Ethnic Fragmentation and School Provision in India

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Abstract

In this paper, we study the differential impact of ethnic fragmentation on the provision of private and public schools to identify the mechanism through which ethnic fragmentation affects public goods. We show that while private schools are affected on the extensive margin, public schools are affected in the intensive margins. Two different channels seem to be operating for the observed differential impact. We show that diverse places have poor governance and coordination leading to bad quality public schools. Private schools are affected because of their inability to mobilise resources in diverse areas as these areas have fewer options to raise funds through informal mechanisms due to lack of a strong social network.

Keywords: Ethnic fragmentation,private schools, public schools, public good provision

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1 Introduction

There is a broad consensus in the literature on the negative impact of ethnic diversity on the provision of public goods (Alesina and La Ferrara (2005)). Alesina et al. (1999) document the negative relationship between ethnic diversity and productive public goods for the US cities. Banerjee and Somanathan (2007) show that a similar relationship holds for the case of India as well. However, the exact channel through which ethnic diversity undermines the provision of public goods is not yet clear. While some evidence points towards heterogeneity in preferences across groups (Alesina et al. (1999); Lieberman (2012)) as the channel, others point towards weak social network in ethnically heterogeneous societies (Miguel (2005); HABYARIMANA et al. (2007)). The exact reason for the negative effect of ethnic diversity on the provision of public goods is far from clear. In this paper, we attempt to pin down the exact mechanism by focusing on the effect of ethnic diversity on a single good, schools, which is provided both publicly and privately in the market. Focusing on schools allows us to study how the provision of goods can influence the relationship between public goods and ethnic fragmentation. Since the private and public schools are provided differently, any differential impact of ethnic diversity on schools will help us understand the relationship between ethnic diversity and public goods, in general, better.

We test the relationship between ethnic fragmentation and the provision of schools for a cross-section of 2011 census districts using two large data sets namely, Indian population Census of 2011 and District Information System for Education (DISE) 2013-14 data. We focus on 2011 census districts because 2011 census is the first census to categorize the schools into private and public, allowing us to estimate the desired differential impact. However, school information in the census data is limited and to exploit the information on infrastructure, enrollment and the number of teachers in a school, we turn to a much richer dataset provided under the DISE data[1]. We use the DISE data for year 2013-14 as it was one of the first attempts to combine the data on elementary and secondary/higher secondary schools. We conduct two sets of tests to estimate the differential impact of ethnic fragmentation on private and public schools. In the first set of tests, we aggregate the school level information up to the district level and perform all our tests at the district level. In the next set of tests, we exploit the within district variation in the number and quality of schools and perform our tests at the school level.

The results of both the sets of tests using the two data sets are consistent with each other and indicate that there is a differential impact of ethnic fragmentation on the provision of private and public schools. While ethnically diverse districts have a lower number of private schools, these schools are not inferior in terms of infrastructure and the number of teachers as compared to homogeneous districts. In contrast, the result for public schools indicates that ethnic fragmentation has no impact on the number of public schools at any level (elementary, secondary and higher secondary) but these schools suffer in terms of quality in diverse places. This is to suggest that while private schools are affected on extensive margin, public schools are affected on intensive margin and hence the results indicate that the relationship between ethnic fragmentation and public goods is sensitive to how the goods are actually provided. Note that one of the reasons for no effect of fragmentation on the number of public schools could be that many policies and programs (Sarva Shiksha Abhiyan, Right to Education Act) aim at universalisation of elementary education in India leaving little variation in public schools in diverse and homogeneous districts. Therefore, it is possible that ethnic fragmentation manifests its effect in public schools by lowering their quality.

We suggest two different channels for the observed differential impact on public and

[1]Detailed description of the DISE data is provided in the data section

private schools. Our conjecture is that public schools are of lower quality in diverse places because of lack of governance and coordination amongst the local population for the maintenance of the schools. The channel suggested for the negative effect on private schools is weak social network in diverse areas which makes it difficult for the private players to raise resources to provide a school. We provide evidence on the channel for public schools by looking at the impact of fragmentation on the participation of the community and school management team in School Management Development Committee (SMDC) meetings. SMDC meetings represent a platform where community members work together with the school administration to build plans for school development. Active participation by community members in these meetings is suggestive of efficient coordination amongst them. However, we find that ethnically diverse districts have a lower number of SMDC meetings, additionally, these meetings see lower participation from the community members in diverse places providing evidence for the channel suggested by us.

In order to provide evidence for the channel operating for private schools, we look at the impact of ethnic fragmentation on the number of self-help groups and agricultural societies. We believe that self-help groups and agricultural societies represent one of the important informal mechanisms to access resources. We then test the impact of self-help groups and agricultural credit societies on the provision of schools. Results indicate that fragmented districts have a lower number of self-help groups and agricultural societies substantiating our claim that social network is weak in diverse areas. We show that the implication of this is a low provision of private schools in diverse areas confirming that weak social network makes it difficult to mobilise resources.

We also address concerns that the observed effect of ethnic fragmentation could be due to low demand of schools rather than the supply side factors. To do so, first, we control for variables that are likely to influence the demand for schooling, namely urbanisation, work participation rate and number of colleges in a district, in all our district level regressions. Second, using school level data on enrollment, we specifically check the impact of ethnic fragmentation on enrollment in various classes. However, we do not find any evidence of lower enrollment in schools in diverse areas, confirming that the observed results are not driven by demand side factors. The rest of the paper is structured as follows: Section 2 provides the literature review, section 3 discusses the data used and the methodology followed to perform our tests, in section 4 we discuss our results and we conclude in section 5.

