constituencies based on the 2001 census data. Therefore, the boundaries and the location of reserved constituencies changed after 2007 but have remained fixed since then. So there are essentially two periods of fixed reservation– 1974-2007 and 2008-present. In Section 3.5.1 I show that the reservation status in Period 2 (2008-present) was not influenced by the reservation status in Period 1 (1974-2007).

Assembly constituencies are smaller than a district but bigger than a village. The reservation of assembly constituencies for SCs therefore primarily depends on their population proportion in the district. On average, each district in India has around 10 assembly constituencies. An illustrative example of the rules of the reservation is provided in Table 3.1. In this example, District 1 has 5 constituencies, and 20 percent of the population in the district are SCs. So 1 constituency will be reserved for SCs ($\approx 0.2 \times 5$). This is the one with the highest proportion of SC population within the district (Constituency 5). The column 'Reserved' indicates the reservation status of a constituency, where 1 means reserved for SC, and 0 means not reserved for SC.

However, if two constituencies in a district were eligible for reservation but they had shared a border, then only one would be reserved. In Table 3.1, two constituencies are to be reserved in District 3 ($\approx 0.3 \times 6$). These should be Constituencies 5 and 6, with the highest SC population. But supposing these constituencies share a border, then only Constituency 5 will be reserved. The second constituency to be reserved will be Constituency 4, which has the next highest SC population.

[2]The Delimitation Commission is a government authority of India responsible for drawing the political boundaries of parliament and assembly constituencies. It ensures that each constituency within a state has roughly the same population.

Table 3.1. Reservation of assembly constituencies

District d	Constituency c	SC_d	SC_c	Reserved
1	1	0.2	0.04	0
1	2	0.2	0.1	0
1	3	0.2	0.2	0
1	4	0.2	0.25	0
1	5	0.2	0.3	1
2	1	0.5	0.1	0
2	2	0.5	0.3	0
2	3	0.5	0.6	1
2	4	0.5	0.7	1
3	1	0.3	0.05	0
3	2	0.3	0.08	0
3	3	0.3	0.15	0
3	4	0.3	0.25	1
3	5	0.3	0.3	1
3	6	0.3	0.4	0

3.3.2 Identification strategy

To identify a causal effect of SC representatives, I use a regression discontinuity (RD) design that follows the rules of the reservation. I first arrange the constituencies in ascending order of their SC population proportion within each district. Then I calculate the cutoff as the average population proportion of the last unreserved constituency and the first reserved constituency. The cutoff varies across districts. Finally, my running variable is normalized by subtracting the cutoff proportion from the SC proportion in each constituency. The calculation of the cutoff and the running variable is illustrated in Table 3.2.

Table 3.2. Calculation of the cutoff and the running variable

District d	Constituency c	SC_d	SC_c	Reserved	Running variable R_c
1	1	0.2	0.04	0	−0.235
1	2	0.2	0.1	0	−0.175
1	3	0.2	0.2	0	−0.075
1	4	0.2	0.25	0	−0.025
1	5	0.2	0.3	1	0.025
2	1	0.5	0.1	0	−0.35
2	2	0.5	0.3	0	−0.15
2	3	0.5	0.6	1	0.15
2	4	0.5	0.7	1	0.25
3	1	0.3	0.05	0	−0.15
3	2	0.3	0.08	0	−0.12
3	3	0.3	0.15	0	−0.05
3	4	0.3	0.25	1	0.05
3	5	0.3	0.3	1	0.2
3	6	0.3	0.4	0	0.25

More generally, the value of the running variable for each constituency c in a district is given by

$$R_c = SC_c - (\frac{SC_{c0} + SC_{c1}}{2})$$

where SC_c is the population proportion of SCs in constituency c. SC_{c0} and SC_{c1} are the population proportion of SCs in the last unreserved constituency and the first reserved constituency respectively. In other words, constituencies that 'just missed' and 'just made' the reservation.

I then estimate models of the form

$$Y_c = \beta \mathbf{1}(R_c \geq 0) + f(R_c) + (\mathbf{1}(R_c \geq 0) \times f(R_c)) + \alpha_d + \varepsilon_c \tag{3.1}$$

where Y_c is a series of development indicators in a constituency. The running variable R_c is how close a constituency is in terms of SC representation to the cutoff for that district. In principle, $R_c > 0$ for all reserved constituencies and $R_c < 0$ for all unreserved constituencies. However, there might be constituencies that are unreserved even when $R_c > 0$ due to the 'shared border' rule. On the other hand, all constituencies with $R_c < 0$ will be definitely unreserved. I also include district fixed effects (α_d) in my model. The inclusion of district fixed effects should not change my estimates of β because every district has at least one reserved constituency. But their inclusion may improve the accuracy of my estimates.

In the simplest case $f()$ is linear, in which case the model is

$$Y_c = \beta_0 + \beta \mathbf{1}(R_c \geq 0) + \beta_1 R_c + \beta_2 (\mathbf{1}(R_c \geq 0) \times R_c) + \alpha_d + \varepsilon_c \tag{3.2}$$

However, a linear model gives equal weights to observations a long way from the cutoff where $R_c = 0$. If the relationship between reservation and the probability of SC representatives is non-linear, a linear model would produce imprecise estimates. Therefore, I use local linear and non-parametric estimation using the methodology of Calonico, Cattaneo, and Titiunik (2014).

The key identifying assumption of my model is that the potential outcomes are balanced at the cutoff. In other words, there are no endogenous factors determining the selection of reserved constituencies. As a result, in the absence of reservation, the expected outcomes would not 'jump' at the cutoff. One way I check for this is by replacing Y_c in Equation (3.1) with a series of predetermined characteristics.

3.4 Data

To undertake my analysis with the RD design, I use four sources of data. Data on elected representative characteristics come from the Trivedi Centre for Political Data. For outcomes, I use development indicators from the Indian Census, a measure of nightlight luminosity from the Defense Meteorological Satellite Program's Operational Linescan System (DMSP) and schooling outcomes from the District Information System for Education (DISE). My data is on the 17 largest states of India[3], all at the assembly constituency level.

3.4.1 Election data

I use state-level election results for the Period 1974-2017 from the Trivedi Centre for Political Data's Lok Dhaba (Agarwal et al., 2021). Firstly, I have information on whether each assembly constituency was reserved for Scheduled Caste (SC) or not.[4] As I have two periods of fixed reservation, my data is split into two time periods– 1974-2007 and 2008-2017.

Secondly, I have information on the winning candidate and their characteristics for each constituency in each election year. For instance, I know their age, gender, and whether or not they are affiliated with a political party. I also know whether the winning candidate is SC or not in Period 2 (2008-2017). In Period 1 (1974-2007), I only know the caste of 11% of the winning candidates.[5] While I do not know the caste of the majority of the winning candidates in Period 1, I do know that a constituency reserved for SC has an SC representative. For unreserved constituencies where caste information is unavailable, I make an assumption that the elected representative will never be SC. Given that in Period 2, only 0.9% of unreserved constituencies had an SC representative, this is a valid assumption.

My data consists of 3,085 constituencies in Period 1, of which 505 are reserved for SCs and 2,580 are unreserved. In Period 2, there are 2,999 constituencies out of which 547 are reserved for SCs and 2,452 are unreserved. Figures 3.A.1 and 3.A.2 show the reserved constituencies in Period 1 (1974-2007) and Period 2 (2008-2017) respectively.

[3] As per Census 2011, the population of the 17 largest states accounts for 95% of India's population.

[4] Some constituencies in state assembly elections are also reserved for Scheduled Tribes (ST). However, for the purpose of this chapter, I drop these constituencies and only compare SC constituencies with General (unreserved) constituencies. This is because ST constituencies are predominantly inhabited by STs and have different constitutional provisions. As a result, ST constituencies are not a good counterfactual.

[5] The Election Commission started collecting information on the caste of candidates only after 2003.

In both periods, reserved constituencies for SCs are quite scattered even within a state. Comparing both figures, it can be seen that the boundaries of constituencies largely changed in Period 2, except in the Northeastern region of India.[6] Some areas do seem to be reserved in both periods, which means that these areas would have had an SC representative for almost 44 years.

Table 3.3 provides some descriptive statistics from the election data for the two reservation periods. In Period 1, 16% of the constituencies had an SC representative, which increased by 3% in Period 2. I also have other information such as the turnout percentage in each election year. This is calculated as the percentage of registered voters who cast their vote in a given election. In Table 3.3, I see that the turnout percentage in assembly elections increased by almost 8% in Period 2. This indicates increased participation among registered voters. Constituencies reserved for SCs might have a larger share of the general population who might be less encouraged to vote for an SC candidate. Turnout percentage is a useful measure to check this.

I observe that the share of independent representatives is small in both periods. In fact, in Period 2 about 98% of the representatives were affiliated with a political party. One important reason could be that it is harder for independent candidates to win against large parties. In India, a candidate with the highest number of votes wins from each constituency, regardless of whether they get more than 50% of the total votes. This often favours large parties that can consolidate votes. A second reason for the low share of independent representatives could be the emergence of new regional and local political parties. A third reason could be challenges to acquiring resources as an independent candidate.

In both periods, only a small share of representatives are females. However, the share of female representatives is higher in Period 2, suggesting increased political participation of women. Table 3.3 also shows that a representative on average is around 49-51 years old.

[6]In this chapter, the 17 largest states automatically exclude the Northeastern region so this is not an issue.

Table 3.3. Summary statistics from election data

	Period 1		Period 2	
	Mean	*SD*	*Mean*	*SD*
SC representatives	0.16	0.37	0.19	0.39
Turnout percentage	62.14	9.69	69.97	10.88
Independent representatives	0.05	0.10	0.02	0.13
Female representatives	0.05	0.12	0.09	0.25
Age of representatives	49.10	10.12	51.51	8.54
Observations	3,085		2,999	

Notes: Period 1 corresponds to the election period 1974-2007 and Period 2 corresponds to the election period 2008-2017.

3.4.2 Census data

To examine the effect of reservation on economic development, I first use outcomes from the household census. India conducts the household census every ten years. Each household in the country is surveyed on a wide range of socio-economic parameters. In 2011, in addition to the general census, the Ministry of Rural Development also conducted the Socio Economic Caste Census (SECC) to measure poverty and deprivation. So I use outcomes from the Census 2001, the Census 2011 as well as some additional measures of development from the SECC.

Further, I use data from the Economic Census, which is conducted periodically in India. The Economic Census is a census of all organized and unorganized business units of the non-agricultural sector in India. The data is collected on various economic parameters including number of enterprises, number of persons employed, type of ownership, and source of finance. While the Economic Census leaves out the agriculture sector, it quite precisely captures the economic activity in manufacturing and services. I use data from the Economic Census 1998 and 2013 as both rounds are closer in years to the Household Census 2001 and 2011 respectively.

I obtain all the census data from the Socioeconomic High-resolution Rural-Urban Geographic Platform (SHRUG) for India (Asher et al., 2021). SHRUG is a village-level data repository put together by the Development Data Lab (DDL). I only use data on outcomes available in SHRUG. This includes development outcomes such as literacy, power supply and new roads from Census 2001 and Census 2011. It also includes rural and urban poverty rates from SECC 2011 and employment in manufacturing and services from the Economic Census. I aggregate the census outcomes at the constituency

level using GIS tools and a weighted average method.[7]

For my analysis of census outcomes, I only use the reservation and discontinuity in Period 1 (1974-2007). So my constituency-level census aggregates only correspond to constituencies in Period 1. This is because reservation in Period 2 starts in 2008, and therefore will have no effects on Census 2001 outcomes. Furthermore, only 3 years passed between the start of Period 2 reservation in 2008 and Census 2011. For representatives elected after 2007, three years is a short time to have any effect on Census 2011 outcomes. This is especially true for outcomes such as literacy rate, which takes longer to change.

