Class size and learning:

Has India spent too much on reducing class size?

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Abstract: Whether class-size reductions improve student learning outcomes is an important policy question for India. This paper investigates the issue using a credible identification strategy to address the endogeneity of class-size. Pupil fixed effects combined with value-added estimation shows no significant relationship between class-size and student achievement, which suggests that under current teaching practices, there is no learning gain from reducing class size. If these findings based on a small sample in one city hold true for the country, they have important policy implications. When generalised, our findings suggest that India experienced a value-subtraction from spending on reducing class-sizes, and that the US$3.6 billion it spends annually on the salaries of the 0.4 million new teachers appointed between 2010 and 2017 is wasteful spending rather than an investment in improving learning. Our findings imply that India could save US$ 19.4 billion per annum by increasing PTR to 40, without any reduction in pupil learning.

JEL classification: I20, I21

Keywords : Class size, student learning, India

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1. Introduction

Reducing class size has been a popular reform across countries in their search for improved quality of education, and many countries have legislated an official maximum class size. In India, at the secondary school level, official policy supports a class size of 30[i] and the Right to Education (RTE) Act 2009 also stipulated a maximum class size of 30 in elementary schools, policies which necessitated the appointment of a large number of new teachers. Between 2010 and 2017, total number of elementary teachers rose from 4,047,070 to 4,451,953, with a corresponding increase in the total teacher salary bill of these 0.4 million extra teachers, an increase of approximately US $3.6 billion per annum in 2017-18 prices.[ii]

As elsewhere, in India too class size is a vexed issue. Inadequate teachers and unfilled teacher vacancies are bemoaned by NGOs and in official documents, and frequently identified as the factor behind low student learning levels[iii]. India's draft New Education Policy (MHRD 2019, p.115) noted that "according to government data, the country faces over 10 lakh [one million] teacher vacancies". It resolved that "teacher vacancies will be urgently filled" (para P2.14, page 56) and recommended increasing the education budget for filling the vacancies (page 414, Appendix A1.4.4)[iv]. However, contrary to widely held belief of an acute teacher shortage, mean pupil teacher ratio (PTR) in public schools is much lower than the RTE-Act-mandated maximum of 30 in elementary schools (grades 1 – 8). In the seven year period between 2010-11 and 2017-18, PTR in public elementary schools fell from 31.2 to 25.1[v]. Even at the secondary school level, as per the official District Information System on Education (DISE) data, PTR in 2017-18 was 27.2.

Against this background of increased public expenditure to reduce class-size[vi], it is important to ask whether class size reduction improves student learning outcomes, i.e. whether the expenditure to reduce class size was an investment in better quality education or merely unproductive spending of scarce taxpayer money. It is known from the Annual Status of Education Report (ASER) (various years) and also from the National Council of Educational Research and Training (NCERT, (2015) that between 2010 and 2015, pupils' learning achievement levels fell, and that over the same period, PTR and class-sizes were also reduced, suggesting simplistically a perverse positive temporal relationship between class-size and pupil achievement, rather than the expected negative one. However, to our knowledge, there are hardly any studies that seek to estimate the causal effect of class size on student achievement in India using micro i.e. individual-pupil level data.

Whether reducing class size improves student outcomes remains a contentious question in the literature. Proponents argue that class-size reductions lead to more individual attention, higher quality instruction, a broader scope for student-centred innovation and teaching, increased teacher morale, less student misconduct and more ease of involvement of students in academic activities such as group work. An extensive literature has sought to measure the causal impact of class size on student learning using a variety of estimation methodologies.

While a meta-analysis by Hanushek (2003) collating findings from 376 educational production functions found no consistent relationship between class-size and student achievement, and Hattie's meta-analysis (2005) demonstrated a typical effect-size that was considered "tiny" or "small" relative to other educational interventions, meta-analyses are questioned on the ground that they mix the studies with credible identification strategies with those that are not capable of yielding a causal inference.