2 Literature review

To the best of our knowledge, we have not come across any paper which looks at the differential effect of ethnic diversity on school provision by the structure of ownership. The papers which come closest to our work are Miguel (2005) and Chaudhary (2009). Miguel (2005) document that ethnic diversity is associated with lower primary school funding and school facilities in rural western Kenya. They show that this is because it is difficult to impose social sanctions in ethnically diverse areas leading to collective action failures. However, the funding that they consider in their paper is private funding for schools and hence it is not sure if the mechanism that they suggest would hold for schools that are provided publicly.

Chaudhary (2009) finds a lower provision of private primary schools in ethnically diverse districts in colonial India, whereas no impact is observed for schools provided by the provincial government or the local board. The differential impact that she observes is very close to the results of this paper. However, even though she argues that the negative impact on private schools could be due to low demand for schooling by disadvantaged groups or due to difficulty in mobilising resources in such areas, no formal results are presented in favour of either argument. It is not clear why public schools are not affected whereas a clear negative effect is observed for private primary schools.

3 Data and Methodology

We use data on a cross-section of 2011 census districts to conduct our analysis. Two distinct datasets, population Census of 2011 and District Information System for Education (DISE) 2013-14, have been used to construct variables that capture the level and the quality of schools. Unlike previous population censuses, village directories in Census 2011 provide information on the number of private and public schools in a given village in a district. We add the number of schools in all the villages in a district to arrive at the district level variable. However, the census has no information on the quality of schools (in terms of infrastructure and teachers hired) and enrollment and hence we turn to a much richer data set provided under the DISE. To review the performance of schools in India and to monitor the performance of policies targeted towards schools, information on all the registered schools started to be maintained from 1995 under the software, DISE. For the DISE data, the schools are asked to fill detailed information on a number of school characteristics like infrastructure, enrollment, results, etc. We use the data collected in 2013-14 as it was one of the first attempts to combine the data on elementary schools with secondary and higher secondary schools[2]. The following table contains the list of variables that have been constructed using the DISE and the census data.

The independent variable in all our tests is ethnic fragmentation. Ethnic fragmentation, as is quite standard in the literature, is measured as, $1 - \sum \beta_i^2$ where β_i is the population share of the i^{th} ethnic group. The different ethnic groups that we consider are

[2]Before 2012-13, DISE data collected information on only elementary schools in India

the ones divided by caste. In India, the Hindu population (the major religious group) is divided into a number of castes with deep social cleavages due to which there is limited social and economic interaction between these caste groups. Therefore, it is reasonable to assume a caste as a separate group. To construct ethnic fragmentation, we use district level data on population shares of different groups from the Indian population census. The last census to record district level data on population shares by different castes was population census of 1931. We use the 1931 shares and scale them by the proportion of Hindu population during 1991, 2001 and 2011 census to arrive at fractionalization indices for 1991 and 2001 (Banerjee and Somanathan 2007). We make this adjustment to account for the migration of Muslims to Pakistan as a result of India-Pakistan partition in 1947. For all the newly created districts after 1931, we weight the caste figures from the original district according to the area of the new district which was taken from them, following (Banerjee and Somanathan 2007). Permanent migration is low in India and therefore previous work and this paper assumes that the caste proportions in local geographies are the same since 1931.

We also use a number of district level controls, namely work participation rate, number of colleges in a district and urbanisation rate, and school level controls, namely, age of the school, dummy, $Urban$, indicating whether the school is located in urban areas and a dummy, $Roadaccess$, indicating if the school is approachable by all weather roads. Data on all the district level controls come from the Indian population Census of 2011 and data on school level controls have been taken from the DISE data.

Using the above mentioned datasets we perform two sets of tests to conduct our empirical analysis. The first set of tests correspond to estimating the impact of ethnic fragmentation on the number and the quality of public and private schools at the district level.

We estimate the following regression equation:

$$School_{ds} = \alpha_s + \beta_1 cfrag_{ds} + X^{'}_{ds}\delta + \epsilon_{ds} \tag{1}$$

where d indexes the district and s indexes the state. Dependant variable, in the above regression equation, is a measure of the number and quality of public and private schools. The main parameter of interest is β_1, the coefficient of $cfrag_{ds}$ which measures ethnic fragmentation, X_{ds} contains all the control variables.

In the above regression equation, the school level dependent variables have been obtained by aggregating the school level information up to the district level. However, this procedure absorbs all the school level variation within a district. In order to exploit the within district variation in the quality of schools, we test the relationship between ethnic fragmentation and school provision by estimating the following equation:

$$School_{ids} = \gamma_s + \beta_2 cfrag_{ds} + \phi private_{ids} + \beta_3(cfrag * private) + X^{'}_{ids}\delta_1 + X^{'}_{ds}\delta_2 + \epsilon_{ids} \tag{2}$$

where i indexes the school d indexes the district and s indexes the state. Variable $Private$ is a dummy which takes a value of 1 if the school is private and 0 otherwise. The coefficient of the interaction term, β_3, gives us the differential impact of fragmentation on private and public schools. The standard errors are clustered at the district level to allow the errors to be correlated within a district. State fixed effects are controlled for in the both the sets of tests.