I also use data from the Census 1971 and the Census 2001 to test my identifying assumption. Specifically, I check if the predetermined characteristics are balanced at the cutoff. For the identifying assumption to hold, there should not be any significant differences in these characteristics between reserved and unreserved constituencies close to the cutoff. For reservation in Period 1 which starts in 1974, I use outcomes from the Census 1971, which took place before the reservation started. Since SHRUG does not include data from Census 1971, I obtain the data from Jensenius (2015). For the purpose of her study, Jensenius (2015) aggregates the outcomes at the assembly constituency level, which I directly use. Similarly, for the reservation in Period 2, which starts in 2008, I use outcomes from the Census 2001 which I obtain from SHRUG.

Descriptives from the census data are given in Table 3.4. I find that all key development indicators have improved between the two census periods. The average employment rate in manufacturing and services, however, is very low in both rounds. The employment rate is the ratio of the number of people employed to the number of people in the working age group. However, SHRUG does not have data on the working-age population. So I calculate the employment rate as a percentage of the total population. Since the total population in a constituency is larger than its working-age population, I get employment rates that are underestimated. As expected, the rural poverty rate is higher than the urban poverty rate. As per Census 2011, 28% of the population in rural areas of a constituency was living below the poverty line.

[7] I first aggregate outcomes at the census block level using census block IDs in SHRUG. I then use GIS mapping to overlay the boundaries of census blocks and assembly constituencies. Details of how I calculate the weights and how I use the weighted average method to get constituency-level outcomes are provided in Appendix 3.A.1.

Table 3.4. Summary statistics from census data

	Census period 1		Census period 2	
	Mean	*SD*	*Mean*	*SD*
General household census				
Literacy rate	0.55	0.13	0.64	0.10
Share of villages with power supply	0.59	0.36	0.67	0.31
Share of villages with new roads	0.67	0.25	0.72	0.25
Economic Census				
Employment rate in manufacturing and services	0.05	0.04	0.09	0.10
Socio Economic Caste Census				
Rural poverty rate			0.28	0.14
Urban poverty rate			0.13	0.08
Observations	3,085		3,085	

Notes: The number of observations is the number of constituencies in the election period 1974-2007. Census period 1 and Census period 2 correspond to 2001 and 2011 respectively for both the general census and the SECC. For the Economic Census, census period 1 corresponds to 1998, and census period 2 corresponds to 2013.

3.4.3 Nightlights data

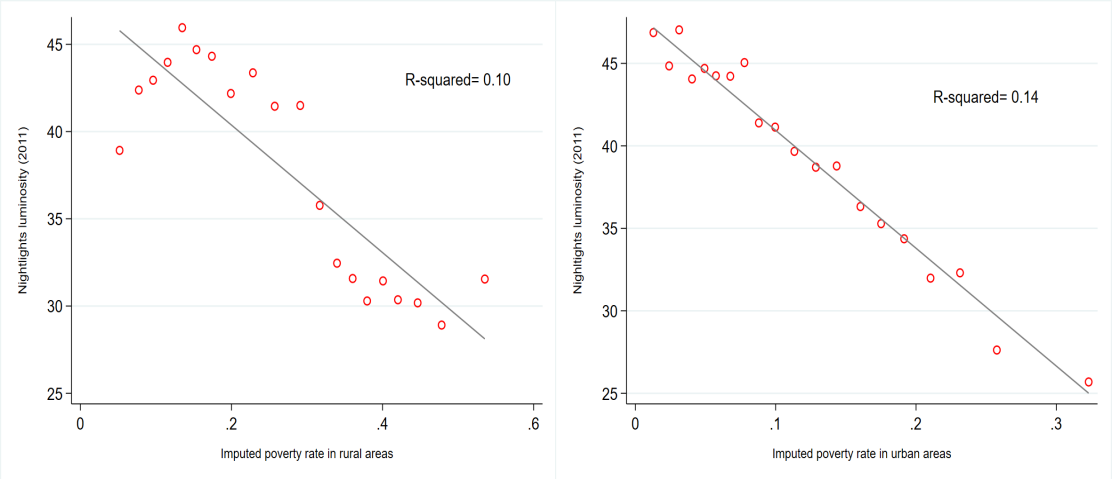
I use data on nighttime lights which are detected using satellites by the DMSP's Operational Linescan System (OLS). The data has a spatial resolution of 2.7km, which means that the satellite sensors can differentiate light sources approximately 2.7km apart. The SHRUG repository includes data on nightlights which has been aggregated at the assembly constituency level. This allows me to directly use this data, which is available for the years 1994-2013.[8] The measure of nightlight luminosity is given by the Digital Number, which is assigned to each pixel (1 km^2). It ranges from 0 to 63, where 0 means darkest and 63 means brightest.

The DMSP-OLS Digital Number seems to be correlated with economic development. As seen in Figure 3.1, there is a linear relationship between constituency-level nightlight luminosity and the poverty rate recorded in the Census data. I see that higher poverty rates are associated with a lower nighttime luminosity. This is precisely what we would expect as constituencies that are poorer (with higher poverty rates) would emit less luminosity. This is because poor areas might not have access to reliable electricity or have many industries and businesses that operate at night. Poor areas might also not receive well-funded public projects such as street lights. The R^2 values suggest that a significant proportion of the variation in nightlights is not explained by poverty rates. As Figure 3.1 uses binscatter plots, not raw scatter plots, some of the original variability in the data may have been smoothed out.

I see that the correlation between nightlight luminosity and the poverty rate is stronger in urban areas. This is consistent with Abay and Amare (2018), who use nightlights as a proxy measure of urbanization to study its effects on women's body weight. It is also consistent with Gibson, Olivia, and Boe-Gibson (2020), who argue that a caveat of the DMSP-OLS nightlights data is that it does not accurately capture the rural areas. Nonetheless, as my unit of analysis is a constituency that includes both rural and urban areas, these errors get relatively smaller (Gibson, Olivia, and Boe-Gibson, 2020). This is because, in a large region, the underestimations and overestimations can be averaged out. Another caveat of the DMSP-OLS data according to Gibson, Olivia, and Boe-Gibson (2020) is that it is subject to temporal errors and is not suited for a pure time-series analysis. However, since I am essentially incorporating a cross-sectional analysis, this is less of a problem.

[8] As many of the DMSP satellites have been aging, the more recent DMSP-OLS nighttime lights data are not free from anomalies. So the data is not available for years after 2013.

Figure 3.1. Correlation of nightlights data with poverty rate



Notes: Nightlight luminosity on the y-axis is the Digital Number from the DMSP-OLS data. Imputed poverty rates on the x-axis are from the SECC 2011.

3.4.4 School data

Finally, I use schooling outcomes from primary school census data known as the District Information System for Education (DISE). DISE is the administrative data of all registered schools in India. I use data from 2010 to 2017 to exploit the government's reform of the education system in 2010 with the implementation of the Right to Education (RTE) Act. DISE collects a wide range of information from the schools regarding enrolment, teachers, examination results, and facilities. For my analysis, I mainly use data on enrolment. Using GIS tools and the same weighted average method I used for census outcomes, I aggregate schooling outcomes at the constituency level (see Appendix 3.A.1 for details).

My data points include the share of total enrolment and the share of enrolment of SC and ST groups, which I calculate for government and private schools separately.[9] This is because, under the RTE Act, primary education was made free in government schools. At the same time, private schools had to reserve at least 25% of their places for SC and ST groups and provide them with free primary education. From DISE I also obtain information on the share of students directly enrolled under this policy in private schools.

To study the effect of the RTE Act on schooling outcomes post-2010, I only use the reservation in Period 2 (2008-2017). This is because unlike census outcomes (e.g.

[9]By government schools, I mean schools that are managed and run by the government. By private schools, I mean schools that are entirely owned and managed by private individuals.

literacy rate), schooling outcomes (e.g. enrolment rate) may change faster over time. Therefore schooling outcomes in a constituency after 2010 are less likely to have been influenced by a representative who was in power before 2008. Moreover, since the RTE Act was enacted in 2010, any change in schooling outcomes induced by it could not be due to representatives prior to 2008. Representatives in Period 1 could not have foreseen the introduction of the RTE Act and its provisions. So all the schooling outcomes in my data have been aggregated at the constituency level in Period 2.

Table 3.5 shows some descriptive statistics from the DISE data. I find that on average, 31% of all students are enrolled in private schools. Of these, 13% belong to SC groups, while only 3% belong to ST groups. I also find that the average enrolment for SC groups is higher in government schools than in private schools, while for ST groups government school enrolment is slightly lower. On average, 20% of all primary schools in a constituency are privately owned. Further, the average share of students directly enrolled under the reservation policy in private schools is only around 8%, much lower than the required 25%.

Table 3.5. Summary statistics from school data

	Mean	*SD*
Share of enrolment in private schools	0.31	0.20
Share of SC enrolment in government schools	0.27	0.13
Share of SC enrolment in private schools	0.13	0.07
Share of ST enrolment in government schools	0.02	0.03
Share of ST enrolment in private schools	0.03	0.05
Share of RTE enrolment in private schools	0.08	0.08
Share of private schools	0.20	0.13
Observations	2,999	

Notes: The number of observations is the number of constituencies in the election period 2008-2017. The schooling outcomes have been averaged across 8 years from 2010, the school year the RTE Act was implemented to 2017, the last school year in the DISE data.

3.5 Results

3.5.1 Balance checks

I first check if the predetermined characteristics are not significantly different at the cutoff of reservation. For the reservation starting in 1974, I use characteristics from Census 1971, and for the reservation starting in 2008, I use characteristics from Census 2001. The results from the balance test for Period 1 are reported in Table 3.A.1 and those for Period 2 are reported in Table 3.A.2. Both tables indicate that there is no difference in the predetermined characteristics between reserved and unreserved constituencies. This implies that these characteristics are balanced at the cutoff. This suggests that the reservation assignment around the cutoff is as good as random.

Second, I check whether the density of the running variable is smooth around the cutoff. If there is a discontinuity in the density of the running variable, it would imply potential manipulation of the cutoff or self-selection into the treatment (reservation). In the context of state elections, a general candidate might prefer to contest from a constituency that favours them due to similar ideologies or personal connections. If the constituency has a share of SC population high enough to be reserved, the candidate will not be able to contest in that constituency. But if the candidate has the political power to influence the Delimitation Committee, they might manipulate the cutoff by drawing the boundaries in a way that the constituency ends up being unreserved. This would violate the identifying assumption and result in biased and inconsistent estimates.

The density of the running variable in Period 1 and Period 2 are shown in Figures 3.A.3 and 3.A.4 respectively. The running variable is the proportion of SCs to the marginal constituency in each district. While almost all districts have a marginal constituency, only large districts with many constituencies have values for the running variable which are outside the [-5,5] bandwidth. The reported t statistic is based on the density test proposed by Cattaneo, Titiunik, and Vazquez-Bare (2020), which uses local polynomial density estimation to check the continuity of the running variable's density function at the cutoff. The test statistic measures the difference in the estimated densities from the left and right sides of the cutoff. The large p-values suggest that there is no evidence of discontinuity of the running variable's density at the cutoffs in both periods. This suggests that there was no manipulation of the cutoffs in either periods.

Finally, I check if there is a correlation between reservations in the two periods (see Figure 3.A.5).[10] The points on the negative quadrants indicate regions that are unreserved and those on the positive quadrants indicate regions that are reserved. I see that the majority of the regions that were unreserved for SCs in Period 1 were also unreserved in Period 2 (where $D1 = 0$ and $D2 = 0$). However, the majority of regions that were reserved in Period 2 (where $D2 = 1$) were unreserved in Period 1 (where $D2 = 1$ and $D1 = 0$). Therefore, a place that was reserved in Period 2 was not more likely to have been reserved in Period 1. This suggests that there was no selection into reservation in Period 2 based on the reservation in Period 1.