A number of individual studies have used techniques to try to identify the causal effect of class size in different contexts. Krueger (1999) used the Randomised Control Trial (RCT) method in the STAR experiment in Tennessee; Angrist and Lavy (1999) used the 'Maimonides Rule' to estimate the effect of class size on student achievement in Israel, finding an exogenous source of variation in class size that is uncorrelated with student unobservables; Case and Deaton (1999) used an instrumental variables approach on South African data; Woessmann and West (2006) used TIMSS data on student performance in 11 countries, combining school fixed effects and instrumental variables to identify random class-size variation between two adjacent grades within individual schools; Altinok and Kingdon (2012) used a pupil fixed effects approach to examine the impact of class size in 47 countries using TIMSS data; Shen and Konstantopoulos (2019) used predicted class size based on Maimonides' Rule as an instrument, to measure the class size effect in four Eastern European countries. The typical finding in these studies is of a non-existent or small beneficial effect from reducing class size[vii].

However, we would expect the impact of class size to be heterogeneous depending on grade level (e.g. primary versus secondary grades) and on the range of class-sizes. For example, in the Tennessee STAR experiment, reduction of class-size from 22-25 to a low class-size of 14-17 students per class, and reduction in class size in early grades, and for disadvantaged students, produced short to medium run learning gains, but this says nothing about the impact of reducing class size from say 40 or 45 to 30 (the situation in most developing countries), or at higher (secondary) grades, or in the science and non-science subject streams.

Most of the studies on the impact of class size (that have a credible identification strategy) use data from developed countries where the range of class sizes is much smaller than the typical class sizes in most developing countries. There are only a few studies on developing countries, where low student achievement is a growing concern. Altinok and Kingdon's (2012) study divided TIMSS data on 47 countries into three groups: developed countries, transition countries, and developing countries. They found a statistically significant negative relationship between class size and pupil achievement only in the developing country group, though the effect size was small: a 1 SD increase in class size in developing countries (by a large 10.9 pupils per class from a mean class size of 37.2) lowered student achievement by only 0.03 SD but this effect was fairly precisely estimated, with a t-value of 2.7. In a study on Bangladesh, Asadullah (2005) used instrumental variable (IV) estimation to find that class size in secondary grade had a perverse sign: the coefficient on class size was positive and statistically significant, i.e. reducing class size in secondary grades reduced pupil achievement, and would not be an efficient policy. Finally, a study by Banerjee et. al. (2007) in 175 government primary schools in two cities of India using RCT found that reducing class size had no impact on test scores, which they say is "consistent with the previous literature suggesting that inputs alone are ineffective".

2. Identifying the effect of class size on pupil learning

Identifying the causal effect of class size on student achievement is challenging because of the potential non-random matching of pupils to schools and, within schools, the non-random matching of students to particular classes. If more able or more motivated students manage to sort themselves into the smaller classes then any expected negative effect of class-size on student achievement will be under-estimated, i.e. there would be a smaller negative (or even a positive) coefficient on class-size than the true negative relationship. Conversely, if schools deliberately put less able children into smaller classes, then any expected negative effect of class size would be over-estimated (the negative coefficient on class size would be a bigger negative than the true relationship), since small class here contains the less than averagely abled children. Any systematic correlation of the unobservables in the error term with the included class-size variable undermines the simple production function's ability to produce causal estimates.

While randomized experiments can in principle be used to fix the problem of non-random matching, in practice there are many problems, as noticed about the STAR experiment study by Krueger (1999). Participants may behave differently if they know they are part of an experiment, especially if the outcomes of the study might have implications for future school funding (Hoxby, 2000). Attrition into and out of small and large class assignments over time in the STAR experiment may have undermined the random allocation: Hanushek (1997a, 1997b, 1999 and 2003) pointed out that only half the participants remained in the study until the end of the third grade (Year 4). Experiment-based studies are costly and other experimental studies are required to check the robustness of the findings of the STAR project (Todd and Wolpin, 2003). While findings from experiments are synthesised in Kremer (2003), the number of truly natural experiments are few (Rosenzweig and Wolpin, 2003).