4 Results

4.1 District level regressions

We begin by discussing the results of district level regressions. Tables 2 and 3 report the regression results from estimating equation 1 using the census data. As indicated from the table, ethnic fragmentation seems to have a weak negative impact on private schools at all levels (primary, middle, secondary and higher secondary). However, there is no evidence of negative impact of ethnic fragmentation on public schools. This finding points weakly towards the differential impact of ethnic fragmentation on private and public schools. Notice that we have controlled for urbanisation, number of colleges and work participation rate in the regression. These variables are likely to have an impact on the demand for education and therefore controlling them in the regression allows us to partially isolate the impact of ethnic fragmentation on the supply of schools from their demand.

Since the school information in the census data is limited, we perform the same test (in addition to others) with the DISE data to see if a similar differential effect exists with the DISE data too. Our finding with the census data gets substantiated with the DISE data, as reported in table 4. Ethnic fragmentation lowers the level of private elementary and private secondary schools without having any impact on the public schools[3]. The public schools, using the DISE data, can further be classified into those that are run by local bodies and by central or state governments. Similarly, private schools can be divided into those that receive aid for their operation from the government and those that are unaided private schools. We test the impact of ethnic fragmentation on this finer classification of schools at the elementary level to get a clear picture of the impact of fragmentation on schools.

[3]Elementary schools have classes up to standard 8. So they include both primary and middle schools.

Results, reported in table 5, indicate that while local government and aided schools are negatively affected by ethnic fragmentation there is no effect for either aided or schools run by state/central government. The observed no effect for aided private and government schools suggests that the level of funding from the government which is required to run government and aided schools is not affected by the local ethnic diversity. Whereas the observed negative effect for unaided schools points that schools which fund their operation costs find it difficult to operate in ethnically diverse places. The result also indicates that local government schools, which are funded and managed by local government bodies, are also sensitive to ethnic diversity, pointing governance and coordination issues in ethnically diverse areas.

We will now substantiate our above-made claim that private schools are affected because of difficulty in mobilising resources and local public schools are affected because of lack of governance and coordination in ethnically diverse places. We do so first for the case of public schools by testing the impact of ethnic fragmentation on School Management Development Committee (SMDC) meetings. All public schools are required to constitute SMDCs as per the Right to Education Act. SMDCs allow the community members, members of the local bodies, parents, Scheduled Caste (SC)/Scheduled Tribe (ST) along with the school management team to build and implement school development plans. Effective implementation of SMDC and an active participation of community members in SMDC meetings is an indication of teamwork and coordination amongst the local community. If our claim is true, then ethnically diverse districts should see less participation by community members in SMDCs and this is exactly what we find in tables 6 and 7. Not only ethnically diverse districts have fewer SMDC meetings (Column 1) they also see less participation by local body members, parents and members of SC/ST groups in these meetings.

We also test the impact of fragmentation on hiring of teachers and infrastructure in tables 7 and 8, respectively. As indicated from the two tables, public schools perform poorly in hiring regular teachers, maintaining furniture and library facilities in fragmented places. On the other hand infrastructure in the private schools are not affected in fragmented districts. This result could be looked upon as an additional outcome of lack of coordination in public schools in maintaining quality for the operation of schools in fragmented places. These findings along with the results of tables 2, 3 and 4 indicate that while the number of public schools does not go down in fragmented districts, their quality and infrastructure suffers. The result for private schools is exactly the opposite, their overall number is less in fragmented places but they are not inferior (in comparison to homogeneous districts) in terms of quality. The result of no impact on public schools is likely driven by the fact that many policies and programs in India (Sarva Shiksha Abhiyan, Right to Education act) aim at universalisation of elementary education in the country, and so their numbers do not vary by fragmented districts.

We now provide evidence to prove our claim that private aided schools are lower in number because private players find it difficult to mobilise resources in ethnically diverse districts. In a developing nation like India, people still rely on informal mechanisms like social network to raise money. It is possible that social network in an ethnically diverse district is not strong enough which makes it difficult to raise money for the provision of private schools. We test the first part of the above-made assertion by looking at the impact of ethnic fragmentation on the number of self-help groups and agricultural credit societies[4]. Self-help groups and agricultural credit societies represent one of the many ways by which people are connected to each other in the society and can use this network to raise money. Table 10 shows that fragmentation lowers the number of self-help groups

[4]We obtain the data on these two variables from the village directories of 2011 Census.

and agricultural societies lending evidence to the fact that social network and informal lending mechanism is weak in fragmented districts. We now show the impact of self-help groups and agricultural societies on the number of private and public schools in table 11 and 12. The results indicate that self-help groups and agricultural societies are positively correlated with private schools but there does not seem to be a clear impact on public schools. These tables suggest that ethnically diverse districts are not that closely knit and do not have a strong social network to facilitate the of mobilisation of funds for private schools.