3.5.2 Effect of reservation on representative characteristics

First, I use my RD model to show that reservation has a very large effect on representatives being SC. I also show that it has a significant effect on other representative characteristics. While the reservation status of a constituency remains fixed in each of periods 1 and 2, other characteristics of the winning candidate like gender can change over time. Moreover, if a constituency is unreserved, the caste of the winning candidate can also change in each election year, at least in principle. Additionally, since all states do not have elections in the same year, the number of years each constituency has a particular representative may also vary. Therefore, to capture these more accurately, I use the proportion of years each constituency has a particular type of representative.[11]

For the regression discontinuity design to work, there should be a discontinuity in the treatment assignment at the cutoff point of the running variable. In other words, the proportion of years a constituency has an SC representative should 'jump' at the cutoff of reservation. In Figure 3.2 I show that the proportion of years with SC representatives increases by approximately 0.9 in Period 1. In Period 2, this increase is bigger and closer to 1, as shown in Figure 3.3.

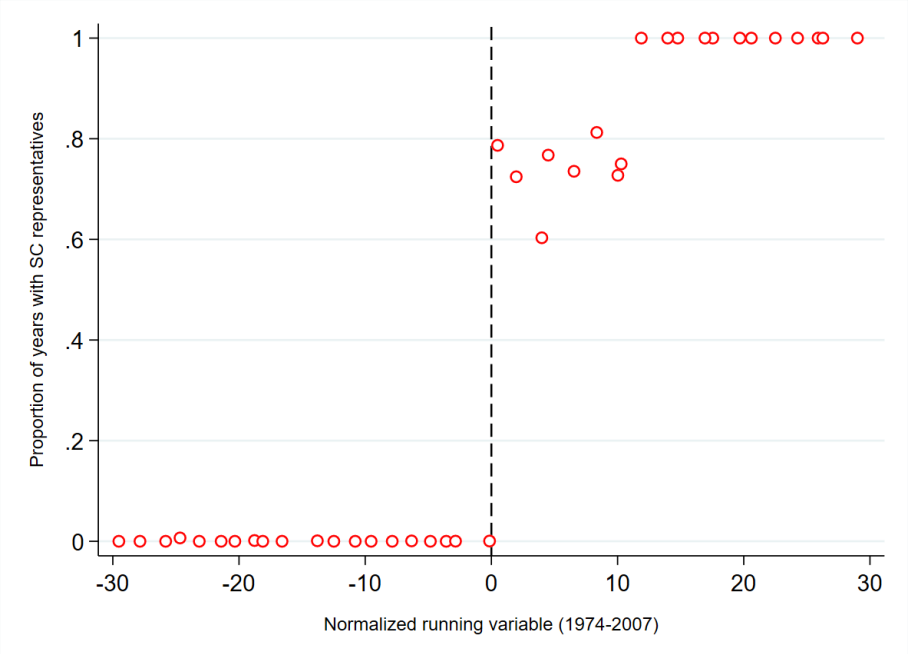
However, due to the additional rule of not reserving constituencies that share a border, the proportion of years with SC representatives is not always 1 when $R_c > 0$. In Period 1, about 30% of districts had at least one constituency which was unreserved despite $R_c > 0$. In Period 2, there were only about 2% of such districts. This could be due to the new boundaries being drawn in a way where this additional rule became re-

[10] Using GIS tools, I overlay the boundaries of constituencies in both periods. I find the overlapping regions and plot the reservation status of all such regions in both periods. All overlapping regions within each constituency have the same reservation status and value of the running variable as the constituency itself depending on the reservation period.

[11] Proportion of years with 'x' representative $= \frac{\text{Number of years with 'x' representative}}{\text{Total number of years with a representative}}$

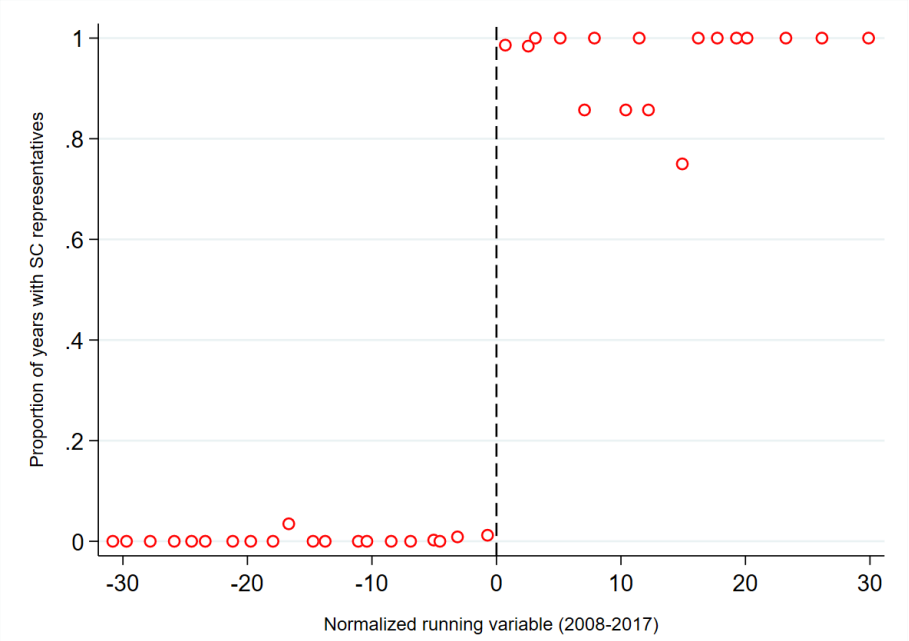
dundant. Nonetheless, overall there are only about 5% of such constituencies in Period 1.

Figure 3.2. Proportion of years with SC representatives in Period 1



Notes: Constituencies that were unreserved for SCs, where $R_c < 0$, the representative could still have been SC. In most constituencies that are unreserved in Period 1, the representatives are non-SC by definition as I only observe the caste of the representatives after 2003. In the remaining few unreserved constituencies where I observe the caste of the representative, there are 18 (0.7%) constituencies where an SC representative won. The actual percentage might be slightly more. So the proportion of years with SC is not always 0 to the left of the cutoff. It is also not always equal to 1 to the right of the cutoff (where, $R_c > 0$) when constituencies are left unreserved due to having a shared border with one or more reserved constituencies. The running variable's range is divided into bins of equal length.

Figure 3.3. Proportion of years with SC representatives in Period 2



Notes: Constituencies that were unreserved for SCs, where $R_c < 0$, the representative could still have been SC. In Period 2, there are 23 (0.9%) such constituencies. So the proportion of years with SC is not always 0 to the left of the cutoff. It is also not always equal to 1 to the right of the cutoff (where, $R_c > 0$) when constituencies are left unreserved due to having a shared border with one or more reserved constituencies. The running variable's range is divided into bins of equal length.

From Figures 3.2 and 3.3 I see that I have a fuzzy-RD design, although the 'jump' is very large and close to 1. So I estimate a local average treatment effect (LATE) similar to an instrumental variable approach (Angrist and Pischke, 2009). The RD estimates corresponding to Figures 3.2 and 3.3 are reported in the first row of Table 3.6. Essentially, these are the first stage estimates if I estimate an IV model. All three columns in Table 3.6 show that the first stage with SC representatives is almost 1. Both figures also show that the relationship between SC representatives and the running variable is non-linear, so I get more precise estimates with non-parametric and local linear models.

Table 3.6. Effect of reservation on representative characteristics

	Period 1 1974–2007			Period 2 2008–2017		
	Non-parametric	Non-parametric with FE	Local linear	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion of years with SC representative	0.905***	0.966***	0.937***	0.971***	0.982***	0.974***
	(0.030)	(0.035)	(0.040)	(0.012)	(0.009)	(0.014)
Turnout percentage	−5.256***	−5.290***	−5.456***	−3.123***	−3.508***	−3.347***
	(0.958)	(0.492)	(0.574)	(1.162)	(0.396)	(0.495)
Proportion of years with female representative	0.010	0.021*	0.010	0.073**	0.081***	0.069*
	(0.012)	(0.011)	(0.013)	(0.033)	(0.029)	(0.037)
Proportion of years with independent representative	−0.018**	−0.014*	−0.017**	−0.019*	−0.004	−0.015
	(0.009)	(0.008)	(0.009)	(0.010)	(0.011)	(0.013)
Average age of representative	−3.252***	−3.415***	−3.114***	−3.398***	−3.852***	−3.208***
	(1.040)	(1.061)	(1.160)	(0.855)	(0.943)	(1.132)
District FE	No	Yes	Yes	No	Yes	Yes
Observations	2,922	2,922	2,922	2,639	2,639	2,639

Notes: Models (1) and (4) present results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Models (2) and (5) include district fixed effects. Models (3) and (6) indicate linear estimates that use an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6 also shows that the discontinuity does not just affect representatives being SC without changing other factors. In both periods I see that reservation decreases the turnout percentage, increases the proportion of years with female representatives, decreases the proportion of years with independent representatives, and decreases the average age of representatives.

I find that the voter turnout is 5 percentage points and 3 percentage points lower in reserved constituencies in Periods 1 and 2 respectively. This implies that people are less likely to cast their votes in reserved constituencies, which potentially reflects a bias against SC candidates. However, by Period 2, the average turnout had increased by 8 percentage points (see Table 3.3) and the gap between the turnout percentages in reserved and unreserved constituencies reduced from 5 to 3 percentage points. This implies that the increase in voter turnout by Period 2 was larger in reserved constituencies. The gap in the turnout percentages between reserved and unreserved constituencies in both periods is also graphically shown in Figures 3.A.6 and 3.A.7.

I also find that constituencies just to the right of the cutoff (reserved) are more likely to have a representative who is female, younger, and affiliated with a political party. In Period 1, I see that reservation increases the proportion of years with female representatives by roughly 2 percentage points. In Period 2, the difference is around 8 percentage points, which is much larger than in Period 1. Given that only 9% of representatives were females in Period 2 (see Table 3.3), an 8 percentage points difference is quite large. On the one hand, the higher share of female representatives in SC constituencies could be a strategic move. As the emphasis on female representation in politics has in-

creased over time, political parties might be replacing male SC candidates with female SC candidates in order to maintain a male majority in general constituencies, which are often wealthier and thus more influential (Jensenius, 2016). On the other hand, it could indicate that political reservation for minority groups has led to increased inclusiveness of women.

There is a negative effect of reservation on independent representatives or representatives who are not affiliated with political parties. In both periods, the proportion of years with independent representatives was roughly 2 percentage points lower in reserved constituencies. However, the difference is not highly significant in Period 2. At the same time, the representatives in reserved constituencies are on average 3 years younger. This could again be correlated with gender as female representatives might be on average younger than male representatives. This was true in village elections of South India as found by Ban and Rao (2008).

The reduced form effect of reservation on outcomes is therefore a combined effect of any change in the representative characteristics and the turnout percentage. Nevertheless, the effect of reservation on outcomes would be largely driven by SC representatives since its largest effect is on caste. The effect of reservation on female representatives, independent representatives and average age can be graphically seen in Figures 3.A.8–3.A.13.

3.5.3 Effect of reservation on development

Next, I present the results of the effect of reservation on the overall development of a constituency, for which I exploit the discontinuity in Period 1. As development outcomes I use indicators from census data and a measure of nightlight luminosity. Since estimation under a fuzzy-RD design is very similar to IV, Equation (3.1) is a reduced form estimation.

The reduced form estimates with development outcomes from the census data are reported in Table 3.7. I find that reservation had no effect on census outcomes in 2001 or 2011. Including district fixed effects drastically reduces the standard errors, however, the estimates are still not statistically significant. To check if the standard errors of my estimates are small, I compare them with the standard errors of the matching estimates in Jensenius (2015). In her paper, Jensenius (2015) reports the matching estimates and the corresponding p-values which I use to calculate the standard errors.[12]

[12] I first calculate the t-values using the inverse distribution function and then the corresponding standard errors using the formula $SE_{\hat{\beta}} = \frac{\hat{\beta}}{|t|}$

Table 3.A.3 reports the estimated coefficients, standard errors, and the absolute values of the t-statistic of the RD model and the matching model. There are only three outcomes that are commonly used in both studies. Nonetheless, I find that except for 'power supply in villages', the absolute t-values of 'literacy rate' and 'employment rate' are higher in the RD model.[13] This suggests that the standard errors in the RD model are lower relative to the estimated coefficients. The estimated coefficients are also slightly different in both models. While the coefficients on the employment rate and power supply are positive in the RD model, they are negative in the matching model albeit statistically insignificant. However, when Jensenius (2015) adjusts for the bias in the matching estimates, the coefficients on both variables become positive. To summarise, my findings confirm those of Jensenius (2015) and provide more accurate estimates.