Since true natural experiments are costly and rare, some researchers have addressed the endogeneity issue by using some valid instrumental variables for class-size, i.e. a class-size predicted by some exogenous variation. Angrist and Lavy (1999) used the hypothetical class-size predicted by (Maimonides') maximum class size rule[viii] as an instrument for class-size with Israeli schools data, and they obtained a significant effect of class size on student achievement. However, in developing countries including India, even though the maximum class-size rule (of 30 students per teacher) exists, it is not closely followed, so generating a valid instrument for the developing countries is difficult. In a similar kind of IV analysis, Woessmann and West (2006) estimated the effect of class size on student achievement in 11 countries by combining the school fixed effect and IV techniques. They found no effect of class-size in nine countries and a large and significant effect only in Greece and Iceland.

In the current paper, we follow a *pupil fixed effects* approach to estimate as nearly as possible the causal effect of class size on student achievement, using data on students of secondary grade 12 from ten different schools of a private school chain in Uttar Pradesh. While using the traditional achievement production function, we allow for pupil fixed effects in cross-section data, as used in Altinok and Kingdon (2012), using across-subject differencing rather than across-time differencing. This methodology is possible as we have data on each student's marks (at one time point) in different subjects, and this enables us to control for all subject-invariant student unobservables. Thus cross-section data allows us to investigate whether the within-pupil variation is class size is associated with within-pupil variation in learning achievement. Students face different class-sizes for different subjects and this permits us to ask whether the class-size in different subjects is correlated with students' marks in the different subjects within the grade in the school. The idea is identical to the panel data estimate of the achievement production function: we estimate the within-pupil across-subject equation of achievement production function rather than within-pupil across-time. The estimation technique is explained in the next section. A similar estimation technique is used in Dee (2005); Ammermuller & Dolton (2006); Kingdon (2006); Holmlund and Sund (2008); Kingdon and Teal, (2010); Aslam & Kingdon (2011); and Altinok and Kingdon (2012).

In addition, we have a measure of the students' subject-specific mark in each subject in the within-school tests earlier in the year. We include this subject score as a control for prior ability in the subject. This should further reduce, though it may not eliminate, endogeneity bias.

3. Estimation Approach

We have adopted the pupil fixed effects approach described in Altinok and Kingdon (2012). The standard achievement production function is specified as follows:

$$A_{ik} = \alpha + \beta X_{ik} + \delta S_k + \mu_i + \eta_k \qquad (1)$$

where the achievement level (A_{ik}) of student i of school k is determined by the vector of his/her personal characteristics (X) and by school specific characteristics (S). μ_i and η_k capture the student and school specific unobservables. S_k captures the class size variable.

In such an OLS equation, the estimated coefficient of the class size variable will suffer from endogeneity bias if student ability is correlated with class size. Removing from our sample students who are deliberately placed in ability-setted classes would reduce the endogenity problem but not necessarily eliminate it. In order to credibly address the issue, a pupil fixed effects approach is feasible where data exists on both achievement scores and class size by subject for each student, and where thus, for each student, there are as many rows of data as there are number of subjects. In such a setup, students are allowed to face different class size for different subjects within the school. This subject-wise variation in class size 'within a student' is what allows us to incorporate class size (along with teacher characteristics that also vary across subjects) as an explanatory variable in a pupil fixed effects (PFE) equation. This is the approach we follow. We estimate the following simple PFE achievement equation.

$$A_{ijk} = \alpha + \beta X_{ik} + \gamma Cj_k + \psi.T_{jk} + (\delta S_k + \mu_{ij} + \eta_{jk} + \varepsilon_{jk}) \qquad (2)$$

where A_{ijk} is the achievement of a student i in subject j and in school k. X is the vector of characteristics of students i. C is class size of subject j, T is a vector of teacher characteristics of subject j, and S is the school specific characteristics of school k. The composite error terms are represented by μ_{ij}, η_{jk} and ε_{jk}. These error terms denote the unobserved characteristics of students, school and subject respectively. A simplified PFE model of two subjects' cases (subject 1 and subject 2) looks like as follows:

$$(A_{i2k} - A_{i1k}) = \gamma(C_{2k} - C_{1k}) + \psi\ (T_{2k} - T_{1k}) + \{(\mu_{i2} - \mu_{i1}) + (\eta_{2k} - \eta_{1k}) + (\varepsilon_{2k} - \varepsilon_{1k})\} \qquad (3)$$

