Targeting poor households in welfare policies: the case of the RTE(12)(1)(c) Act*

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Abstract

Welfare policies in LMICs targeting underprivileged people need to address the constraints that they might face in accessing the benefits. I study the take-up rates in a high-cost affirmative action education policy that aims to address the de facto segregation by socioeconomic classes between private and public schooling by providing equal education opportunities. Under the policy, eligible households of Chhattisgarh (an Indian state) can apply for lottery-based government-sponsored schooling in nearby private schools. I combine various datasets to obtain village-level aggregates and analyze the variation in application rates. By constructing a metric of school quality, I show that there is not much difference between private and public schools in most villages, decreasing the incentive for applying for policy benefits. In addition, higher literacy rates, higher internet facilities, and lower distances to neighboring towns correlate with higher application rates. I report that villages with higher poverty rates exhibit lower application rates, underscoring the stronger constraints faced by economically disadvantaged households. Addressing these constraints is imperative to ensure the policy effectively reaches its intended beneficiaries.

*At the time of writing this paper, I was employed as a Research Assistant with Professor Abhijeet Singh and Professor Mauricio Romero on an experimental project towards identifying application constraints in Chhattisgarh RTE policy, furthering their previous work (Romero and Singh, 2022). This project was undertaken as a side project, and I am very thankful for their guidance. All mistakes are my own.

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Developing nations frequently use welfare schemes to promote equitable economic development, allocating approximately 1.5% of their national GDP to support these schemes (World Bank, 2018). Research has shown that well-implemented schemes, such as the school deworming program in Kenya and the rural employment guarantee scheme (NREGS) in India, have a transformative impact on disadvantaged communities (Miguel and Kremer, 2003; Imbert and Papp, 2015; Muralidharan et al., 2023). However, many programs do fall short of achieving desired outcomes due to design-level or implementation-level imperfections, despite substantial financial investments (Anderson et al., 2018). For successful targeting of welfare policies toward the underprivileged, policymakers and implementers must carefully consider the contextual factors and address the constraints faced by the disadvantaged (Parekh and Bandiera, 2020).

In this paper, I examine an affirmative action policy designed to improve the schooling options available to underprivileged households. To address socio-economic disparities in access to quality education, the government of India passed the RTE Act in 2019.[1] This legislation acknowledges that high-quality private schools are financially out of reach for economically disadvantaged individuals, resulting in unequal educational opportunities from childhood itself. To address this issue, Section 12(1)(C) of the RTE Act mandates the state to sponsor the education of some underprivileged students in private schools of their choosing. This study focuses on the Act's implementation in the Chhattisgarh state of India, where eligible parents must submit an online application to participate in a school-level lottery for state-funded private school seats. I analyze how various village characteristics influence the application rate (ratio of applicants to eligible students) in the village.

Before delving into this analysis, however, it is necessary to consider the significant restriction imposed by the supply side – the available schooling options. The decision of a household to apply for the RTE depends inherently on the quality of private schooling alternatives available under the policy. I construct a measure of school quality, the "School Value Index" (SVI), using school facilities as explanatory variables in a linear model. The coefficients for this linear model are calculated by regressing the logarithm of School Fees over these facilities while controlling for the village-fixed effects. Since school fees denote the economic value households assign to education in a school with specified resources, SVI has a natural interpretation of school quality or value. I examine the improvement in schooling options offered to the poor by the RTE Act using the difference between SVIs of private and public

[1] Legislation link: https://www.education.gov.in/sites/upload_files/mhrd/files/upload_document/rte.pdf

schools in Chhattisgarh villages, and study how it influences the RTE application rates.

To understand the role of demand-side constraints, I obtain village-level aggregates by integrating data from multiple sources such as national survey data, spatial wealth data, and school enrollment data. The geographical datasets are aggregated at the village level by using village shapefiles. The resulting data describe villages' facilities, their economic prosperity, schooling options, and various demographic statistics (literacy levels and poverty rates). While this data might not directly capture the demand-side challenges encountered by eligible households, it serves as a starting point for understanding the mechanisms through which these constraints impact application rates.

There are four main findings in the paper. Firstly, through a comparative analysis of the School Value Index (SVI) between private and public schools, I show that, on average, private schools possess more resources than their public counterparts. However, considering the substantially higher number of public schools compared to private schools, the best private and public schools in a village are often of similar quality. The second finding I report is that villages with a higher difference between private and public schools have significantly higher application rates. In other words, regions where RTE applications considerably improve schooling options demonstrate higher application rates. Unfortunately, many regions do not experience actual improvement in schooling options from the Act. Consequently, the Act has appreciable welfare implications in only a few villages (that have good private schools), and households in these villages are significantly more likely to apply for the RTE seats. These results underscore the importance of complementary institutions for policy impact, which are often lacking in quality in developing countries (World Bank, 2020; Dorward et al., 2004).

The third set of findings pertains to the relation between village characteristics and application rates. Application rates are higher for villages with higher adult literacy levels, access to the internet, or lower distance to the closest town. The final finding I report is that as the proportion of poor households in a village increases, the application rates decline (after controlling for the mean wealth level of the village). These findings reflect the variation in application constraints faced by an average household in the village, showing that poor and uneducated parents residing in more rural areas face challenges in benefitting from the policy. Addressing these constraints can significantly improve the efficacy of the policy in achieving its desired results, and authors of study (Romero and Singh, 2022) are presently (2023) working on an experiment evaluating multiple interventions to address these constraints.