Table 3.7. Effect of reservation on census outcomes: reduced form estimates

	Census period 1			Census period 2		
	Non-parametric	Non-parametric with FE	Local linear	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)	(4)	(5)	(6)
Literacy rate	−0.010	−0.004	−0.005	−0.008	−0.005	−0.006
	(0.011)	(0.005)	(0.006)	(0.009)	(0.004)	(0.005)
Employment rate in manufacturing and services	0.003	0.002	0.002	0.008	0.007	0.005
	(0.003)	(0.002)	(0.002)	(0.010)	(0.009)	(0.009)
Villages with power supply	−0.016	0.008	0.008	0.003	0.011	0.007
	(0.034)	(0.010)	(0.012)	(0.029)	(0.012)	(0.013)
Villages with new roads	−0.023	0.003	−0.004	0.003	−0.003	0.003
	(0.021)	(0.010)	(0.012)	(0.022)	(0.008)	(0.009)
Rural poverty rate				0.007	−0.001	−0.001
				(0.013)	(0.005)	(0.005)
Urban poverty rate				0.005	−0.002	−0.001
				(0.009)	(0.006)	(0.007)
District FE	No	Yes	Yes	No	Yes	Yes
Observations	2,922	2,922	2,922	2,922	2,922	2,922

Notes: The running variable and the discontinuity are based on the reservation in period 1 (1974-2007). Census period 1 and Census period 2 correspond to 2001 and 2011 respectively for both the general census and the SECC. For the Economic Census, census period 1 corresponds to 1998, and census period 2 corresponds to 2013. Models (1) and (4) present results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Models (2) and (5) include district fixed effects. Models (3) and (6) indicate linear estimates that use an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

To capture the actual effect of SC representatives on development, I use the two-stage least squares (2SLS) model. I instrument the proportion of years with SC representatives with the discontinuity in the dummy variable for reservation. I also include the interaction of the dummy with the running variable (R_c) as an additional instrument. The second-stage estimates are reported in Table 3.A.4. The results are consistent with Table 3.7, and the estimates are very similar to the reduced form estimates. I find that

[13] Employment rate in the RD model represents total population employed in manufacturing and services. Employment rate in the matching model represents total population employed in full-time or part-time work. Power supply in villages refers to the share of villages with electricity in a constituency in the RD model, whereas in the matching model, it refers to share of rural population with electricity in a constituency.

there was no effect of SC representatives on census outcomes.

I now turn to my second set of measures of development, which come from nightlight luminosity. One of the advantages of using nightlights data is that it can capture areas where a significant portion of the economic activity is in the informal sector and is not captured in the census data— such as 'employment' in the economic census. Additionally, the census data from DDL does not cover all census outcomes. So, there might be some other relevant development indicators that I have not accounted for in the analysis. Thus, utilizing nightlights data could provide a more comprehensive view of overall economic development.

Table 3.8 reports the results of the effect of reservation on nightlight luminosity. For the purpose of rescaling, I take the log of the Digital Number in each year from 1994 to 2013 and average it across the 20-year period. I cannot reject the null that reservation had no effect on nightlight luminosity in a constituency, but my estimates are far less precise than those from census indicators. In the model with census outcomes, the R^2 is above 0.8 for all measures except the employment rate, for which it is around 0.4–0.6. On the other hand, the R^2 in the nightlights model is much lower (around 0.35 on average). This means that the more than 65% variation in nightlight luminosity is not explained by reservation. The second stage estimates are also very similar to the reduced form estimates.

I also find that the standard errors relative to the estimates are much larger in the nightlights model. This is even more evident when I estimate the effect of reservation on nightlight luminosity each year separately, as shown in Figure 3.A.14. Again I find that there was no significant difference in nightlight luminosity between reserved and unreserved constituencies in any year. But the confidence intervals are extremely wide, resulting in imprecise and statistically insignificant estimates. This implies that the measure of nightlights from the DMSP-OLS data is not a reliable proxy for economic development.

Table 3.8. Effect of reservation on average nightlight luminosity

	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)
Reduced form	−0.022	0.009	0.085
	(0.083)	(0.071)	(0.057)
Second stage	−0.040	0.010	0.044
	(0.086)	(0.075)	(0.076)
District FE	No	Yes	Yes
Observations	2,908	2,908	2,908

Notes: The dependent variable is the average of log nightlight luminosity from 1994 to 2013. The running variable and the discontinuity are based on the reservation in period 1 (1974-2007). Model (1) presents results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Model (2) includes district fixed effects. Model (3) indicates linear estimates that use an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

3.5.4 Effect of reservation on schooling

My final set of results is the effect of reservation on schooling outcomes following the implementation of the RTE Act (2010). For this, I exploit the discontinuity in the reservation in Period 2. As the school data is available from 2010 to 2017, all outcomes have been averaged across 8 years. The reduced form estimates with schooling outcomes are reported in Table 3.9. The non-parametric model with district fixed effects produces estimates with the lowest standard errors, so I prefer Model (2).

First, I find that reservation had a positive and significant effect on the overall enrolment in private schools. Constituencies reserved for SCs had on average a 2 percentage points higher share of enrolment in private schools between 2010 and 2017. At the same time, in reserved constituencies, the share of SC enrolment in private schools was also higher by close to 1 percentage point. However, there was no effect of reservation on SC enrolment in government schools.

On the other hand, reservation of constituencies for SCs had no effect on the enrolment of ST children in government or private schools. Nonetheless, there was a positive effect of political reservation on enrolment directly under the RTE Act's reservation policy in private schools. This includes children from both SC and ST groups. The share of enrolment under the policy was almost 1 percentage point higher in reserved constituencies ($p < 0.05$). Finally, I also find that the share of private schools was 1.6 percentage points higher in reserved constituencies. The R^2 associated with each outcome variable

is high (around 0.75 on average). However, the magnitude of the effect is not very large for any of the variables.

Table 3.9. Effect of reservation on schooling outcomes: reduced form estimates

	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)
Share of enrolment in private schools	0.021	0.020***	0.018*
	(0.017)	(0.008)	(0.010)
Share of SC enrolment in government schools	0.007	0.003	0.003
	(0.014)	(0.004)	(0.006)
Share of SC enrolment in private schools	0.009	0.009***	0.008**
	(0.007)	(0.003)	(0.004)
Share of ST enrolment in government schools	−0.000	−0.000	−0.001
	(0.003)	(0.001)	(0.002)
Share of ST enrolment in private schools	−0.001	−0.002	0.000
	(0.005)	(0.003)	(0.004)
Share of RTE enrolment in private schools	0.001	0.009**	0.005
	(0.008)	(0.005)	(0.006)
Share of private schools	0.016	0.016***	0.012
	(0.012)	(0.006)	(0.008)
District FE	No	Yes	Yes
Observations	2,638	2,638	2,638

Notes: The running variable and the discontinuity are based on the reservation in period 2 (2008-2017). Model (1) presents results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Model (2) includes district fixed effects. Model (3) indicates linear estimates that use an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

The second stage estimates are consistent and are reported in Table 3.10. Constituencies with SC representatives had a higher share of overall enrolment in private schools by 1.6 percentage points on average. They also had a higher share of private schools by 1.3 percentage points. Further, having an SC representative resulted in a 0.8 percentage points increase in private school enrolment of SC children. It also led to a 1 percentage point increase in enrolment under the RTE policy, similar to Table 3.9.

Table 3.10. Effect of reservation on schooling outcomes: second stage estimates

	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)
Share of enrolment in private schools	0.024	0.016**	0.008
	(0.019)	(0.007)	(0.007)
Share of SC enrolment in government schools	0.010	0.004	0.002
	(0.014)	(0.004)	(0.004)
Share of SC enrolment in private schools	0.010	0.008***	0.006**
	(0.007)	(0.003)	(0.003)
Share of ST enrolment in government schools	−0.000	−0.001	−0.001
	(0.003)	(0.001)	(0.001)
Share of ST enrolment in private schools	−0.001	−0.001	−0.004
	(0.005)	(0.003)	(0.003)
Share of RTE enrolment in private schools	0.001	0.009**	0.006
	(0.009)	(0.005)	(0.005)
Share of private schools	0.014	0.013**	0.009
	(0.011)	(0.005)	(0.006)
District FE	No	Yes	Yes
Observations	2,638	2,638	2,638

Notes: The running variable and the discontinuity are based on the reservation in period 2 (2008-2017). Model (1) presents results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Model (2) includes district fixed effects. Model (3) indicates linear estimates that use an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

There might be a concern that I get some significant estimates as a result of using many dependent variables. This problem of multiple modelling arises when we carry out multiple simultaneous tests that increase the likelihood of Type 1 errors. In other words, there is an increased chance of falsely rejecting the null hypothesis in at least one case. To counteract this problem, I use the Bonferroni correction method which makes the statistical testing more rigorous. However, a drawback of this method is that it is too rigid and increases the likelihood of type 2 errors (failing to not reject the null hypothesis falsely). Therefore, I also use the Holms-Bonferroni correction method which controls for type 1 errors while adjusting for type 2 errors.

The results from the multiple model corrections are reported in Table 3.A.5 for statistically significant estimates. I essentially compare the p-values obtained from my original RD model and the corrected p-values obtained after using the Bonferroni and Holms-Bonferroni methods. I find that except for enrolment under the RTE reservation policy, all other estimates continue to be statistically significant, although the level of significance is reduced. The effect on total enrolment in private schools is now only significant at the 10% level under both methods. The effect on SC enrolment in private schools is significant at the 10% level under the Bonferroni method (Column 2). But controlling for type 2 errors increases the significance level to 5% (Column 3). Similarly, the effect on the share of private schools is significant at the 5% and 1% levels under the Bonferroni and Holms-Bonferroni methods respectively.

I find that the strongest effect of SC representatives is on the supply of private schools followed by SC enrolment in private schools. In Chapter 2, I found that after 2010 there was a huge increase in the supply of low-cost private schools in India. In this chapter, I find that the share of private schools and total enrolment in private schools was higher in constituencies reserved for SCs after 2010. In Chapter 1, I found that the share of disadvantaged children significantly increased in private schools after 2010. Subsequently, in this chapter, I find that reserved constituencies had a higher SC enrolment in private schools.

Another potential channel that could explain better schooling outcomes in reserved constituencies is the higher share of female representatives. I find that compared to Period 1, reserved constituencies in Period 2 had a 6 percentage points higher share of female representatives. There are numerous studies that find a positive effect of women's empowerment on children's education outcomes (Behrman and Wolfe, 1984; Ilon and Moock, 1991; Lavy, 1996; Currie and Moretti, 2003; Chaudhry and Rahman, 2009). A deeper investigation is needed to see if more female leaders in reserved constituencies positively affected schooling outcomes.

3.6 Conclusion

In this chapter, I provide evidence of the causal effect of political representative characteristics on economic development in the context of India. In particular, I investigate whether assembly constituencies reserved for disadvantaged communities such as Scheduled Castes (SCs) had worse development outcomes. To estimate a causal effect, I cannot simply compare the outcomes between reserved and unreserved constituencies as reserved constituencies in state elections are not selected randomly. However, the reservation of constituencies is based on the population proportion of SCs, which enables me to use a regression discontinuity (RD) design.

I first find that at the cutoff of reservation, the proportion of SC representatives is higher by almost 1. I also find that at the cutoff, constituencies have a higher proportion of representatives who are female, affiliated with a political party and younger in age. However, my main results show that reserved constituencies do not perform poorly in terms of development relative to unreserved constituencies.