PFE is self-evidently a within-school phenomenon since a student studies in a single school. If school unobservables are not subject specific (i.e. η does not have j subscript) and pupils' unobservable are not subject specific (i.e. μ does not have j subscript), then within school PFE model looks like as follows:

$$(A_{i2k} - A_{i1k}) = \gamma(C_{2k} - C_{1k}) + \psi\ (T_{2k} - T_{1k}) + (\varepsilon_{2k} - \varepsilon_{1k})$$

Or simply

$$(A_{i2} - A_{i1}) = \gamma(C_2 - C_1) + \psi\ (T_2 - T_1) + (\varepsilon_2 - \varepsilon_1) \qquad (4)$$

Regressing difference in a pupil's test score across subjects on the difference in class size across subjects nets out the effect of all student subject-invariant unobserved characteristics. However, if student ability varies by subject, that is not netted out but (μ_{i2} - μ_{i1}) remains in the error term. Although it remains in the error term, it will not create a problem in our estimation unless it is correlated with the (C_2 – C_1). For this correlation to exist, students should be able to match to specific classes of a subject within their grade in the school, e.g. pupils who are bright in a subject systematically match to the smaller – or the larger – classes of that subject (within their grade). Moreover, subject-specific *school* unobservables (η_{2k} - η_{1k}) remain in the error term and may in principle be correlated with (C_2 – C_1). While some subject-varying aspects of school should be captured in class-size (e.g. if a school emphasises a particular subject, it is often reflected in, or is because of, small class-size in that subject), not all subject-varying aspects will be captured in class-size, and they remain a potential source of endogeneity.

For consistent estimation of the effect of class-size, it is also required that *class* level (i.e. subject-specific) unobserved characteristics (such as class-resources, teacher quality etc.) be unrelated to the included class size variable:

$$E[(C_{2k} - C_{1k})(\varepsilon_{2k} - \varepsilon_{1k})] = 0. \tag{5}$$

For example, if more skilled teachers are assigned to teach larger classes, a class level unobservable (teacher skill level) will be correlated with both class-size and with pupil scores. Since omitted class-level variables in ε_1, ε_2 may be correlated with both class-size (C_1, C_2) and with pupil achievement A_1, A_2, we cannot say that PFE estimation permits us to interpret the class-size effect as causal. We do include a number of teacher quality characteristics in the PFE achievement equation (the subject teacher's qualifications, training and experience), which should reduce this source of endogeneity, but it may not necessarily eliminate it. While across-subject PFE estimation resolves one source of endogeneity (i.e. correlation between μ and C), it does not solve this potential source of endogeneity (the possible correlation between ε and C). This is analogous to the standard panel data estimation where class unobservables remain in the error term.

We wish to allow for the possibility that the relationship between class size and student achievement may be non-linear, and also for the possibility that our estimates can suffer from endogeneity bias if students' ability varies across subjects.

We therefore proceed with estimation in the following steps. First, we allow our model to be non-linear in class size by including both class size and the square term of class size.

$$\text{Achievement}_{ijk} = \alpha + \delta_1(\text{Class Size}) + \sum_1^m \beta_m(T_m)_{ijk} + \psi_i + \theta_j + \varepsilon_{ijk.} \quad (6)$$

$$\text{Achievement}_{ijk} = \alpha + \delta_1(\text{Class Size}) + \delta_2(\text{Class Size})^2 + \sum_1^m \beta_m(T_m)_{ijk} + \psi_i + \theta_j + \varepsilon_{ijk.} \quad (7)$$

Achievement_{ijk} is the marks (estimated in terms of Z-score) of student i in the j^{th} subject in the k^{th} school. T_m is the set of teacher characteristics. We have also added subject-specific fixed effects (θ_j) and pupil-fixed effect (ψ_i) to control unobserved factors across different subjects and pupils.