4.2 School level regressions

In order to exploit the within district variation in the school quality and to test the differential impact observed with the district level data, we now present the results for school level regressions. Table 13 tests the impact of ethnic fragmentation on the hiring of teachers. The results show that the coefficient of fragmentation is negative but the coefficient of the interaction term is positive. Thus, as was observed with district level regressions, fragmentation has a negative and significant impact on teachers per total enrollment and teachers per number of classes for public schools. The negative impact of fragmentation which is observed for public schools, however, goes down when one looks at private schools. Notice that the number of observations falls considerably in columns 1 and 2 when we divide the number of teachers by enrollment. This is because information on enrollment is available for only 15% of the total number of schools. Since the enrollment data is missing for 75 % of the sample, while doing the regressions with enrollment data there are concerns of selection bias due to misreporting. That is schools that do not report enrollment data might be systematically different from schools that do which can drive the results that we observe. To check how different are the two groups of schools, we conduct a comparison of the means test and the results are reported in table 14. This table shows that the schools which do not report enrollment data are more public, have less number of teachers, classrooms, and furniture, are more rural and less accessible by roads. This points that the schools with missing information are of lower quality and we aim to address this partially by controlling for road access, age and $urban$ dummy in all our school level regressions.

Tables 15 and 16 test the impact of fragmentation on a number of variables which indicate the quality of infrastructure of the school, namely the proportion of teachers that are regular (column 1), the number of single teacher schools (columns 2 and 3), number of classrooms and library facility (table 16). We again find that fragmentation reduces the proportion of regular teachers in public schools and the number of classrooms available for students and increases the number of single-teacher public schools. There is either no or somewhat positive impact of fragmentation on the proportion of regular teachers for private schools and classrooms, which is again in line with what we find in the case of district level regressions. We also test the impact of fragmentation on the number of SMDC meetings and participation by community members in these meetings. Table 17, which reports the results, shows that consistent with district level regressions, there are less SMDC meetings in fragmented districts and these meetings see lower participation by its members specifically members of local bodies.

In order to make sure that the negative effect of fragmentation on the number of schools is not being driven by low demand for schools in ethnically diverse areas, we test the impact of fragmentation on enrollment. To construct our dependent variable, we look at the enrollment distribution (for a particular class) of schools and create a dummy, $highenrolc_i$, that takes a value of 1 if the school lies in the top quantile of the distribution, thus indicating the school to be a high enrollment school. Results reported in table

18, show that even though ethnic fragmentation has no impact on the proportion of public schools that have high enrollment, it increases the proportion of private schools with high enrollment. Clearly, there is no evidence of fall in enrollment in fragmented places confirming that the observed effect of fragmentation on schools is not being driven by low demand. We also directly test the impact of ethnic fragmentation on enrollment in various classes in table 19. Although we get somewhat different results as compared to the previous table, as ethnic fragmentation increases the enrollment in public schools with no differential impact, we still do not find evidence of fall in enrollment in fragmented places.

Additionally, we test that do fragmented districts also have more diverse student population (by social groups) in the schools? If the answer is no, then this will indicate that students from different social groups do not study together (probably because they do not want to), which can be one of the reasons for driving low provision of schools rather than the mechanisms that we suggested. To test this we create enrollment fragmentation (that is how heterogeneous is the enrollment by social groups in a given school in a class) for each class by using the information on enrollment by social groups in DISE. DISE data reports enrollment from SC, ST, OBC and general category. Since we consider very broad categories to construct our fragmentation measure of the school, our ethnic fragmentation measure for this test is also created using the broad social groups (SC, ST, others) reported in 2011 Census. The results reported in table 20 show that ethnically fragmented districts have diverse public schools (with no negative differential impact for private schools) suggesting that fragmentation does not lead to segregation in enrollment (at least for the existing schools).

5 Conclusion

The paper provides evidence for the existence of differential impact of ethnic fragmentation on private and public schools. While private schools are affected only on the extensive margin, public schools, on the other hand, are affected on the intensive margin. Using district and school level regressions we show that the differential impact is due to two different channels operating for public and private schools. Private players find it difficult to raise resources in ethnically diverse districts leading to less number of private schools. Lack of coordination and governance among the local population in diverse places results in poor quality public schools.

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Table 1: Variable definition and data source

Variable	Definition	Source
G (P) element	Public (private) elementary schools (per thousand population) in a district	Census and DISE
G (P) secondary	Public (private) secondary schools (per thousand population) in a district	Census and DISE
G (P) highsecondary	Public (private) higher secondary schools (per thousand population) in a district	Census and DISE
Local elementary	Elementary schools (per thousand population) in a district provided by local bodies	DISE
Aided elementary	Aided private elementary schools (per thousand population) in a district	DISE
Unaided elementary	Unaided private elementary schools (per thousand population) in a district	DISE
Reg techers gvt (pvt)	Average number of regular teachers in a public (private) school in a district	DISE
Contract techers gvt (pvt)	Average number of contract teachers in a public (private) school in a district	DISE
G (P) furniture	Proportion of public (private) schools with furniture in a district	DISE
G (P) library	Proportion of public (private) schools with library in a district	DISE
SMDC meetings	Average number of SMDC meetings held in a school in a district	DISE
Males (females)	Average number of male (female) members in SMDC	DISE
SMDC meetings	Average number of SMDC meetings held in a school in a district	DISE
Males (females)	Average number of male (female) members in SMDC	DISE
Local gvt males (females)	Average number of male (female) members from local bodies in SMDC	DISE
SCandST males (females)	Average number of SC/ST male (female) members in SMDC	DISE