Using outcomes from Census 2001 and Census 2011, I do not find that SC representatives had a negative effect on the overall development of a constituency. Therefore, contrary to popular belief, SC MLAs are no less effective than non-SC MLAs in India. This chapter corroborates the findings from Jensenius (2015), who finds a similar result with 2001 census outcomes. I demonstrate that even after a decade, the effect on socioeconomic indicators from the census remains unchanged. This is despite representatives now receiving the MLA-LAD funds for development works in their constituency.

Nonetheless, looking at schooling outcomes, I find a positive effect of SC MLAs on private education. The share of primary enrolment in private schools, as well as the share of total private schools, was higher in reserved constituencies by almost 2 percentage points. Moreover, the share of SC student enrolment in private schools was higher by almost 1 percentage point. This suggests that SC MLAs had a positive effect on private education after 2010, especially for SC children. The effects are potentially tied to the RTE Act, implemented in 2010, that made private education of disadvantaged groups a priority of the government. My results are also in line with existing studies that find a positive relationship between political representatives and the redistribution of resources to their interest groups.

My results show that representatives after 2008 were significantly more likely to be women. The increase in the share of female representatives from SC constituencies was much higher after 2008 than before. This could have resulted in more resources being diverted towards education. Female representatives might have also more closely

adhered to the guidelines of the RTE Act. At the same time, as highlighted in Section 3.2, studies have found that female representatives sometimes contribute more towards SC communities at the village-level. Thus, the positive effect on SC enrolment could be a combined effect of representatives being SC and females.

This chapter, however, does have a few limitations. Firstly, I cannot identify why there was no difference in outcomes between reserved and unreserved constituencies from 1974 to 2007. It could be that SC representatives were just as productive as non-SC representatives. It could also be that MLAs in general had no effect on the economic development of a constituency during this time.

Secondly, when I use nightlight luminosity as a proxy for development, even though I get similar results as census outcomes, my estimates are noisy. According to Gibson, Olivia, and Boe-Gibson (2020), the DMSP-OLS nightlights data were intended for Air Force pilots and so some of the measurement errors in the data might make it less suitable for economic analysis. Gibson, Olivia, and Boe-Gibson (2020) suggest the use of nightlights data from the Visible Infrared Imaging Radiometer Suite (VIIRS), which is more spatially accurate. The VIIRS data is available for years after 2011, which I intend to use in my future research to get more precise estimates of nightlights.

References

Abay, K.A. and Amare, M. (2018). "Night light intensity and women's body weight: evidence from Nigeria". In: *Economics & Human Biology* 31, pp. 238–248.

Acemoglu, D., Egorov, G., and Sonin, K. (2013). "A political theory of populism". In: *The quarterly journal of economics* 128.2, pp. 771–805.

Agarwal, A., Agrawal, N., Bhogale, S., Hangal, S., Jensenius, F.R., Kumar, M., Narayan, C., Nissa, B.U., Trivedi, P., and Verniers, G. (2021). *TCPD Indian Elections Data v2.0*.

Angrist, J.D and Pischke, JS. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Asher, S., Lunt, T., Matsuura, R., and Novosad, P. (2021). "Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in India using the shrug open data platform". In: *The World Bank Economic Review* 35.4.

Ban, R. and Rao, V. (2008). "Tokenism or agency? The impact of women's reservations on village democracies in South India". In: *Economic Development and Cultural Change* 56.3, pp. 501–530.

Bardhan, P.K., Mookherjee, D., and Parra Torrado, M. (2010). "Impact of political reservations in West Bengal local governments on anti-poverty targeting". In: *Journal of Globalization and development* 1.1.

Behrman, J.R. and Wolfe, B.L. (1984). "Who is Schooled in Developing Countries? The Roles of Income, Parental Schooling, Sex, Residence and Family Size". In: *Economics of Education Review* 3.3, pp. 231–245.

Besley, T., Montalvo, J.G., and Reynal-Querol, M. (2011). "Do educated leaders matter?" In: *The Economic Journal* 121.554, F205–227.

Besley, T., Pande, R., Rahman, L., and Rao, V. (2004). "The politics of public good provision: Evidence from Indian local governments". In: *Journal of the European Economic Association* 2.2-3, pp. 416–426.

Burgess, R., Jedwab, R., Miguel, E., Morjaria, A., and Padró i Miquel, G. (2015). "The value of democracy: evidence from road building in Kenya". In: *American Economic Review* 105.6, pp. 1817–1851.

Bussell, J. (2012). *Corruption and reform in India: Public services in the digital age*. Cambridge University Press.

Calonico, S., Cattaneo, M.D., and Titiunik, R. (2014). "Robust nonparametric confidence intervals for regression-discontinuity designs". In: *Econometrica* 82.6, pp. 2295–2326.

Cattaneo, M.D., Titiunik, R., and Vazquez-Bare, G. (2020). "Analysis of regression-discontinuity designs with multiple cutoffs or multiple scores". In: *The Stata Journal* 20.4, pp. 866–891.

Chattopadhyay, R. and Duflo, E. (2004). "Women as policy makers: Evidence from a randomized policy experiment in India". In: *Econometrica* 72.5, pp. 1409–1443.

Chaudhry, I.S. and Rahman, S. (2009). "The impact of gender inequality in education on rural poverty in Pakistan: an empirical analysis". In: *European Journal of Economics, Finance and Administrative Sciences* 15.1, pp. 174–188.

Chin, A. and Prakash, N. (2011). "The redistributive effects of political reservation for minorities: Evidence from India". In: *Journal of development Economics* 96.2, pp. 265–277.

Chopra, V.K. (1996). *Marginal players in marginal assemblies: The Indian MLA*. Orient Longman.

Clots-Figueras, I. (2011). "Women in politics: Evidence from the Indian States". In: *Journal of public Economics* 95.7-8, pp. 664–690.

Currie, J. and Moretti, E. (2003). "Mother's education and the intergenerational transmission of human capital: Evidence from college openings". In: *The Quarterly journal of economics* 118.4, pp. 1495–1532.

Dhillon, A., Krishnan, P., Patnam, M., and Perroni, C. (2016). "Electoral Accountability and the Natural Resource Curse: Theory and Evidence from India". In.

Dunning, T. and Nilekani, J. (2013). "Ethnic quotas and political mobilization: caste, parties, and distribution in Indian village councils". In: *American political Science review* 107.1, pp. 35–56.

Ferreira, F. and Gyourko, J. (2009). "Do political parties matter? Evidence from US cities". In: *The Quarterly journal of economics* 124.1, pp. 399–422.

Gibson, J., Olivia, S., and Boe-Gibson, G. (2020). "Night Lights in Economics: Sources and Uses". In: *Journal of Economic Surveys* 34.5, pp. 955–980.

Gilens, M. (2005). "Inequality and democratic responsiveness". In: *Public Opinion Quarterly* 69.5, pp. 778–796.

Gulzar, S., Haas, N., and Pasquale, B. (2020). "Does political affirmative action work, and for whom? Theory and evidence on India's scheduled areas". In: *American Political Science Review* 114.4, pp. 1230–1246.

Ilon, L. and Moock, P. (1991). "School attributes, household characteristics, and demand for schooling: A case study of rural Peru". In: *International Review of Education* 37.4, pp. 429–451.

Iyer, L. and Mani, A. (2012). "Traveling agents: political change and bureaucratic turnover in India". In: *Review of Economics and Statistics* 94.3, pp. 723–739.

Jensenius, F.R. (2015). “Development from representation? A study of quotas for the scheduled castes in India”. In: *American Economic Journal: Applied Economics* 7.3, pp. 196–220.

— (2016). “Competing inequalities? On the intersection of gender and ethnicity in candidate nominations in Indian elections”. In: *Government and Opposition* 51.3, pp. 440–463.

Kaletski, E. and Prakash, N. (2016). “Does political reservation for minorities affect child labor? Evidence from India”. In: *World Development* 87, pp. 50–69.

Kapur, D., Mehta, P.B., and Vaishnav, M. (2018). *Rethinking public institutions in India*. Oxford University Press.

Kim, J., Wang, M., Park, D., and Petalcorin, C.C. (2021). “Fiscal policy and economic growth: some evidence from China”. In: *Review of World Economics* 157.3, pp. 555–582.

Kramon, E. and Posner, D.N. (2016). “Ethnic favoritism in education in Kenya”. In: *Quarterly Journal of Political Science* 11.1, pp. 1–58.

Lavy, V. (1996). “School supply constraints and children’s educational outcomes in rural Ghana”. In: *Journal of Development Economics* 51, pp. 291–314.

Pande, R. (2003). “Can mandated political representation increase policy influence for disadvantaged minorities? Theory and evidence from India”. In: *American economic review* 93.4, pp. 1132–1151.

Pathak, Y. and Macours, K. (2017). “Women’s political reservation, early childhood development, and learning in India”. In: *Economic Development and Cultural Change* 65.4, pp. 741–766.

Prakash, N., Rockmore, M., and Uppal, Y. (2019). “Do criminally accused politicians affect economic outcomes? Evidence from India”. In: *Journal of Development Economics* 141: 102730.

Priebe, J. (2017). “Political reservation and female empowerment: evidence from Maharashtra, India”. In: *Oxford Development Studies* 45.4, pp. 499–521.

Sukhtankar, S. and Vaishnav, M. (2015). “Corruption in India: Bridging research evidence and policy options”. In: *India Policy Forum*. Vol. 11. National Council of Applied Economic Research Delhi, India, pp. 193–276.

Appendices

3.A.1 Aggregation of census blocks to constituencies

I have blocks labeled $b = 1,\ldots,B$. For each block, I have information x_b which contains, for example, a measure from the Census or a measure from DISE in that block.

Constituencies are labelled $c = 1,\ldots,C$. Each block lies within one or more constituencies and each constituency lies within one or more blocks. Define $A_{b,c}$ to be the area of the region that lies within both block b and constituency c. The total area of constituency c is therefore

$$A_c = \sum_{b \in \mathscr{B}_c} A_{b,c}$$

where $\mathscr{B}_c$ is the set of blocks that have some area overlapping with constituency c. The share, or "area weight" of block b in constituency c is then $w_{b,c} = A_{b,c}/A_c$.

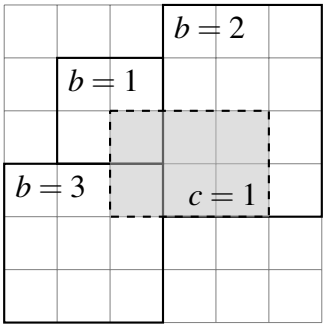
The estimated value of x_c for each constituency is the weighted sum of the x_b for all $b \in \mathscr{B}_c$, which is

$$\hat{x}_c = \sum_{b \in \mathscr{B}_c} w_{b,c} x_b.$$

For example, suppose x_b is the average age in block b. Then if a constituency covers two blocks $b = 1$ and $b = 2$, the average age in the constituency is the weighted average of x_1 and x_2.

However, if the information in x_b is a count or a total, it needs to be first divided by the total area of each block. For example, consider Figure 3.A.1

Figure 3.A.1. Three census blocks overlapping with one constituency area



Suppose there are three blocks $b = 1,2,3$ with areas 4, 12 and 9. The constituency $c = 1$ overlaps each of these blocks with $A_{1,1} = 1$, $A_{2,1} = 4$ and $A_{3,1} = 1$. So the weights are $w_{1,1} = 1/6$, $w_{2,1} = 4/6$ and $w_{3,1} = 1/6$. Now suppose that x_b is "miles of road in block b" and takes the value $x_1 = 10$, $x_2 = 15$, $x_3 = 20$. I can either normalise x_b by the

area of each block, giving me "miles of road per km^2":

$$\hat{x}_{1.} = \left(\frac{1}{6}\right)\left(\frac{10}{4}\right) + \left(\frac{4}{6}\right)\left(\frac{15}{12}\right) + \left(\frac{1}{6}\right)\left(\frac{20}{9}\right) = 1.62,$$

or I can use weights for the proportion of each block in the constituency, which gives me an estimate of "miles of road":

$$\hat{x}_{1.} = \left(\frac{1}{4}\right)10 + \left(\frac{4}{12}\right)15 + \left(\frac{1}{9}\right)20 = 9.72.$$

Note that the first estimate (1.62) is just the second estimate (9.72) divided by the area of the constituency (6).