Since the estimates of equation (7) may suffer from ability bias, in the next step we add the subject-wise Mean Score in the Previous Exams (MSPE) or 'lagged achievement in the subject' to equation (7) as a proxy for the student's subject specific ability. The estimates of equation (8) reduce the problem of endogeneity to a large extent, without necessarily eliminating it entirely.

$$\text{Achievement}_{ijk} = \alpha + + \delta_1(\text{Class Size}) + \delta_2(\text{Class Size})^2 + \sum_1^m \beta_m(T_m)_{ijk} + \tau(\text{MSPE})_{ijk} + \psi_i + \theta_j + \varepsilon_{ijk.} \quad (8)$$

At the end of this section, we briefly discuss the implications of including the lagged dependent variable.

In equation (8) we imposed a quadratic relationship between class size and student achievement. To explore the functional form in more detail, we introduce splines by creating dummy variables of class size. We divided our class size variable into 7 quantiles (given the structure of our data, creation of 7 quantiles provides sufficient and almost equal proportion of data in each quantile as opposed to 8 or 10 quantiles). We therefore estimate the following equation to verify the functional form of equation (8)

$$\text{Achievement}_{ijk} = \alpha + \sum_{n=2}^{n=7} \beta_m(n^{th}\ Quantile\ of\ class\ size)_{ijk} + \sum_1^m \beta_m(T_m)_{ijk} + \tau(\text{MSPE})_{ijk} + \psi_i + \theta_j + \varepsilon_{ijk} \quad (9)$$

The lagged test score (in each subject) in the estimated equations 8 and 9 is intended to capture the contribution of all previous inputs and any past unobservable endowments. While this inclusion is a significant improvement over a non-dynamic (contemporaneous) specification which links current test scores to only current inputs, a downside is that estimates remain subject to possible bias from measurement error in the lagged achievement measure. A wide literature on value-added models summarised in Singh (2015) which builds on Todd and Wolpin (2003), as well as models with simulated data with a variety of non-random assignment mechanisms (Guarino, Reckase & Wooldridge, 2012), suggest that a specification including lagged dependent variable is the most robust and reliable under most settings.

4. Data

The estimation strategy presented above requires a specific type of database. First, it is needed to have students' test score across different subjects. Second, there has to be enough variation in class size between subjects. We collected subject-wise test scores of each student of grade 12, from ten different schools of a private school chain in Uttar Pradesh. To pass grade 12, students take six subjects from a pool of 16 subjects, where the compulsory and optional subjects are specified within each of two major streams: science and commerce[ix]. English is examined in two different papers, Language and Literature, and the score division is 50-50 for a 100 marks exam. The mark we obtain for English is the consolidated mark of English-Language and Literature. Therefore, in our analysis, we have given equal marks to both the subjects. For example, if a student scored 78 per cent mark in English, we have given 78 for English-Language and 78 for English-Literature, as the two subjects are taught by different teachers in most of the campuses. We have also restricted our sample by removing the scores of Physical-Education (PEd) from our analysis[x]..

Grade 12 students are typically aged 17 years old at the start of the school-year, which begins generally around 1st April each year. In the sample school chain, a typical grade 12 student takes three compulsory internal examinations (before facing the external Board exam the following March): the First Comparative exam, the Second Comparative and the Pre-Board exam. The First Comparative exam happens in late June, by when only one-third of the syllabus is covered. The Second Comparative examination, also called the Half-yearly exam, takes place in September, by when two-thirds of the syllabus is covered. By the Pre-Board exam in mid-December, all of the syllabus is covered. From mid-December to February is revision/review time. Finally the class 12 external exam set by the exam board is typically spread over the month of March.

For the analysis, one should ideally use students' Board exam marks as the external exam answer sheets are anonymously evaluated by Board-appointed examiners, usually in another city. However, the distribution of marks in the Board exam is highly non-Gaussian. On the other hand, the distribution of the school's internal Pre-board exam marks is more Normal. Figure 1 shows that the board exam marks' distribution is always to the right of the internal Pre-board exam marks' distribution, which need not in itself be a problem. What is problematic is that the marks distribution is distinctively (rightward) skewed rather than Normal: the most extreme case is illustrated in the Computer Science marks, where the 'moderation' policy adopted in the Board exam leads to a distribution where no candidate has received marks less than 46, and the vast bulk of students have marks between 85 and 100. The Maths and Economics marks distributions are bimodal, with a lot of students given grace marks that take them just above the pass mark of 35, and there are an unduly large number of students getting marks between 90 and 100 per cent. The board marks' distribution is also generally narrower than the internal exam marks' distribution, e.g. see the kernel density distributions for Computer Science and English.