Private	Dummy, equals 1 if the schools is private; 0 otherwise	DISE
Reg teachers	Total number of regular teachers in a school	DISE
Reg teachers/classes	Total number of regular teachers divided by the highest class in a school	DISE
Highclass	Highest standard in a school	DISE
Urban	Dummy, equals 1 if the school is located in an urban area; 0 otherwise	DISE
Road access	Dummy, equals 1 if the school is accessible by all weather roads; 0 otherwise	DISE
Estdyear	Age of the school	DISE
Furnstu	Dummy, equals 1 if the school has furniture; 0 otherwise	DISE
Clrooms	Total number of classrooms in a school	DISE
Toilets b (g)	Total number of toilet for boys (girls)	DISE
High enroll c_i	Dummy, equals 1 if the school lies in the top quantile of the enrollment (in class i) distribution	DISE
Enrol c_i	Total number of students enrolled in class i in a school	DISE
$frag_i$	Etnic fragmentation in class i in a school	DISE
Single reg teach schools	Dummy, equals 1 if the school has a single regular teacher; 0 otherwise	DISE
Good condn	Total number of classrooms in good condition	DISE

Table 2: Effect of ethnic fragmentation on provision of schools (Census data)

	(1) G_prim	(2) P_prim	(3) G_middle	(4) P_middle
Ethnic frag	-0.0101	-0.1047^{+}	0.1829	-0.0726^{+}
	(0.970)	(0.144)	(0.198)	(0.134)
college_dis	0.1452***	0.0017	0.0681***	0.0002
	(0.000)	(0.321)	(0.000)	(0.841)
urbanisation	-0.1023	0.0142	0.0080	0.0377**
	(0.266)	(0.564)	(0.870)	(0.024)
workrate	1.1477***	-0.1210	0.1784	-0.0905
	(0.002)	(0.211)	(0.352)	(0.166)
State FE	Yes	Yes	Yes	Yes
Observations	348	348	348	348

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effect of ethnic fragmentation on provision of schools (Census data)

	(1) G_second	(2) P_second	(3) G_srsecond	(4) P_srsecond	(5) G_coll	(6) P_coll
Ethnic frag	-0.1261*	-0.0600*	-0.0312	-0.0401*	-0.4012	-0.4019
	(0.096)	(0.081)	(0.484)	(0.050)	(0.733)	(0.733)
college_dis	0.0312***	0.0011	0.0185***	0.0002		
	(0.000)	(0.186)	(0.000)	(0.736)		
urbanisation	0.0258	0.0218*	0.0120	0.0155**	-0.4071	-0.4093
	(0.321)	(0.066)	(0.435)	(0.028)	(0.313)	(0.311)
workrate	0.0624	-0.0795*	0.0371	-0.0712**	4.5372***	4.5462***
	(0.540)	(0.087)	(0.537)	(0.010)	(0.004)	(0.004)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348	348

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of ethnic fragmentation on school provision (DISE data)

	(1) G_element	(2) P_element	(3) G_second	(4) P_second	(5) G_highsecond	(6) P_highsecond
Ethnic frag	0.0122	-0.1586***	-0.0075	-0.0572**	0.0054	-0.0072
	(0.938)	(0.001)	(0.777)	(0.011)	(0.765)	(0.596)
urbanisation	-0.4299***	0.0712***	-0.0202**	0.0254***	-0.0025	0.0204***
	(0.000)	(0.000)	(0.031)	(0.001)	(0.698)	(0.000)
college_dis	0.0675***	-0.0007	0.0104***	-0.0001	0.0071***	0.0010***
	(0.000)	(0.532)	(0.000)	(0.821)	(0.000)	(0.009)
workrate	1.1305***	-0.1202**	0.0629*	-0.0805***	0.0368+	-0.0530***
	(0.000)	(0.041)	(0.056)	(0.004)	(0.121)	(0.003)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	396	394	396	394	384	380

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of ethnic fragmentation on school provision (DISE data)

	(1) Local_elementary	(2) G_elementary	(3) Aided_elementary	(4) Unaided_elementary
Ethnic frag	-0.1121+	-0.2039	-0.0004	-0.1583***
	(0.117)	(0.251)	(0.986)	(0.000)
urbanisation	-0.1739***	-0.1933***	-0.0097	0.0810***
	(0.000)	(0.002)	(0.181)	(0.000)
college_dis	0.0028*	0.0661***	-0.0003	-0.0004
	(0.094)	(0.000)	(0.558)	(0.679)
workrate	0.0459	0.1911	-0.0713***	-0.0484
	(0.604)	(0.385)	(0.006)	(0.358)
State FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of ethnic fragmentation on SMDC

	(1) SMDC meetings	(2) Males	(3) Females	(4) Local gvt males	(5) Local gvt females
Ethnic frag	-3.1474**	-2.6814+	-1.8987*	-0.4880**	-0.4113***
	(0.018)	(0.100)	(0.061)	(0.042)	(0.006)
urbanisation	-0.8919*	-3.0297***	-1.2831***	-0.3991***	-0.2412***
	(0.056)	(0.000)	(0.000)	(0.000)	(0.000)
college_dis	-0.0051	-0.0118	0.0019	0.0106*	0.0089**
	(0.868)	(0.755)	(0.935)	(0.056)	(0.011)
workrate	1.0548	3.3184+	1.3910	0.4771+	0.2220
	(0.522)	(0.101)	(0.267)	(0.108)	(0.232)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396

p-values in parentheses

SMDC stands for School Management Development Committee.