3.A.2 Figures

Figure 3.A.1. Assembly constituencies in Period 1 (1974-2007)

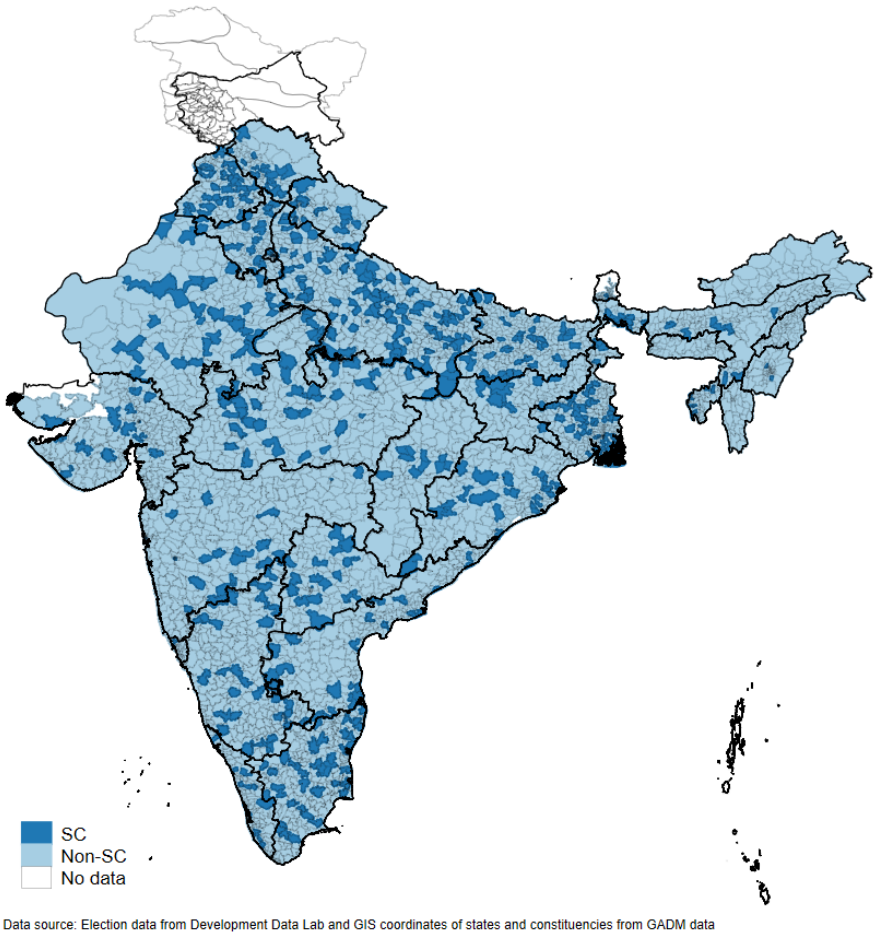
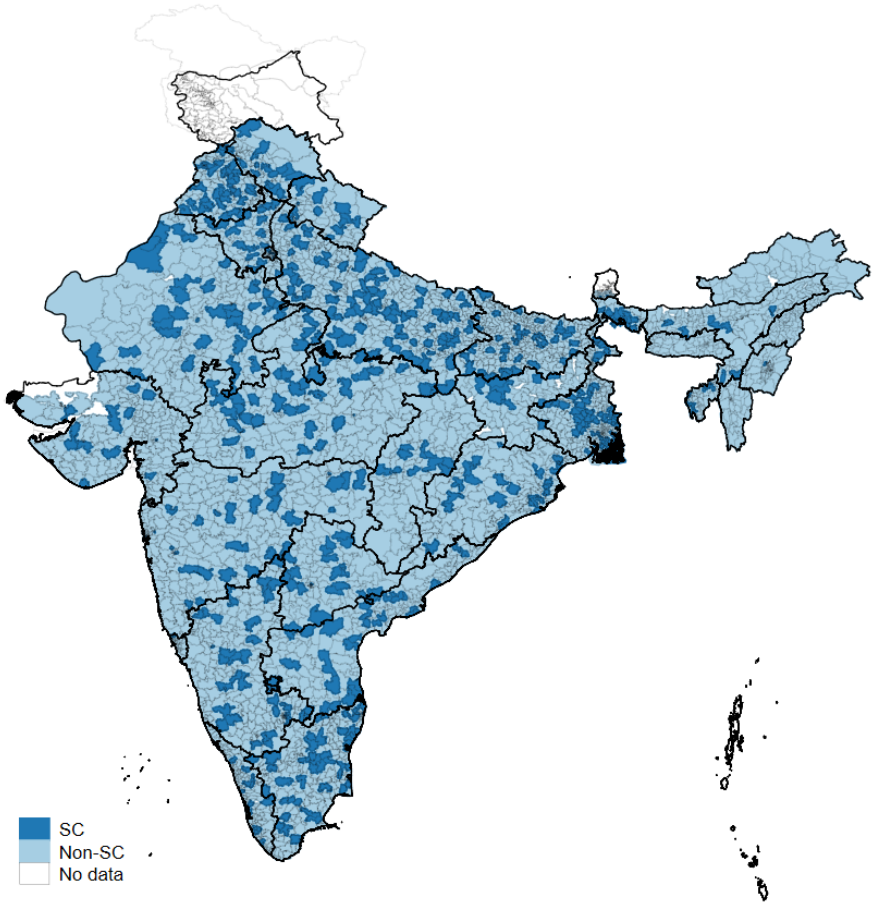


Figure 3.A.2. Assembly constituencies in Period 2 (2008-2017)



Data source: Election data from Development Data Lab and GIS coordinates of states and constituencies from GADM data

Figure 3.A.3. Density of running variable in Period 1

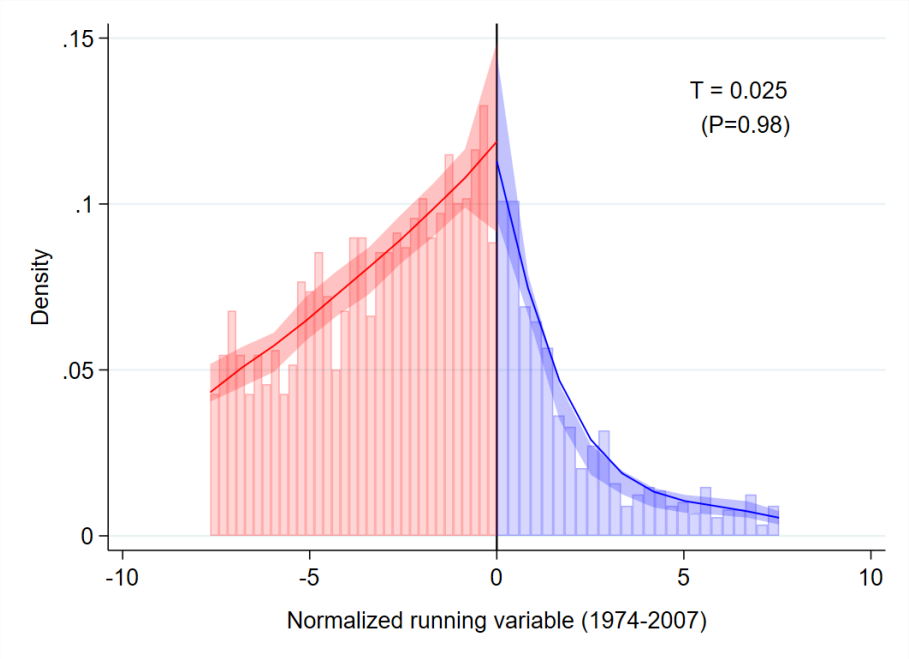


Figure 3.A.4. Density of running variable in Period 2

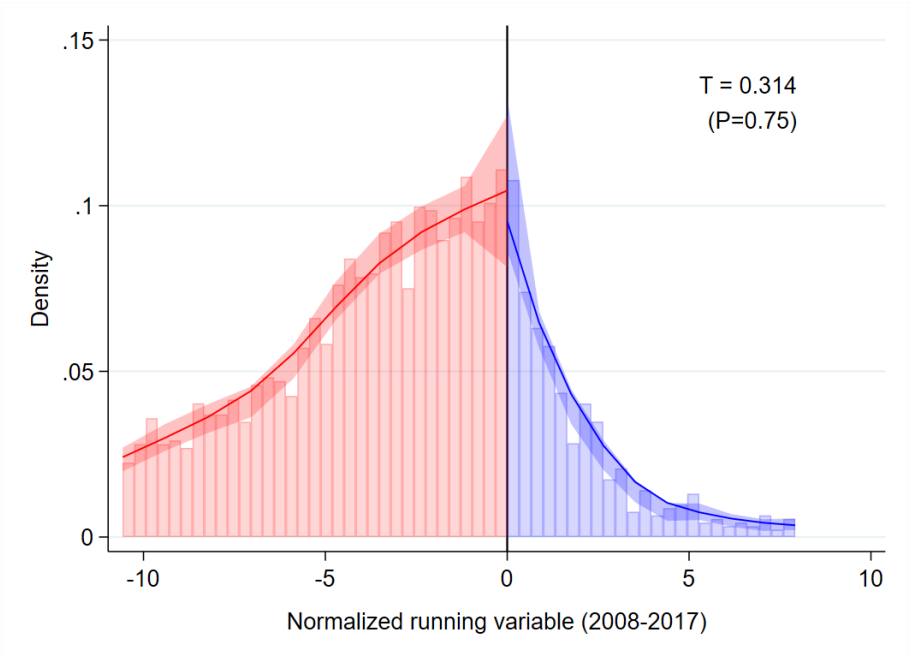
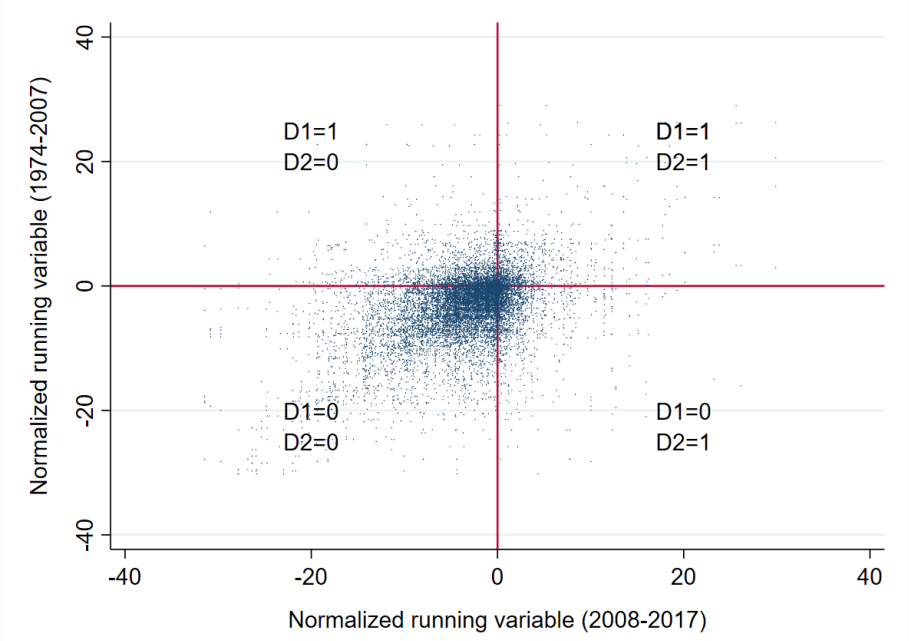
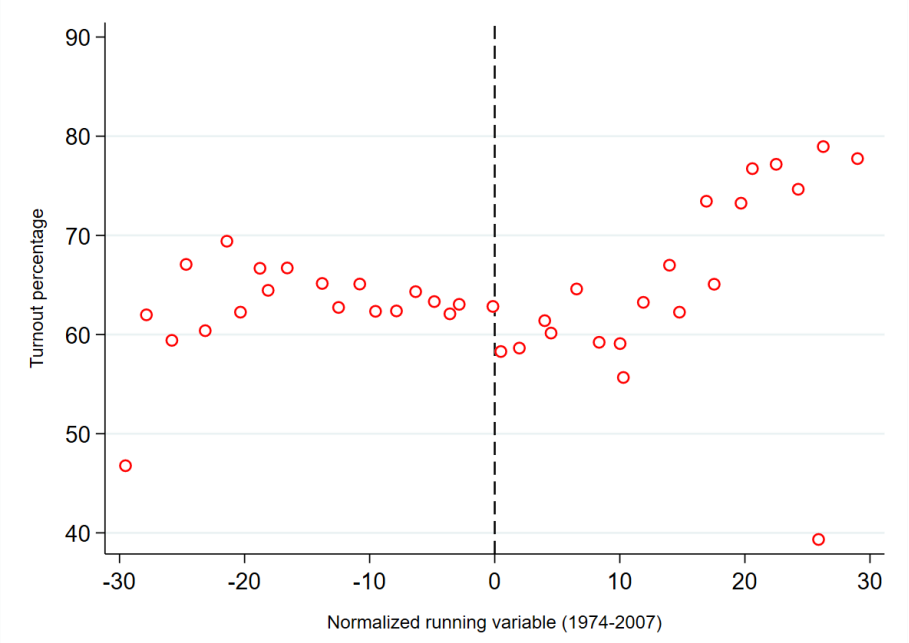