The regressive selection elucidated by these results reflects major underlying challenges in targeting welfare schemes in low-income settings. First, reliable income information is seldom available in developing countries, rendering traditional income eligibility thresholds ineffective for targeting benefits (Hanna and Karlan, 2017). In response, governments use other criteria to determine eligibility. This can inadvertently allow some better-off households to become eligible for policy benefits. Since resource constraints are often larger for poor households, better-off households find it easier to procure the benefits, leading to regressive selection among recipients (Baird et al., 2013). This possibly explains the negative relation between village poverty and RTE application rates. Many better-off households can apply for the RTE seats since their caste affiliation determines eligibility.[2] Romero and Singh, 2022 show that about half of the students who get free education under the RTE Act would have enrolled in the same school by paying fees if they were not provided the free option.

This paper is structured as follows. Section 1 starts with a concise overview of public and private schooling in India, delving into how the increasing prevalence of fee-charging private schools contributes to de facto segregation in education. This underscores the necessity for the RTE 12(1)(c) Act, with Section 1 elaborating on the Act and its execution in the state of Chhattisgarh. Section 2 introduces different datasets I use in this paper. Section 3.1 outlines the construction of the School Value Index, comparing this metric between private and public schools within the sampled villages. Section 3.2 describes how demand-side constraints influence RTE application rates, and analyses the variation in the application rates using village-level aggregates. Section 4 concludes.

1 Background and Context

India has made significant strides in education, with the net enrollment rate in primary education increasing from 77% in 1990 to 92% in 2013. In 2020, gross enrollment rates were 75% for secondary and 29% for higher education. This success is attributed to improved school access, with the government constructing over 350,000 public schools in the first decade of the 'Sarva Siksha Abhiyan' program, covering around 99% of rural habitations with a

[2] Caste is a hereditary social classification system prominent in India, and due to historical reasons, upper-caste households are typically much more wealthier than lower-caste households.

functional school in a 1 km radius.[3] An even more telling story is that of the growth of private Schooling, which has transformed the Education landscape in India. The count of private schools nationwide surged from 220,000 in 2010 to 330,000 in 2020, with a third of all primary school students in rural India now attending private institutions (Kingdon, 2020).

The impact of private schools in transforming India's education landscape goes beyond these numbers. Unlike public schools, private schools profit from the fees they charge, which means that their quality would be more sensitive to market demand. This means that a private school's quality is influenced by the demands of the population segment living in the vicinity of the school (Neilson, 2021). Given the high levels of income inequality among different geographical regions, perhaps it is not surprising that there is a huge variation in the quality of private schools (Kumar et al., 2022; Chudgar and Quin, 2012). Market competition is another factor influencing private school quality, with competition not only from other private institutions but also from tuition-free public schools. Consequently, in regions with high school density, private schools often have better infrastructure and facilities so they can target wealthier households(Bau, 2022). This argument about better resources in private schools only applies to markets with substantial competition in schooling supply. Several studies have been carried out to identify private school value-added while accounting for sorting by socio-economic levels. They yield interesting findings, ranging from low or modest improvements in some subjects to large improvements in English (Singh, 2015; Muralidharan and Sundararaman, 2015; French and Kingdon, 2010). The large value-added in English is probably the result of English being the language of instruction in most Indian private schools, while regional languages are used in public schools. Learning gains in English have important labor market consequences, and Chakraborty and Bakshi, 2016 show that a 10% higher probability of English education at primary school increases expected labor market earnings by 8%. In addition to these, parents often believe that private schools offer better learning environments and higher social status, leading them to prefer private schooling for their children.

Despite the strong desire for private schooling across the entire socio-economic spectrum (Romero and Singh, 2022; Alderman et al., 2001), usually, only high-income and middle-income families send their children to private schools, while economically underprivileged families are compelled by budget constraints to send their children to public schools. This,

[3] "Sarve Skisha Abhiyan", translating to "education for all mission", was launched in 2001. For more details, see https://archive.pib.gov.in/ndagov/Comprehensive-Materials/compr10.pdf

coupled with the proliferation of private schools in the last two decades, has resulted in de facto economic segregation in school enrollment across the private and public sectors. (Bagde et al., 2022). This segregation has both social and economic implications. Since economic status is linked to social classification, this economic segregation in schooling impedes the social integration of historically underprivileged classes. On the economic front, the actual and the perceived higher returns of private schooling make a strong case that this segregation hampers inter-generational mobility and also potentially creates poverty traps (Barham et al., 1995).