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effect of ethnic fragmentation on SMDC

	(1) SCandST males	(2) SCandST females	(3) Parents
Ethnic frag	-0.6169**	-0.4378**	-2.0043***
	(0.017)	(0.020)	(0.001)
urbanisation	-0.2833***	-0.1708***	-0.7915***
	(0.002)	(0.010)	(0.000)
college_dis	0.0046	0.0089**	0.0453***
	(0.444)	(0.041)	(0.001)
workrate	1.6940***	1.1302***	2.1278***
	(0.000)	(0.000)	(0.005)
State FE	Yes	Yes	Yes
Observations	396	396	396

p-values in parentheses

SMDC stands for School Management Development Committee.

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effect of ethnic fragmentation on hiring of teachers

	(1) Reg_teachers_gvt	(2) Reg_teachers_pvt	(3) Contract_teachers_gvt	(4) Contract_teachers_pvt
Ethnic frag	-1.6681*	0.6468	0.6030**	0.7077
	(0.054)	(0.809)	(0.012)	(0.625)
urbanisation	1.8677***	2.9712***	0.0117	-1.1578**
	(0.000)	(0.002)	(0.889)	(0.023)
college_dis	-0.0678***	0.0074	0.0030	-0.0340
	(0.001)	(0.905)	(0.588)	(0.312)
workrate	-3.0441***	0.2225	0.0770	-0.7703
	(0.005)	(0.947)	(0.795)	(0.669)
State FE	Yes	Yes	Yes	Yes
Observations	396	394	396	394

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effect of ethnic fragmentation on school infrastructure

	(1) G_furniture	(2) P_furniture	(3) G_library	(4) P_library
Ethnic frag	-0.3103**	-0.1747	-0.3129*	-0.2054
	(0.024)	(0.210)	(0.089)	(0.235)
urbanisation	0.1029**	0.1422***	0.1542**	0.1166*
	(0.033)	(0.004)	(0.017)	(0.054)
college_dis	0.0085***	0.0015	0.0024	0.0007
	(0.007)	(0.648)	(0.570)	(0.854)
workrate	-0.2789^{+}	-0.3702**	-0.0187	-0.0139
	(0.102)	(0.033)	(0.934)	(0.949)
State FE	Yes	Yes	Yes	Yes
Observations	396	394	396	390

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of fragmentation on self-help groups and agricultural credit societies

	(1)	(2)
	SHgroup	Agrisociety
Ethnic frag	-0.5411***	-0.4178**
	(0.001)	(0.022)
urbanisation	0.0068	0.0980*
	(0.879)	(0.052)
workrate	-0.1509	-0.2948+
	(0.349)	(0.104)
litrate_11	0.0340	-0.1155
	(0.708)	(0.258)
State FE	Yes	Yes
Observations	274	274

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Impact of self help groups on school provision

	(1)	(2)	(3)	(4)	(5)	(6)
	P_element	G_element	P_second	G_second	P_highsecond	G_highsecond
SHgroup	0.0711***	-0.3506***	0.0222***	0.0075	0.0069*	-0.0037
	(0.000)	(0.000)	(0.000)	(0.157)	(0.071)	(0.238)
urbanisation	0.0815***	-0.3994***	0.0114+	-0.0061	0.0135***	0.0132***
	(0.000)	(0.000)	(0.130)	(0.333)	(0.003)	(0.001)
workrate	-0.1538***	2.3372***	-0.0448**	0.2473***	-0.0595***	0.1134***
	(0.009)	(0.000)	(0.029)	(0.000)	(0.000)	(0.000)
education_prop	0.3966*	1.2890**	0.3527***	-0.4380***	0.1992***	0.0048
	(0.054)	(0.035)	(0.000)	(0.000)	(0.000)	(0.892)
nsdp_l	-0.0000***	-0.0001***	0.0000***	-0.0000***	0.0000***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0680	-0.1233	-0.0442**	0.0295*	-0.0072	-0.0290***
	(0.234)	(0.468)	(0.027)	(0.080)	(0.552)	(0.004)
Observations	331	331	330	331	311	315

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Impact of agricultural credit societies on school provision

	(1) P_element	(2) G_element	(3) P_second	(4) G_second	(5) P_highsecond	(6) G_highsecond
Agrisociety	0.0491**	-0.2776***	-0.0014	-0.0012	0.0033	0.0097**
	(0.042)	(0.000)	(0.873)	(0.858)	(0.495)	(0.018)
urbanisation	0.0810***	-0.3920***	0.0134*	-0.0053	0.0139***	0.0115***
	(0.000)	(0.000)	(0.083)	(0.406)	(0.002)	(0.002)
workrate	-0.1484**	2.2928***	-0.0512**	0.2446***	-0.0592***	0.1198***
	(0.014)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)
education_prop	0.1479	2.5483***	0.2901***	-0.4584***	0.1768***	0.0082
	(0.466)	(0.000)	(0.000)	(0.000)	(0.000)	(0.810)
nsdp_l	-0.0000***	-0.0000***	0.0000***	-0.0000***	0.0000***	-0.0000***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
Observations	331	331	330	331	311	315

p-values in parentheses

This is a district level regression. Fragmentation numbers are based on 1931 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Impact of fragmentation on teachers