Concern has been expressed about the 'grace marks' and moderation practices of the various exam boards in India (Sanghi, 2013; Bhattacharji, 2015; *Times of India*, 2018; Kingdon, 2019; see Appendix B for details). Board exam results in India are also not trusted for entrance to prestigious universities such as the Indian Institutes of Technology (IIT) and for medicine and engineering courses at other colleges. Thus, instead of using Board Exam results for our analysis, we have used marks in the school's internal 'Pre-board' exam since, by the time of the Pre-board, the entire syllabus is covered, and since students from all the schools in the sample school-chain appear for same exam, on the same date and with the (same) question papers prepared by an independent authority[xi].

The distribution of pre-board exam marks in the different subjects can be different, e.g., the distribution of internal pre-board marks in physics and chemistry are lower and less dispersed than marks in maths (not shown). In order to render them comparable and to use student achievement in different subjects as the dependent variable, it is thus necessary to standardize the marks. We standardize the score by the average score in the subject, that is, we use the z-scores of achievement. The z-score is the score of the pupil in a given subject minus the overall average score in that subject, divided by the standard deviation of the overall score in that subject. Therefore, by construction, z-score of each subject has a mean of 0 and a standard deviation of 1.

5. Results

This section presents the results of our regression analysis and also robustness checks. Results are presented in Tables 1-5. To prevent the analysis from being unduly affected by outliers, we removed the bottom and top two percent of observations of class-size, which led to removing class sizes below 18 and above 59. Mean class size is 43.64, though the whole-school pupil teacher ratio is lower, at 28.3 due to music, dance, sports, and art teachers, class-coordinators, section incharges, librarians, lab-technicians, swimming coaches, psychologists, career counsellors, band-masters, etc.

We follow two approaches in this paper that are not very common: the value-added approach (including a student's prior subject-specific achievement level) and the pupil fixed effects approach. However, our most preferred approach is pupil fixed effects with value-added. The OLS results change when we include pupil fixed effects[xii].

We estimate the (preferred) pupil fixed effects (PFE) equations of the achievement production function, as shown in the methodology section equations (6) to (9). Since different teachers teach different subjects to the same pupil, it was possible to include teacher variables in the PFE equations. The teacher variables included as controls are teacher's educational level, professional training, gender, and teacher's experience. Student variables (gender and religion) drop out since we estimate PFE equations. We have also added a dummy variable for each subject in all equations.

Table 1 presents our achievement production functions with teacher controls and subject fixed effects, and clusters standard errors at the class level, since the intervention of interest – change in class size – is a class-level variable. We include linear and quadratic terms of class size, and in the last column, we include splines of class size, in order to not impose any particular shape on the relationship.

Since the coefficient on class size could suffer from endogeneity bias, i.e. since student ability may be correlated with class-size *within the school*, e.g. more able or more motivated students systematically get selected into small or large classes (of their grade) within the school,[xiii] we attempt to control for students' subject-specific ability. We measure a student's subject-specific ability by the average mark of the student in the subject in the previous two internal i.e. within-school exams called the First and the Second Comparative exams (see para 2 of section IV on data, above), and include this as a control.

In Table 1, adding pupil fixed effects (column 'e' onwards) reduces the coefficients on both the linear and quadratic class size terms in the OLS equations, and renders them both statistically insignificant. Columns (g), (h) and (i) combine pupil fixed effects (PFE) with a value-added approach and they show that subject-specific ability has a large and statistically very significant coefficient. Adding prior subject-ability (column h) reduces the point estimates on the class-size variables (column f).