In an effort to promote inclusive education and address disparities, Section 12(1)(c) of the Right to Education Act, 2009 mandates that private aided and un-aided schools (excluding minority and residential schools) reserve a minimum of 25% of their entry-level seats for children from economically weaker and disadvantaged sections of society. The schools must provide free education to children admitted under this provision, and states shall reimburse the schools for these students at a pre-specified monetary value. As education falls under the Concurrent list, the RTE 12(1)(c) act establishes the framework for providing free private school education to underprivileged children while allowing states to formulate state-specific implementation rules.[4]

Chhattisgarh was among the first Indian states to adopt this policy. Under the policy, students from backward castes (Scheduled Caste or Scheduled Tribe) or economically weaker sections of society are eligible for the RTE quota seats. Schools offer seats in either pre-primary (if available) or First grade, and the state reimburses enrolled students' education until they finish primary schooling. The state reimburses the school fee up to a limit of Rs 7000 per student, and the schools are not allowed to charge extra fees to students even if the fees exceed this limit. This limit is set to be commensurate to the expenses incurred per student by the state in public schools. Parents must submit an application for their child on an online platform, in which they list their preferences for schools in their habitation. The matching between schools and applicants happens through a centralized algorithm, which assigns seats to oversubscribed schools through a lottery. This aspect of the Act has received a positive response from parents and NGOs, and the application rates have substantially increased in the last decade. In 2020, 64.75% of the quota seats were filled compared to 50.20% just two years ago. However, there is significant scope for improvements, as only a

[4]The Concurrent list of the Indian constitution is the list of policy items that fall under the purview of both union and state government.

fraction of eligible students benefit, and many families face significant constraints in applying for RTE seats.

2 Data

For the analysis that follows, I merged data from different sources. I use the Application data to identify the RTE application rates, and then try to explain the variation in these rates using village-level characteristics. For this, I use aggregate data from household-level surveys, spatial relative wealth data, and school facilities in the village. This section gives a brief overview of all the datasets used in this work.

2.1 SHRUG village polynomial boundaries

The Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) is an open data set with high geographic resolution data from various national surveys aggregated at the level of cities, towns, and villages (Asher et al., 2021). These regions are created in SHRUG so that region-level aggregates can be consistently reported across different national Census. Pivotal to the analysis presented here is the GIS shapefiles themselves, which assign a unique identifier "shrid" to every region. Using the "point-in-polynomial" method, the school locations are mapped to SHRUG regions, and this is also how the mean Relative Wealth Index is calculated. There are 16019 villages and 317 towns in Chhattisgarh in the SHRUG dataset, which have been classified according to the 2011 National Population Census of India.

2.2 DISE administrative Data

The Data Information System for Education (DISE) is an exhaustive database encompassing comprehensive information about all officially acknowledged educational institutions in the Republic of India. This repository encompasses extensive data concerning school management, facilities, student enrollment statistics, the composition of teaching staff, and various other pertinent details of these institutions. DISE has information about more than 57,000 schools in Chhattisgarh state, which is publicly available on the UDISE website.[5] I merged the DISE data was merged with School location data [6] to obtain the geographical coordinates of all schools in Chhattisgarh. Using these coordinates, I use the "point-in-polygon"

[5] The detailed school level data was scraped from the public repository https://src.udiseplus.gov.in/locateSchool/schoolSearch using selenium in python.

[6] The school location data was obtained from https://schoolgis.nic.in/ using the rest API. This website contains the geographical coordinates of all Indian schools indexed by their DISE code.

method in GIS to assign schools to villages and then compute the village-level aggregates as described in 3.

I construct two measures using the school-level data from DISE. The first is the School Value Index (SVI), which captures details about school facilities such as the teacher-student ratio, the number of rooms, the status of the building, and the availability of computers per student. Construction of SVI is outlined in section 3.1. There is a significant variation in school facilities in the state, even among the schools situated in the same region. There is an especially large variation in facilities among Private schools, reflecting the underlying heterogeneity among different socio-economic classes. The mean fee is Rs 6700 compared to the standard deviation of Rs 7600. The student-to-toilet ratio varies from 16 at the 25th percentile to 54.5 at the 75th percentile. However, these variations in school qualities are not limited just to private schools. Even though the variation in facilities among public schools is lower than the variation in private schools, the absolute value of variation is quite big, considering that their management and resource allocation are centralized at the state level. The student-teacher ratio at the 25th percentile is 13.67, more than twice the ratio of 30 at the 75th percentile, while the student-to-toilet ratio varies from 9.5 at the 25th percentile to 29 at the 75th percentile. These variations can be attributed to historical differences in development levels, administrative inefficiencies, and geographical limitations. The SVI is constructed to reflect this variation using a 1-dimensional measure.

The other school-level measure that I use is the total number of students in the village who are eligible for RTE quota seats. Utilizing the enrolment data from DISE, I identified the total number of students registered in pre-primary and Class 1 separately and then multiplied this number by "proportion of Scheduled Caste and Scheduled Tribe people in population" from the census data to obtain an estimate of the number of eligible students.

2.3 RTE Application Data

The main outcome variable, the proportion of eligible students who apply for the RTE quota, is constructed using the 2022 RTE application data obtained from the Government of Chhattisgarh. The detailed data contains student-wise preference of schools, student details, and the final outcome of the school assignment algorithm. In 2022, more than 110,000 students applied for approximately 81,000 seats in 6,422 schools, and around 57,000 students were allocated an RTE seat. This large difference in number of seats and number of allocations is due to over-subscription in some schools and under-subscription in others. An applicant applies to 2.09 schools on average, with 56.3% of applicants only applying to a single school.