	(1) Teachers/enrol	(2) Reg teachers/enrol	(3) Teachers/classes	(4) Reg teachers/classes
Ethnic frag	-0.0465**	-0.0519***	-0.1365	-0.1987*
	(0.040)	(0.009)	(0.209)	(0.069)
private	-0.0395**	-0.0366**	-0.1639	0.0719
	(0.040)	(0.048)	(0.549)	(0.758)
cfrag_private	0.0419**	0.0401**	0.6020**	0.3789+
	(0.042)	(0.043)	(0.040)	(0.132)
urban	0.0021**	0.0019*	0.2044***	0.1965***
	(0.033)	(0.051)	(0.000)	(0.000)
Road access	-0.0010	-0.0002	0.1016***	0.0972***
	(0.415)	(0.807)	(0.000)	(0.000)
age	-0.0002***	-0.0001***	0.0039***	0.0040***
	(0.000)	(0.000)	(0.000)	(0.000)
college_dis	0.0018*	0.0009**	-0.0101***	-0.0087***
	(0.058)	(0.015)	(0.000)	(0.000)
workrate	-0.0138	-0.0182*	-0.3027**	-0.3302***
	(0.207)	(0.094)	(0.011)	(0.006)
State FE	Yes	Yes	Yes	Yes
Observations	75866	75866	505881	505881

p-values in parentheses

This is a school level regression. Fragmentation numbers are based on 1931 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Difference in the means test

Variable	Mean (nonmissing)	Mean (missing)	Difference	t value
Private	0.565	0.185	-0.380***	(-264.71)
Reg teachers	11.465	3.576	-7.889***	(-418.48)
Reg teachers/highclass	1.046	0.604	-0.443***	(-208.02)
Highclass	10.749	5.856	-4.893***	(-931.27)
Urban	0.290	0.127	-0.162***	(-130.18)
Road access	0.953	0.897	-0.0573***	(-55.46)
ESTDYEAR	1981.196	1979.490	-1.706***	(-11.34)
Furnstu	0.830	0.564	-0.266***	(-149.45)
Clrooms	6.297	4.436	-1.861***	(-132.63)
Toilets b	2.577	1.045	-1.532***	(-195.03)
Toilets g	2.846	1.101	-1.746***	(-212.25)

Table 15: Impact of fragmentation on teachers

	(1) Regular/total teachers	(2) Single teach schools	(3) Single reg teach schools
Ethnic frag	-0.1637***	0.1095+	0.1557**
	(0.002)	(0.127)	(0.049)
private	0.2445*	0.1249+	-0.2534**
	(0.050)	(0.131)	(0.014)
cfrag_private	-0.1629	-0.2260**	0.0920
	(0.225)	(0.012)	(0.401)
urban	0.0009	-0.0181***	-0.0260***
	(0.859)	(0.003)	(0.000)
Road access	0.0170***	-0.0735***	-0.0717***
	(0.003)	(0.000)	(0.000)
age	0.0005***	-0.0015***	-0.0015***
	(0.000)	(0.000)	(0.000)
college_dis	-0.0005	0.0062***	0.0057***
	(0.717)	(0.001)	(0.002)
workrate	-0.0775	0.1176*	0.1267+
	(0.168)	(0.069)	(0.103)
State FE	Yes	Yes	Yes
Observations	499625	505916	505916

p-values in parentheses

This is a school level regression. Fragmentation numbers are based on 1931 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Impact of fragmentation on school infrastructure

	(1) Classrooms/enroll	(2) Classrooms/classes	(3) Good condn/total classrooms	(4) Library
Ethnic frag	-0.0391**	-0.0668	0.1523	-0.1299
	(0.029)	(0.492)	(0.205)	(0.488)
private	-0.0213	-0.2966	0.2992***	0.4572***
	(0.243)	(0.194)	(0.002)	(0.000)
cfrag_private	0.0346*	0.7718***	-0.2222**	-0.4428***
	(0.081)	(0.002)	(0.033)	(0.001)
urban	0.0083***	0.2059***	0.0526***	-0.0008
	(0.000)	(0.000)	(0.000)	(0.927)
Road access	-0.0029*	0.0661***	0.0298***	0.0423***
	(0.090)	(0.000)	(0.000)	(0.000)
age	-0.0002***	0.0045***	-0.0014***	0.0032***
	(0.000)	(0.000)	(0.000)	(0.000)
college_dis	0.0009	-0.0121***	-0.0032	0.0018
	(0.156)	(0.000)	(0.153)	(0.660)
workrate	-0.0091	-0.3139**	-0.2449***	-0.1646
	(0.630)	(0.011)	(0.009)	(0.392)
State FE	Yes	Yes	Yes	Yes
Observations	75866	505881	497378	460059

p-values in parentheses

This is a school level regression. Fragmentation numbers are based on 1931 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Impact of fragmentation on SMDC meetings and participation