Figure 3.A.5. Correlation between the running variables in both periods



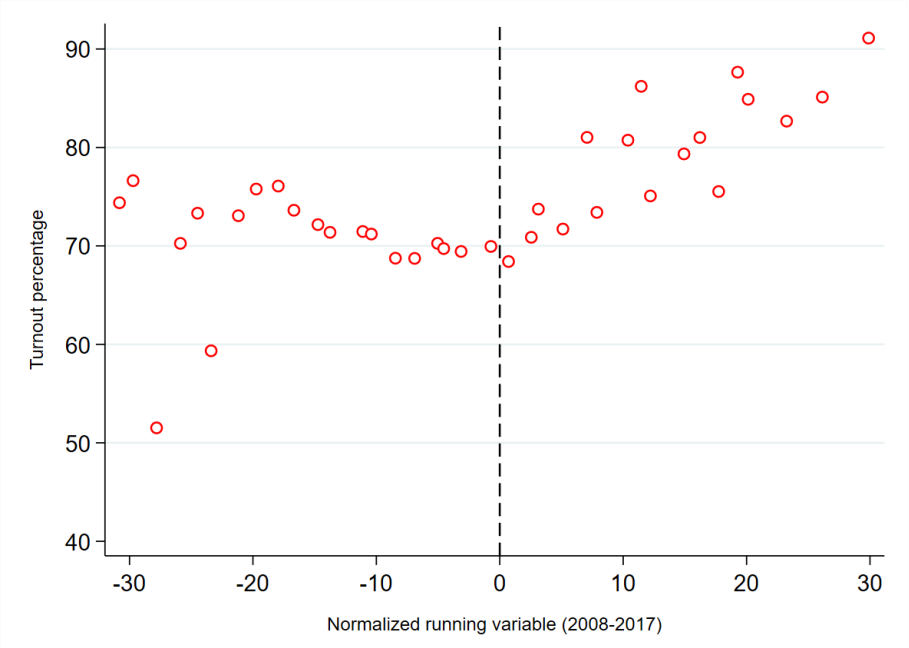
Notes: The Y-axis denotes the running variable in Period 1. The X-axis denotes the running variable in Period 2. $D1 = 1$ and $D2 = 1$ indicate regions reserved in both periods. $D1 = 1$ and $D2 = 0$ indicate regions reserved in Period 1 and unreserved in Period 2 respectively. $D1 = 0$ and $D2 = 0$ indicate regions unreserved in both periods. $D1 = 0$ and $D2 = 1$ indicate regions unreserved in Period 1 and reserved in Period 2 respectively.

Figure 3.A.6. Turnout percentage in Period 1



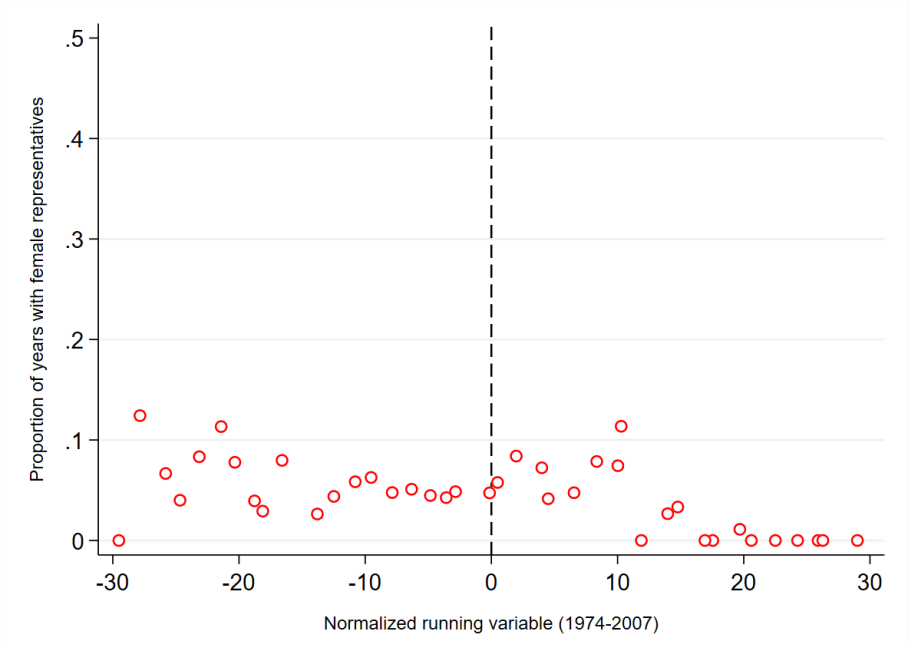
Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.7. Turnout percentage in Period 2



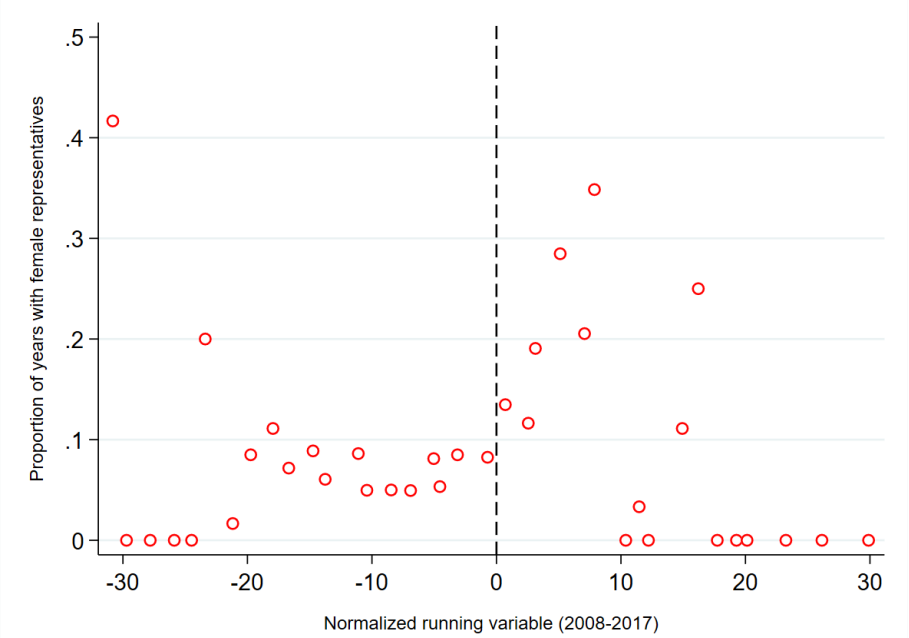
Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.8. Proportion of years with female representatives in Period 1



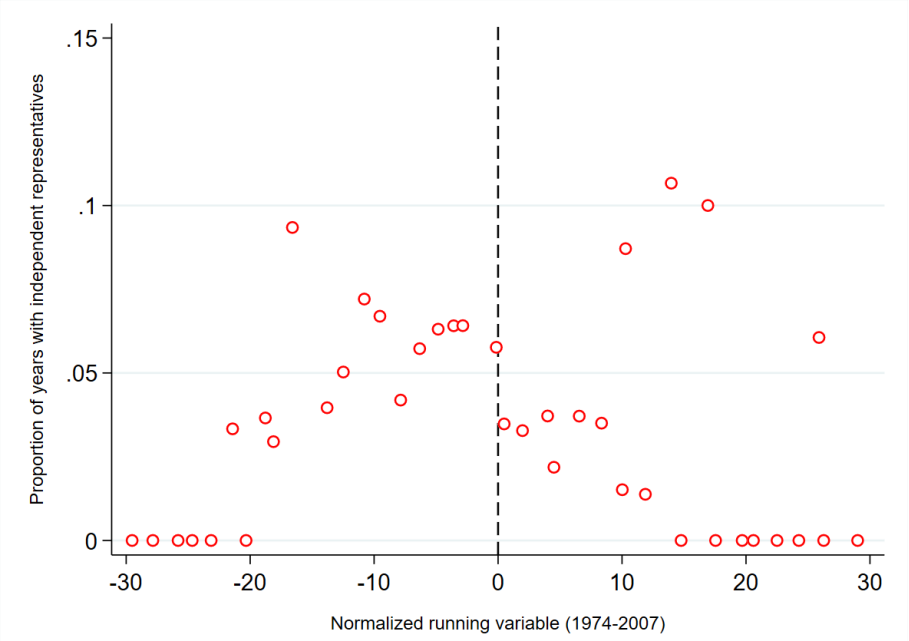
Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.9. Proportion of years with female representatives in Period 2



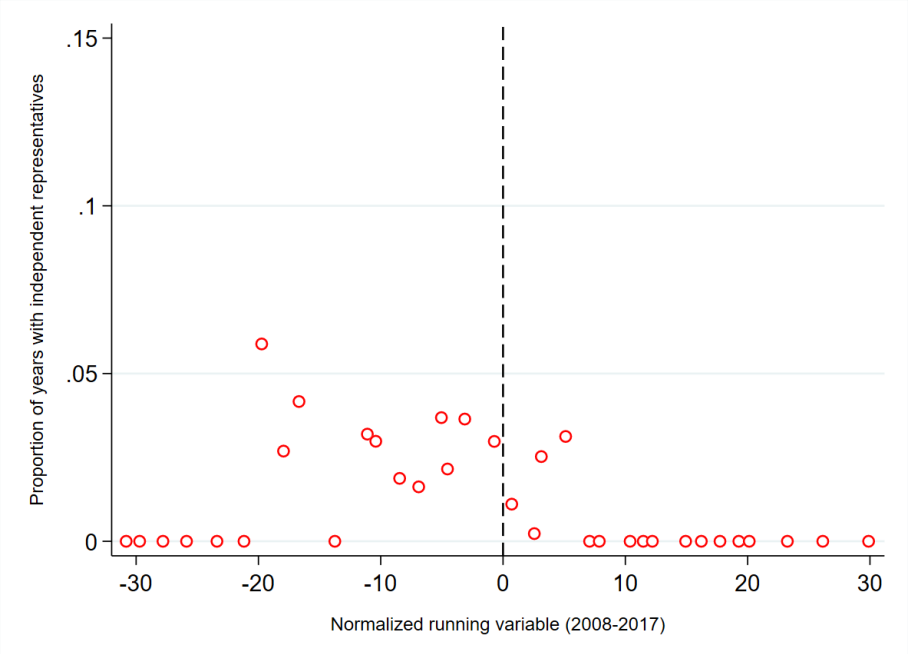
Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.10. Proportion of years with independent representatives in Period 1