I use the application data to identify the number of applicants from each village. This was done by first mapping all schools to villages, and then assigning a student to the village where the majority of schools that the applicant applied to were situated. The final outcome variable, the proportion of eligible students who apply for RTE quota seats, is constructed by taking the ratio of the number of applicants to the number of eligible students. The RTE application rate in village v is given by

$$\text{RTE Application Rate} = \frac{\text{Number of applicants}}{\text{Number of eligible students}} \tag{1}$$

2.4 Indian National Survey datasets

The Indian Population Census, undertaken in 2011, is an exhaustive enumeration of all households in India. It consists of information about the population composition broken into gender, age, caste, employment, and literacy categories. In 2011, along with the Population Census, the government of India also conducted the Socio-Economic and Caste Census (SECC-2011), which collected details about income, asset ownership, and caste categories for all households. The government published the aggregate data at the village and town level for both the Population Census 2011 and SECC-2011. The decadal Population census could not be carried out in 2021 due to the COVID-19 pandemic. Therefore, the analysis relies only on ratios among population groups from the census. According to the data collected, 70.28% of the population in Chhattisgarh have received some education, out of which less than 2% have had secondary education.

Mission Antyodaya survey was conducted by the government of India in 2020 with the aim of improving efficiency in the management of resources allocated to villages under various government schemes. The antyodaya survey collects information about village infrastructure, beneficiaries under government schemes, and inventory of resources allocated by the government through these schemes. This data is collected at the village level. The data from all these national surveys have been compiled and made available in (Asher et al., 2021).

2.5 Relative Wealth Index

The Relative Wealth Index (RWI) is a public dataset developed by Meta [7] that estimates wealth and poverty at a geographical grid of 2.4 km resolution across India (Chi et al., 2022). The estimates come from a Machine Learning prediction model, with the target variable being the wealth estimated from India Demographic and Health Survey 2015-2016. The model uses predictors developed by aggregating data from various sources, such as satellite images, mobile phone networks, topographic maps, and connectivity data from Facebook. The spatially gridded RWI data is aggregated at the village level by computing mean RWI across all points lying inside the village boundaries. As expected, the distribution of mean RWI among Chhattisgarh villages is left-skewed with a heavy tail on the positive side.

3 Empirical Method and Results

The determinants influencing RTE application rates are likely to vary significantly between rural and urban regions. Factors such as school choices, income levels, and application constraints, including information and internet access, are expected to play distinct roles in shaping application rates in urban and rural settings. This study focuses specifically on the factors impacting application rates in the villages of Chhattisgarh. In rural areas, where schooling options are limited, socio-economic heterogeneity is lower, and access to resources like information and the Internet is more uniform, village-level aggregates can be employed with higher confidence in the analysis and the resulting point estimates are easier to interpret. The intersection of the Chhattisgarh village list from the 2011 Population Census and the 2020 Antyodaya survey is used to classify habitation as rural. From this universe of Chhattisgarh villages, a subset comprising villages that have at least one private school offering RTE quota seats and at least one public school is defined as the study sample. The final sample comprises 1,850 villages with at least one private school, with populations ranging from 544 at the 10th percentile to 3,763 at the 90th percentile. Among these villages, there are 13,637 schools, with 3,324 offering RTE quota seats and 10,303 being free public schools.

[7] The dataset and information about its construction is freely available at https://dataforgood.facebook.com/dfg/tools/relative-wealth-index. This data has been aggregated and made available on SHRUG platform (Asher et al., 2021) by Data Development team.

3.1 School Value Index

School choice is one of the most important decisions parents make for their children, and parents spend considerable time and resources in making these decisions. The RTE quota essentially relaxes the budget constraints for eligible households but adds other application constraints, such as informational constraints and application procedure know-how. If these constraints were absent, utility-maximizing households would likely submit an RTE application if a feasible private school has better facilities and offers a better learning environment. Therefore, to study the effect of these supply-side factors on application rates, I construct a School Value Index (SVI) as a linear function of school facilities. SVI is not sufficient to compute school preference since it does not capture heterogeneity in preferences of households, such as distance to school or peer preference. However, it should still explain the supply-side component of school preference.

Under standard economic assumptions, the school fee is t he equilibrium market value of the education provided by the school. In perfectly competitive markets, school fees should equal the value of resources expended per child by the school on their education. I construct the SVI by identifying how various school facilities explain the variation in school fees. More specifically, I construct a linear model of the logarithm of school fees using school facilities as predictors and define SVI as the predicted value using this model. Constructed this way, the SVI has a diminishing marginal return to monetary expenditure similar to the utility function, a fact that will help later in motivating the empirical model. The school fees data is available only for private schools, and I use data from all private schools in the state (including villages not in the sample) to train the model and then predict SVI for all private and public schools. The first step of the model is the linear regression of $\log(\text{School Fee})_{sv}$ of school s in village v on school facilities vector $\mathbf{F}_{sv}$

$$\log(\text{School Fee})_{sv} = \theta^{(SVI)}\mathbf{F}_{sv} + c_v + \eta_{sv} \tag{2}$$

c_v are the village fixed effects to capture the effect of market characteristics such as population characteristics and other school options. Clustering of standard errors is irrelevant as only the point values will be used in the calculations ahead. The results of the regression have been tabulated in Table 1 column (1). The size of the school has a significant impact on the log fee, and so do school resources such as generators, the number of computers per student, access to the internet, and the presence of a digiboard or webcam. At the infrastructure level, whether the school has a solid or permanent building also significantly affects log fees. On the other hand, the presence of a printer or a library does not significantly affect the log fee. It is surprising that the coefficients of the teacher-student ratio and the toilet facilities do not significantly determine the log fee either. Care must be taken not to interpret these coefficients causally, and since there is a high positive correlation among the covariates, the confidence intervals are not very informative about the role of individual facilities in affecting School fees.