	(1) SMDCMEETING	(2) LOCAL_M	(3) LOCAL_F	(4) Males total	(5) Females total
Ethnic frag	-3.7650**	-0.4779+	-0.3459*	-3.4775+	-1.8948
	(0.027)	(0.115)	(0.075)	(0.135)	(0.284)
urban	-0.7634***	-0.3260***	-0.1705***	-1.8975***	-0.8821***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Road access	0.0311	-0.0171	-0.0077	-0.0015	-0.0410
	(0.675)	(0.518)	(0.638)	(0.992)	(0.764)
age	0.0185***	0.0069***	0.0037***	0.0392***	0.0209***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
college_dis	-0.0226	0.0151	0.0143	-0.0759+	-0.0146
	(0.286)	(0.383)	(0.206)	(0.124)	(0.642)
workrate	0.9643	0.7848***	0.4149**	6.9122***	2.5685+
	(0.578)	(0.007)	(0.046)	(0.002)	(0.108)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	79308	79308	79307	79308	79308

p-values in parentheses

SMDC stands for School Management Development Committee. This is a school level regression. Fragmentation numbers are b

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Impact of fragmentation on enrollment distribution of schools

	(1) High_enroll_c1	(2) High_enroll_c5	(3) High_enroll_c8	(4) High_enroll_c10	(5) High_enroll_c12
Ethnic frag	-0.0497	0.0469	-0.0324	0.0079	-0.0118
	(0.485)	(0.330)	(0.255)	(0.829)	(0.803)
private	-0.8775***	-0.4360***	-0.3113***	-0.0975	-0.5397***
	(0.001)	(0.007)	(0.006)	(0.171)	(0.002)
cfrag_private	0.7872***	0.3496**	0.2622**	0.0431	0.4176**
	(0.004)	(0.043)	(0.028)	(0.574)	(0.024)
urban	0.0069	0.0040	-0.0019	-0.0140***	0.0015
	(0.246)	(0.432)	(0.542)	(0.000)	(0.746)
Road access	-0.0303***	-0.0286***	-0.0123***	-0.0147***	-0.0384***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age	-0.0004***	-0.0002+	0.0001*	0.0002***	0.0003***
	(0.001)	(0.105)	(0.064)	(0.000)	(0.001)
college_dis	0.0004	0.0005	-0.0012**	-0.0011*	0.0014*
	(0.681)	(0.658)	(0.017)	(0.068)	(0.069)
workrate	-0.0196	0.0071	0.0094	0.0326	0.0266
	(0.623)	(0.866)	(0.710)	(0.173)	(0.386)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	505916	505916	505916	505916	505916

p-values in parentheses

This is a school level regression. Fragmentation numbers are based on 1931 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Impact of fragmentation on enrollment by standard

	(1) Enrol_c1	(2) Enrol_c5	(3) Enrol_c8	(4) Enrol_c10	(5) Enrol_c12
Ethnic frag	21.7020***	41.5413***	35.7281*	49.6547*	36.6050**
	(0.005)	(0.002)	(0.079)	(0.075)	(0.032)
private	8.3733	35.2815**	-4.1021	27.5613	38.6122*
	(0.450)	(0.032)	(0.815)	(0.279)	(0.050)
cfrag_private	5.9131	-21.4254	16.7104	-15.1749	-23.2049
	(0.622)	(0.225)	(0.382)	(0.577)	(0.271)
urban	9.1251***	9.5753***	11.6950***	4.9193**	11.1766***
	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)
Road access	0.3866	1.3661^{+}	3.9324***	13.8693***	8.9618***
	(0.544)	(0.121)	(0.000)	(0.000)	(0.000)
age	-0.1300***	0.1462***	0.6277***	0.8560***	0.8973***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
college_dis	-0.0065	-0.5227**	-0.8223***	-0.7013*	-0.3564
	(0.961)	(0.039)	(0.008)	(0.098)	(0.186)
workrate	-14.0669*	-10.3859	-54.6905**	-62.8500**	-9.9792
	(0.089)	(0.326)	(0.020)	(0.022)	(0.591)
State FE	Yes	Yes	Yes	Yes	Yes
Observations	76168	76168	76168	76168	76168

p-values in parentheses

This is a school level regression. Fragmentation numbers are based on 1931 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Impact of fragmentation on distribution of students by caste

	(1) frag_1	(2) frag_5	(3) frag_10	(4) frag_12
frag_cen	0.2251***	0.4032***	0.3060***	0.3470***
	(0.003)	(0.000)	(0.000)	(0.000)
private	-0.0227	0.1132***	-0.0054	-0.0285
	(0.400)	(0.001)	(0.789)	(0.205)
frag_private	0.1925***	-0.1339+	-0.0049	-0.0570
	(0.005)	(0.121)	(0.919)	(0.315)
Enrol_c1	-0.0001+			
	(0.102)			
urban	0.0015	-0.0041	-0.0033	-0.0017
	(0.834)	(0.546)	(0.492)	(0.772)
Road access	0.0194***	0.0246***	0.0156***	0.0119*
	(0.009)	(0.000)	(0.002)	(0.094)
age	0.0005***	0.0011***	0.0011***	0.0009***
	(0.001)	(0.000)	(0.000)	(0.000)
college_dis	-0.0005	-0.0015	-0.0031**	-0.0020
	(0.840)	(0.619)	(0.046)	(0.264)
workrate	-0.4091***	-0.2303+	-0.3232***	-0.3032***
	(0.001)	(0.113)	(0.001)	(0.004)
Enrol_c5		0.0000		
		(0.889)		
Enrol_c10			0.0001***	
			(0.000)	
Enrol_c12				0.0001***
				(0.000)
State FE	Yes	Yes	Yes	Yes
Observations	23309	33355	81706	29864

p-values in parentheses

This is a school level regression. Fragmentation numbers are based on 2011 census

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$