In the quadratic concave relationship of class size with student achievement (column h), the turning point occurs at a class size of 48, i.e., up to a class size of 48, learning does not fall (if anything, it gently increases) as class size increases. The results with splines of class size also show a roughly similar pattern. However, the results are not statistically significant: there are large confidence intervals, as seen in Figures 2a (quadratic specification) and 2b (specification with splines). Thus we fail to reject the null hypothesis at even the 10% significance level. We conclude that learning is non-decreasing in class-size[xiv].

The fact that learning does not fall with class size is consistent with the bulk of the literature on class size internationally and in India cited in section I above. However, this does not mean that class size can never matter. Our results suggest that under current teaching practices there is no learning gain from reducing class sizes.

Next we examine whether the class-size effect differs across boys and girls. We estimate the pupil fixed effects equation with control for subject-specific ability separately for girls and boys. Standard errors are again clustered at the class level. The results in Table 2 suggest that among boys, we fail to reject the null hypothesis that there is no significant relationship between class size and achievement, whereas among girls the relationship between class size and achievement it is linearly positive, also seen in Figure 3a. In other words, girls thrive the higher the class size. This is an interesting finding and we explore it further in Table 4, to see if peer learning could be an explanation.

So far we controlled for ability bias in two ways: (i) we estimated pupil fixed effects – which removes unobservable differences across students, and ensures that identification of the class-size effect comes only from differences *within a pupil* across subjects; (ii) we included the student's prior achievement mark in the subject, to control for the fact that subject specific ability of the same pupil across subjects remains a source of endogeneity bias. However, since these two approaches may not fully control for subject-specific ability, we go further and estimate a PFE equation with subject-specific ability control, *separately for the two subject-groups* (the science-subjects group and non-science subjects group[xv]), since subject-specific ability would be more similar for subjects within such a grouping than for subjects across groupings, and we continue to control for subject-specific ability too, within the subject group. Estimating the equation separately for the two subject groups also allows us to see whether the shape of the relationship varies by subject.

The two subject streams are the science and non-science[xvi] subject streams. Table 3 shows no significant relationship between class size and student achievement within either the science-stream classes or the non-science stream classes, as we fail to reject our null even at the 10% significance level. This is also seen in Figure 3b. This is consistent with the findings of Table 1.

In summary, we find no statistically significant relationship between class size and student learning, and we find that this continues to be the case within the science-side (STEM) subject classes and also within the non-science (non-STEM) subject classes. However, when we bifurcate by gender, we observe that while for boys there is no relationship between class size and achievement, girls' learning flourishes with larger classes.

Explaining the observed relationship

We do not find the expected negative relationship between class size and learning, and indeed for girls, we find a positively sloped relationship. Could the lack of a negative relationship be because there are two countervailing forces at work, i.e. that as class size increases, learning falls because of lesser teacher attention to each student, but learning also increases as there is a bigger pool of students to peer-learn from; this positive effect of class size may be plausible if students give peer-feedback, and take ownership in the role of giving feedback to their peers in the class.

We explore some peer-group effects to examine whether a positively sloped relationship shows that children learn from each other, presuming that larger class-sizes permit more learning from peers (peer learning). We first constructed three peer-group variables:

1. “Mean achievement of class-peers” (mean mark of all the class peers, i.e. all pupils in the class, excluding the index student);
2. “Mean achievement of ability-peers” (mean mark of the peer group in the achievement decile of the student within the class, again excluding the index student);
3. “Variation in pupil ability within the class” (measured by the within-class standard deviation of achievement in the prior ‘Comparative exam’ in the subject, which captures the heterogeneity of the ability distribution in the class).

A student may learn not only from the teacher, but also from her/his peers – i.e. from students in the whole class group (class-peers), or from others in her ability group within the class (ability-peers), and weaker students may learn from bright students, i.e. the greater the ability distribution in a class, the greater may be such learning by the weak from the able. The extent to which such peer learning happens may differ by subject. For example, it is often said that maths and science require more explanation and attention by a teacher but that language learning can benefit from peer interaction as it is not so dependent on a teacher’s explanations or personal attention. If this is so, we would expect less peer learning in science than in the non-science stream. Students may learn from class peers or ability peers either through watching their work (demonstration effect) or from getting direct help from them. Finally, if science subjects require the attention of a teacher rather than being self-learnt or learnable from peers, then a high variation in ability level across children in a class would deter science learning because some of the teacher’s attention will be given to the weaker students. By the same token, if non-science lends itself to learning from peers, then weaker students will benefit from interaction with smarter peers and the smarter peers may learn themselves too, by teaching their less able peers.