The aim is to map school facilities to school quality irrespective of the village, therefore, the model (equation 3) does not use the village fixed effects in computing SVI. This allows a direct comparison of schools in different villages according to their facilities while ignoring the regional effects such as village prosperity or caste composition.

$$SVI_{sv} = \theta^{(SVI)}\mathbf{F}_{sv} \tag{3}$$

In the sample villages, the mean SVI of private schools is 3.71 compared to 3.64 for public schools (p-value for two-sample t-test is less than 0.001). By inverting the logarithm in the definition of SVI (equation 3), this translates to an improvement of 16% in monetary value associated with private schooling. From the quantile function (figure 1), it can be seen that while the bottom 40% of private schools are comparable to the bottom 40% of public schools, the private schools at higher quantiles are better than the public schools at the same quantile. This shows that while private schools do tend to be better than public schools, this is not always the case.

To consider the improvement in schooling options due to the RTE Act, it is instructive to see the difference between private and public schools in the village. For this comparison, I consider two quantities, $dSVI\_max$ and $dSVI\_mean$. "Differential School Value Index (max)" $dSVI\_max$ is the difference between the best private and the best public school available in the village. It indicates the best possible improvement in school quality available to poor students once the financial constraints are removed by the RTE 12(1)(c) Act. However, SVI only captures school quality in terms of facilities. It cannot by itself completely explain the school choice as various household characteristics also influence the choices, such as distance to school and preference of peers. Since I do not have household-level data, I take the class-1 enrollment weighted SVI of schools to average out these factors. Hence, the expected improvement in Schooling choice due to the RTE Act for an average household is measured using the "Differential School Value Index (mean)" $dSVI\_mean$, which is the difference over the weighted average of SVI for private and public schools. Using $S_{pri,v}$ and $S_{pub,v}$ as notation for the sets of private schools and public schools in a village v, $dSVI\_max_v$ and $dSVI\_mean_v$ are defined as

$$dSVI\_max_v = \max_{s \in S_{pri,v}} \{SVI_{sv}\} - \max_{s \in S_{pub,v}} \{SVI_{sv}\} \tag{4}$$

$$dSVI\_mean_v = \frac{1}{|S_{pri,v}|} \sum_{s \in S_{pri,v}} SVI_{sv} - \frac{1}{|S_{pub,v}|} \sum_{s \in S_{pub,v}} SVI_{sv} \tag{5}$$

Figure 2 shows the distribution of $dSVI\_max$ (panel A) and $dSVI\_mean$ (panel B) among villages. Panel B shows that although there is a significant proportion of villages where $dSVI\_mean < 0$, in most villages (57.5%), the weighted average SVI among private schools is higher than public schools. The mean value of $dSVI\_mean$ across villages is 0.25. Notably, the distribution has heavy-tail in the positive direction, implying that private schools are much more resourceful in some villages than public schools. On the other hand, the distribution of $dSVI\_max$ has a negative mean of -0.016, implying that, on average, the best private school in the village has a lower SVI than the best public school. This could potentially be explained by the removal of poor-quality public schools from calculations when taking the maximum, which does not happen as often among private schools. This is fairly possible, as a village has only 1.8 private RTE schools compared to 5.5 public schools on average. The average difference between the SVI of a village's best and average private schools is 0.026, whereas the difference is 0.083 for public schools. To verify this hypothesis, Figure 3 shows that there are very few villages with a low value of the best-SVI public school (panel A), while there are many more villages with a low value of worst SVI public school (panel B). This implies that the correlation between public school SVIs in the same village is low. This finding is further supported by the low Moran's I correlation of 0.18 (0.006) for SVIs of public schools, compared to 0.21 (0.018) for private schools, calculated using a binary weight matrix with a distance cut-off at 3km.

This is the first finding of the paper – in a village, an average private school is usually better than an average public school, but the best private school usually has comparable resources to the best public school. The RTE 12(1)(c) Act improves the schooling options available to an average applicant in a village. However, for parents who are already sending their child to the best public school, the Act does not typically offer better schooling options.

3.2 RTE application rates

There is a considerable variation in the application rate among villages, from 14.6% at the 25th percentile to 74.2% at the 75th percentile, with the median value being only 32.2%. This likely reflects the large heterogeneity among villages in Chhattisgarh. In this section, I analyze how village-level characteristics explain the variation in Application rates.

On the supply side, a village in the sample offers a free public schooling option, a paid private schooling option, and a lottery-based free private schooling option through RTE seats. The RTE policy moves students from either of the first two options to free private schooling. Parents would submit RTE applications if the expected utility gain is larger than the cost. Although the monetary cost of submitting an RTE application is very low, agents face significant demand-side constraints as discussed in (Romero and Singh, 2022). Information constraint is one of the major constraints, with a significant number of eligible parents simply being unaware of the policy. The second constraint that eligible households face is the lack of documentation necessary for applications. Since the policy targets underprivileged households, the application process requires submitting proof of eligibility such as income level or caste certificate. However, many households in rural areas simply do not have the necessary documents which would prove their eligibility. The final major application friction that households face is the technological ability required to fill the online form since the application process is mainly online. I take the view that the lack of documentation and technological ability can be considered as a component of heterogeneous costs faced by families instead of constraints. This is justified as, unlike the information constraint, households will be able to obtain documents and will find methods to fill out the online form (through relatives or by visiting kiosk centers set up by the government) if the expected utility gain from the application is sufficiently large. Therefore, let the overall cost c_i that a randomly selected household i from the village faces for an RTE application be distributed according to distribution Γ. Then, the decision of application by a randomly selected eligible household i is given by