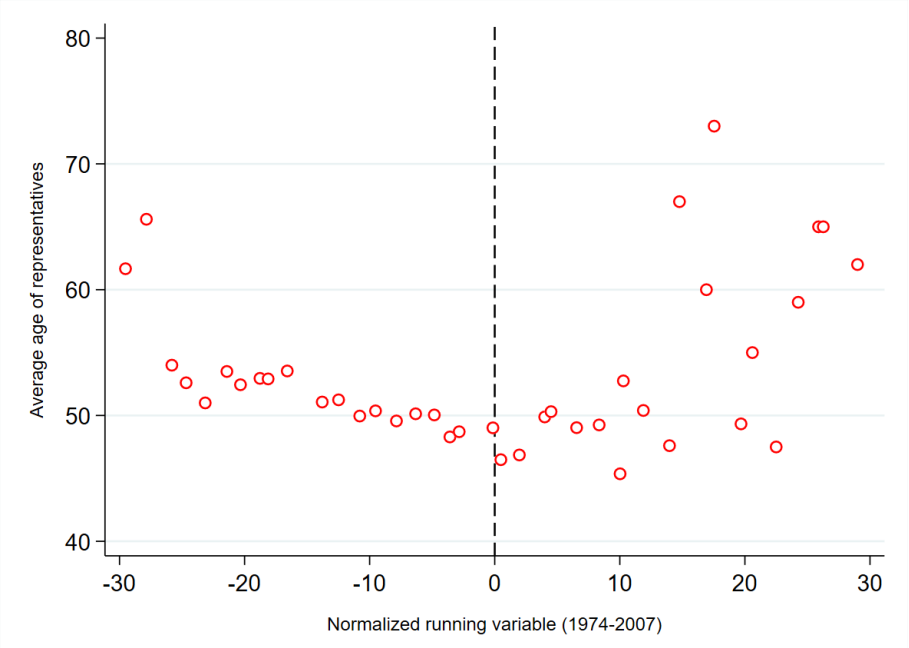
Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.11. Proportion of years with independent representatives in Period 2



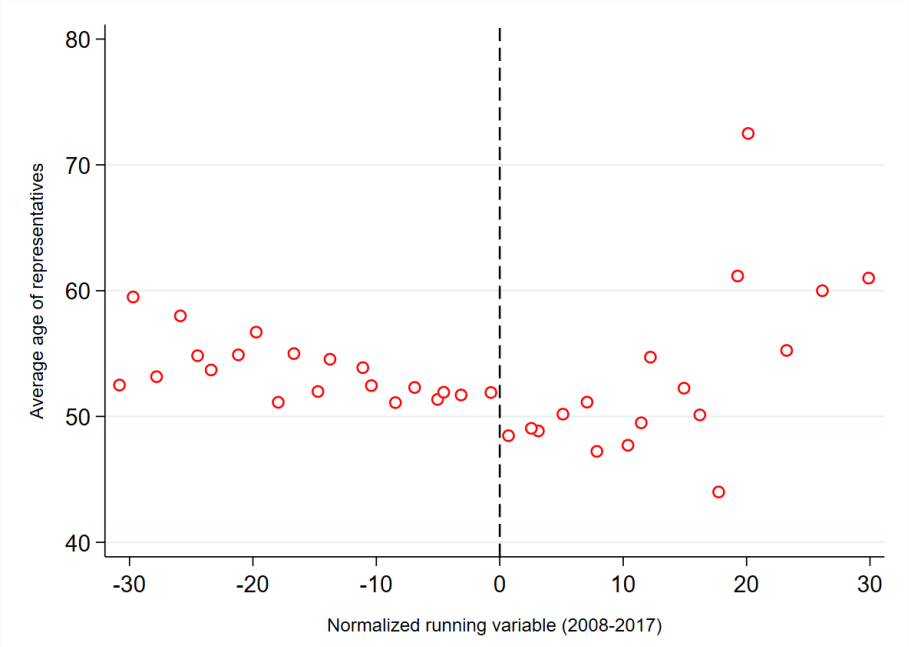
Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.12. Average age of representatives in Period 1



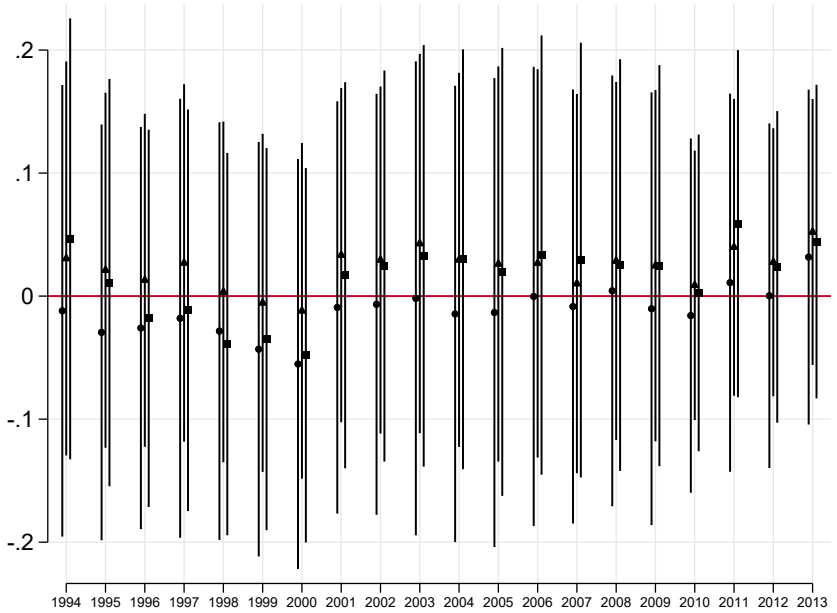
Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.13. Average age of representatives in Period 2



Notes: Constituencies are unreserved for SCs to the left of the cut-off (where $R_c < 0$), and predominantly reserved for SCs to the right of the cutoff (where $R_c > 0$). The running variable's range is divided into bins of equal length.

Figure 3.A.14. Effect of reservation on yearly nightlight luminosity: reduced form estimates



Note: For each year, the circle denotes the non-parametric estimate, the triangle denotes the non-parametric estimate with district fixed effects and the square denotes the linear estimate using the optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014).

3.A.3 Tables

Table 3.A.1. Balance test of 1971 characteristics

	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)
Share of ST population	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Literacy rate	−0.011	−0.004	−0.005
	(0.010)	(0.006)	(0.006)
Literacy rate among SCs	−0.008	0.001	0.002
	(0.009)	(0.003)	(0.004)
Literacy rate among non-SCs	−0.012	−0.006	−0.008
	(0.011)	(0.006)	(0.007)
Employment rate	0.002	0.002	0.002
	(0.006)	(0.002)	(0.002)
Employment rate among SCs	0.004	0.005	0.006
	(0.008)	(0.003)	(0.004)
Employment rate among non-SCs	0.001	0.001	0.001
	(0.005)	(0.002)	(0.002)
Agricultural laborers among SCs	0.006	0.010	0.12
	(0.022)	(0.010)	(0.011)
Agricultural laborers among non-SCs	−0.014	−0.006	−0.004
	(0.012)	(0.005)	(0.006)
District FE	No	Yes	Yes
Observations	2,743	2,743	2,743

Notes: The running variable is based on the reservation in period 1 (1974-2007). Model (1) presents results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Model (2) includes district fixed effects. Model (3) indicates linear estimates that use an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

Table 3.A.2. Balance test of 2001 characteristics

	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)
Share of ST population	−0.004	−0.003	−0.003
	(0.008)	(0.004)	(0.005)
Literacy rate	0.005	−0.002	−0.005
	(0.011)	(0.004)	(0.005)
Share of rural population	−0.015	0.001	−0.004
	(0.018)	(0.012)	(0.015)
Average household size	−0.046	−0.008	−0.001
	(0.084)	(0.019)	(0.025)
Share of primary schools	−0.001	−0.002	−0.003
	(0.010)	(0.005)	(0.006)
District FE	No	Yes	Yes
Observations	2,572	2,572	2,572

Notes: The running variable is based on the reservation in period 2 (2008-2017). Model (1) presents results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Model (2) includes district fixed effects. Model (3) indicates linear estimates that uses an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

Table 3.A.3. Comparison of RD estimates and Matching estimates of Census 2001 outcomes

	RD model		Matching model	
	$\hat{\beta}$	$\lvert t \rvert$	$\hat{\beta}$	$\lvert t \rvert$
	(1)	(2)	(3)	(4)
Literacy rate	-0.004	0.8	-0.002	0.67
	(0.005)		(0.003)	
Employment rate	0.002	1	-0.001	0.5
	(0.002)		(0.002)	
Power supply in villages	0.008	0.8	-0.011	1.22
Observations	2,922		896	

Notes: Columns (1) and (2) report the non-parametric estimates from our RD model and the corresponding absolute t-values respectively. Columns (3) and (4) report the estimates from the matching model in Jensenius (2015) and the corresponding absolute t-values respectively. Standard errors in parentheses are clustered at the constituency level in Column (1) and state level in Column (3).

Table 3.A.4. Effect of reservation on census outcomes: second stage estimates

	Census period 1			Censu period 2		
	Non-parametric	Non-parametric with FE	Local linear	Non-parametric	Non-parametric with FE	Local linear
	(1)	(2)	(3)	(4)	(5	(6)
Literacy rate	−0.011	−0.004	−0.004	−0.009	−0.005	−0.005
	(0.012)	(0.005)	(0.005)	(0.010)	(0.004)	(0.004)
Employment rate in manufacturing and services	0.003	0.003	0.003	0.011	0.007	0.007
	(0.003)	(0.002)	(0.002)	(0.011)	(0.010)	(0.010)
Villages with power supply	−0.023	0.008	0.006	−0.001	0.012	0.012
	(0.039)	(0.010)	(0.010)	(0.031)	(0.011)	(0.012)
Villages with new roads	−0.028	0.003	0.004	−0.005	−0.000	0.000
	(0.026)	(0.009)	(0.010)	(0.022)	(0.009)	(0.009)
Rural poverty rate				0.005	−0.003	−0.005
				(0.014)	(0.005)	(0.005)
Urban poverty rate				0.004	−0.004	−0.007
				(0.009)	(0.005)	(0.006)
District FE	No	Yes	Yes	No	Yes	Yes
Observations	2,922	2,922	2,922	2,639	2,639	2,639

Notes: The running variable and the discontinuity are based on the reservation in period 1 (1974-2007). Census period 1 and Census period 2 correspond to 2001 and 2011 respectively for both the general census and the SECC. For the Economic Census, census period 1 corresponds to 1998, and census period 2 corresponds to 2013. Models (1) and (4) present results based on Calonico, Cattaneo, and Titiunik (2014) with polynomial order one and a triangular kernel for weighting. Models (2) and (5) include district fixed effects. Models (3) and (6) indicate linear estimates that use an optimal bandwidth chosen by the non-parametric method of Calonico, Cattaneo, and Titiunik (2014). Standard errors are clustered at the constituency level. *** p<0.01, ** p<0.05, * p<0.1

Table 3.A.5. Results from the multiple model corrections

	Original p-values (1)	Bonferroni corrected p-values (2)	Holms–Bonferroni corrected p-values (3)
Share of enrolment in private schools	0.009	0.063	0.063
Share of SC enrolment in private schools	0.008	0.056	0.04
Share of RTE enrolment in private schools	0.049	0.343	0.098
Share of private schools	0.007	0.049	0.007

Notes: Column (1) reports the p-values from the original non-parametric estimation with district fixed effects. Columns (2) and (3) report the new p-values after employing the Bonferroni correction method and Holms-Bonferroni correction method respectively to rectify the problem of multiple modelling.