$$\mathbb{1}(\text{i submits RTE application}) = \mathbb{1}(\text{i is aware of policy}) * \mathbb{1}(\Delta U_i > c_i) \tag{6}$$

where $\mathbb{1}$ is the identity function and ΔU_i is the expected utility gain from submitting the RTE application. By averaging overall households in the village, the left side of the above equation becomes the outcome variable - the RTE application rate. A few important insights can be obtained by equation 6. The likelihood of submitting an application increases as the utility difference between schooling at a private and public school increases, and also as a higher share of the eligible population becomes aware of the scheme. The RTE application rate increases as the distribution of cost shifts to the left, i.e. it becomes easier for households to apply for RTE seats. This can happen due to improvements in internet access, higher education level of parents so they can navigate the application process, or improving the ease of access to documents required for proving eligibility for RTE quota seats. Although it is not possible to precisely quantify the effects of these factors in influencing RTE application rates without explicit survey data, it is nevertheless possible to explore the relationship between RTE application rates and village-level characteristics through the lens of the discussion above.

$$AR_v = dSVI_v + \beta X_v + \gamma \overline{SVI}_v + \delta Z_v + \epsilon_v \tag{7}$$

I use equation 7 to empirically analyze the variation in village RTE application rates AR_v. I use the differential School Value Index as a proxy for the utility gain by shifting to a private school from a public school. This is because SVI_s is a measure of resources available at the school, which would be an important component in utility gained by going to school s. However, without identifying why some parents prefer low-SVI, it is not *a-priory* obvious whether the utility gain will be reflected by $dSVI\_max$ or $dSVI\_mean$. Therefore, I regress the equation 7 separately using $dSVI\_max$ or $dSVI\_mean$ and show that using either of these does not affect the inferences. The enrollment weighted average School Value Index ($\overline{SVI}_v$) is also included as a covariate to control for the average school quality of the village.

X_v is a vector describing village characteristics. It includes the proportion of different groups of the population, such as the share of people who have had some education, the share of people who have completed secondary school, and the proportion of poor (poverty rate) in the village. The village facilities are captured by indicators for access to a "common service center" (a government kiosk center for access to digital services), access to internet facilities, and the presence of all-weather roads in the village. The distance to the nearest town is also included in vector X_v. On the other hand, Z_v is a vector of control variables containing the average Relative Wealth Index, population density, and presence of middle and secondary schools.

The results of regression 7 are presented in table 2. Column 1 shows the result of regressing 7 using $dSVI\_max$ as a proxy for Utility gain, while Column 2 shows the regression results with $dSVI\_mean$ as the proxy. For reference, column 3 shows the regression result if supply-side factors $dSVI$ and $\overline{SVI}$ are not included in the estimation regression. Application rates increase if the differential school quality increases, calculated using either the best or average private and public schools. However, the application rate is more sensitive to $dSVI\_max$, with the application rate increasing by 2.2 percentage points if $dSVI\_max$ increases by one standard deviation. This is the second result of the paper - The application rate increases with the difference in the quality of the private and public schools available in the village. Households will be more likely to apply for the RTE seats if the possible improvement in school quality is higher.

Analyzing the possible mechanisms through which available covariates affect the RTE application rates can help in understanding the roles of the constraints. Education levels of the population, distance to the nearest town, and the presence of internet facilities can all impact the awareness of policy, which is likely a significant constraint. Educated parents seem less constrained in applying for RTE seats. Application rates increase as the share of educated adults in the population increases, and it further increases as the share of adults who have finished secondary schooling increases. Given everything else constant, having higher access to internet facilities improves the application rates, probably because submission of an application is an online process. Distance to the nearest town, after controlling the wealth of the village and education levels, indicates both urbanization and job opportunities. Both of these influence the demand for education, which increases the application rates. It is unsurprising that the presence of an all-weather road does not impact the application rate, as it influences the accessibility of private and public schools in a similar manner. However, it is surprising the presence of a common service center has no effect (with a negative point estimate) since it significantly relaxes the application constraints for households who want to apply but do not have enough technological knowledge to submit the application.

Despite being a policy designed for the underprivileged, a 10 percentage point increase in the village poverty rate, while controlling for the village's wealth, decreases the application rate by 1 percentage point. This is probably because the constraints faced by poor households are larger than those faced by eligible well-off households. This indicates the Regressive Selection discussed by Romero and Singh, 2022. For the policy to effectively target poor people, the specific constraints severely affecting poor households need to be identified, and additional steps should be taken to address these constraints.

4 Conclusion

I demonstrated that village-level aggregate data can be used to study the variation in application rates within the RTE 12(1)(c) Act, albeit at a preliminary level. This inter-village variation is consistent with the findings of Romero and Singh, 2022, highlighting significant application challenges faced by underprivileged individuals seeking government-sponsored education in private schools. The finding that application rates tend to be lower in villages with lower literacy rates and higher poverty rates suggests that the hurdles faced by underprivileged households are more substantial than their better-off counterparts. Given the RTE Act's goal of fostering equity and inclusivity, greater constraints for economically disadvantaged or less educated parents signify a concerning targeting inefficiency. In light of the policy's considerable fiscal cost, implementing cost-effective measures such as enhancing awareness or simplifying application procedures could yield substantial equity gains.

Another important consideration affecting the policy's take-up is the supply of private schooling. The Act attempts to mitigate the budget constraints faced by the economically disadvantaged and counter the *de facto* segregation in the classroom. However, many villages do not have private schools of good enough quality to encourage households to apply for the RTE seats. I demonstrated that as the disparity in resources between private and public schools narrows, application rates decline. The analysis is confined to villages with at least one private school, excluding over 14,000 villages in Chhattisgarh from the purview of the RTE 12(1)(c) Act. Consequently, while improving the targeting efficiency of the Act is useful, a more pressing need is the improvement of public schools in habitations without private schools or habitations with only low-quality private schools. This would provide residents with better education facilities.

This paper opens up several avenues of future research in addition to the current (2023) ongoing study to address the application constraints by authors of Romero and Singh, 2022. One of these is the incorporation of additional factors affecting school choice in the analysis. While the School Value Index attempts to measure school quality through facilities assessment, it is insufficient to explain the household's preferences as it does not incorporate household characteristics such as distance between schools and peer preference. It will be interesting to examine the conflicting effects of parents' peer preference in schools and the RTE Act's goal of promoting inclusive education. Another compelling empirical inquiry would be to study the relationship between SVI and value-added by the school, aiming to discern whether parents base schooling choices on observable school facilities (SVI) or unobservable value-added. This line of investigation could shed light on the nuanced decision-making processes underlying school selection. Exploring these dimensions would contribute to a more comprehensive understanding of the complexities involved in school selection.

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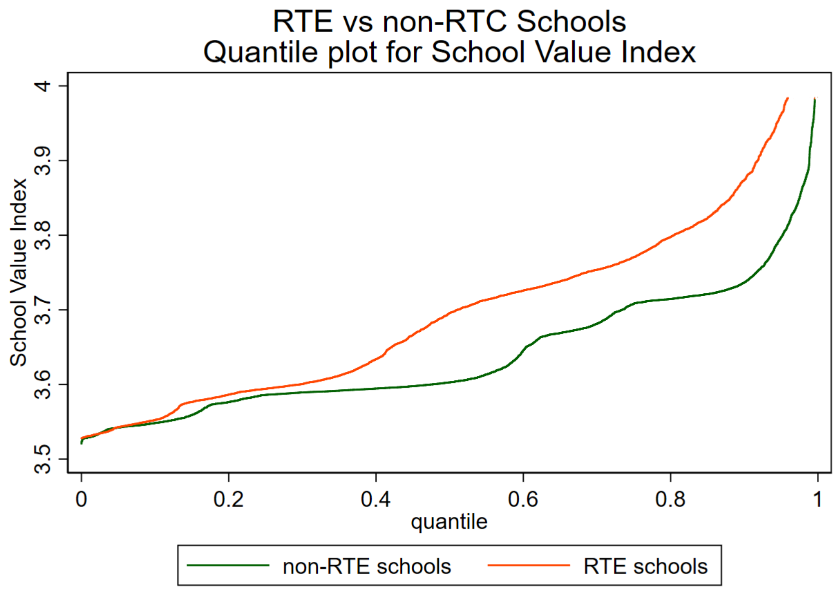
Figures

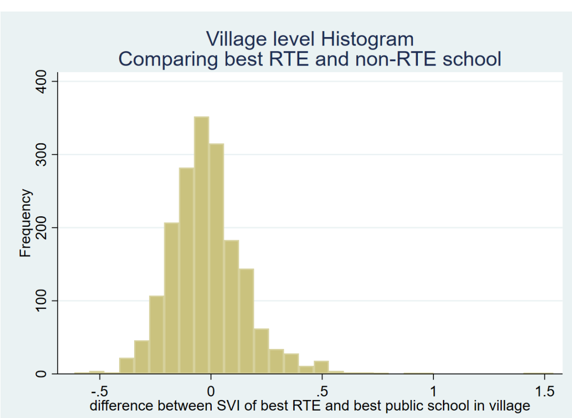
Figure 1. SVI Quantile plot for RTE and public schools



This shows the quantile distribution of SVI for RTE and non-RTE (public) schools separately. SVI above 4 is not plotted for ease of visualisation.

Figure 2. Histogram of village-level difference in SVI of private and public schools

(A) best RTE and non-RTE school



(B) avg RTE and non-RTE school

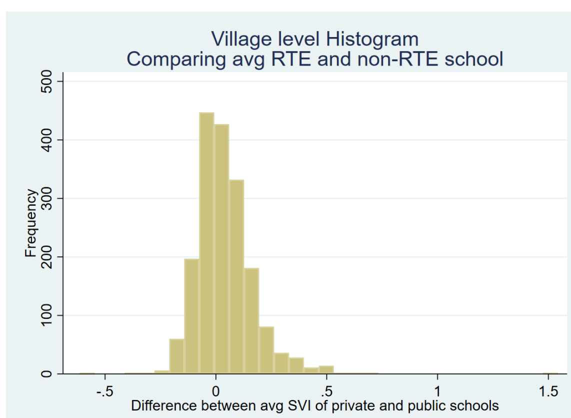
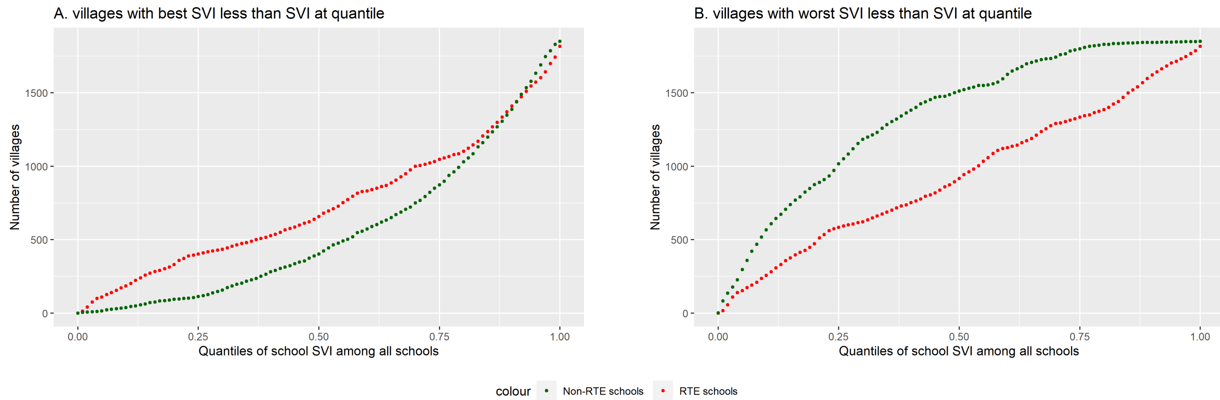


Figure 3. Number of villages against the quantile position of schools



Panel A shows the number of villages for whom the best school's SVI's quantile position is below the x coordinate's value. This shows that there are very few villages where all public schools are of poor quality, but there are many more villages with all private schools below this quality.
Panel B shows the number of villages with the worst school's SVI quantile position less than the x coordinate's value. This shows that more villages have some low-quality public schools compared to the number of villages that have private schools of similarly low quality.
This plot also suggests that there is a larger in-village quality variation among public schools than private schools. This is because a typical village in the sample has many more public schools than private schools.

Tables

Table 1. SVI calculation coefficients

	(1) village fixed effects	(2) no fixed effects
Total Students in School	1.87e-4***	1.32e-4***
	(0.34e-4)	(0.12e-4)
Has solid boundary walls	0.045*	0.048***
	(0.02)	(0.01)
Has functional generator	0.051*	0.062***
	(0.02)	(0.01)
Has library	-0.005	-0.014
	(0.02)	(0.01)
Has internet access	0.123***	0.084***
	(0.02)	(0.01)
Number of toilets per student	0.190	0.155*
	(0.21)	(0.06)
has CWSN toilet	0.009	0.000
	(0.01)	(0.01)
Teacher Student Ratio	0.045	0.059
	(0.17)	(0.07)
Number of Desktops/ Laptops per student	0.454	0.298***
	(0.24)	(0.05)
has scanner or printer	0.020	0.036***
	(0.02)	(0.01)
has digiboard	0.114***	0.148***
	(0.03)	(0.02)
has webcam	0.055**	0.063***
	(0.02)	(0.01)
constant	3.515***	3.561***
	(0.03)	(0.01)
Observations	2470	4746
No. of individuals	1550	
Overall-R^2	0.25	
R^2	0.23	0.25

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are reported in parenthesis.
The regression coefficients are obtained by regression logarithm of School fees on school facilities from DISE 2021-22 data. Column (2) is the basic regression, while column (1) uses village fixed and clusters standard errors at the village level. Coefficients from column (1) are used to calculate School Value Indexes.

Table 2. Effect of village characteristics on application rates

	(1) Reg with $dSVI\_max$	(2) Reg with $dSVI\_mean$
$dSVI\_max$	0.022**	
	(0.008)	
$dSVI\_mean$		0.019*
		(0.008)
log(distance to nearest town)	-0.031***	-0.031***
	(0.009)	(0.009)
Do villages have a Common Service Centre?	-0.029	-0.030
	(0.018)	(0.018)
Do villages have internet facilities?	0.063***	0.062***
	(0.018)	(0.019)
Share of population - some education	0.745***	0.741***
	(0.110)	(0.110)
Share of population - secondary education	-0.318*	-0.316*
	(0.138)	(0.138)
Poverty rate of village	-0.103***	-0.104***
	(0.030)	(0.030)
Do villages have an all-weather road?	0.045	0.045
	(0.028)	(0.028)
Observations	1832	1832
R^2	0.12	0.12

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table reports the coefficients obtained by regression village RTE application rates on aggregate village characteristics (equation 7). The controls are not shown in the table above. The "differential School Value Index" is defined using equations 4 and 5, and they capture the difference between school facilities of private and public schools in a village. In Column (1), the application rates are regressed over $dSVI\_max$ and other covariates, while it is replaced by $dSVI\_mean$ in column (2). $dSVI\_max$, $dSVI\_mean$ and log(distance to nearest town) have been standardized before regression.