Our peer-group results are set out in Table 4. This shows that controlling for the effect of peer learning does not alter the coefficient on the class-size variable, compared to Table 1 (column h). It is seen that for a girl, the more able the class peers, the significantly higher is her learning: a one SD increase in class mean peer achievement raises the index girl’s achievement mark by 0.12 SD. For a boy, the more able the ability-peers, the higher his learning, though the coefficient here is significant only at 10% level.

When we examine the effect of peer variables in the science and non-science subjects in Table 4, we see that the achievement level of 'class peers' benefits a student's attainment in non-science subjects (at the 10% level of significance), but not in the science subjects. This supports the maintained view that science needs explaining and is learnt mostly from a teacher, but that in the non-science subjects, one can learn from one's peers. The size of the peer-learning effect is also large: *ceteris paribus*, a one SD increase in class-peer mean achievement[xvii] raises the index student's achievement by 0.19 SD. Table 4 also shows that while in the non-science subjects, *variation in class ability* does not matter to learning, in the science subjects, it weakly harms learning. This may be because in science, a teacher needs to give individual attention to each student: the greater the variability of ability in a class, the more the teacher's attention is divided as there is greater need for differentiated teaching for pupils of different levels of ability, and there is less individual attention.

6. Cost-Benefit Analysis

Our data suggest that pupil learning does not decrease as class size increases, over the observed range of class sizes. This has important policy implications for optimal pupil teacher ratios (PTRs) and thus for teacher appointment decisions in India, based on considerations of cost-effectiveness and economic efficiency. In this section, we compare the fiscal cost of existing class-size policies with the cost of hypothetical class-size policies, based on our finding that learning does not suffer with larger classes.

Recent education policies in India reflect the tacit belief that to improve student performance, class size must be reduced by recruiting more teachers. The Right to Education (RTE) Act 2009 mandates a maximum PTR of 30 for elementary schools, and the Ministry of Human Resource Development (MHRD) guidelines for the secondary education program RMSA (*Rashtriya Madhyamik Shiksha Abhiyan*) mandate a minimum of 5 teachers for up to 160 students (implying a PTR of 32) and then a further teacher for each 30 students thereafter. As mentioned in Section 1, the draft National Education Policy (NEP, 2019) also identifies pupil teacher ratios above 30 as a major cause of lack of learning (page 63, section 2.14). It states that the country faces over one million teacher vacancies (page 115), and suggests that government's education budget share should increase by 1.05 percentage points, for filling teacher vacancies and better resourcing (page 417, Table A1.4). This additional recruitment of teachers would create a permanent fiscal liability for government.

In reality data show that public schools are operating at much lower levels of PTR than the mandated 30 pupils per teacher. Appendix Table A2 shows that in 2017-18, nationally, PTR at the elementary school level was 22.8[xviii] and that in 8 out of 20 major Indian states it was below 16. At the secondary and higher secondary levels the PTR was 27.9 in 2016-17[xix] (27.3 for 20 major states).

However, it is important to highlight that the elementary and secondary PTRs of 22.8 and 27.9 are *prima-facie* PTRs, being the total reported pupil enrolment divided by the total number of appointed teachers. These use uncritically what are known to be inflated enrolment numbers based on fake/ghost names entered by the school to show a higher than actual enrolment. This happens because grains for mid-day meals, bags, shoes, sweaters, cloth for school uniforms, other freebies and ultimately even teacher appointments are all based on the schools' self-reported enrolments. The Comptroller and Auditor General of India found 20% inflation in DISE pupil enrolment data at the elementary school level in Uttar Pradesh (CAG, 2017)[xx], and the Mid-Day Meal Authority also reports overstated enrolment in public schools (*Times of India*, 2015). Given that real enrolment is lower than reported (inflated) numbers, the real PTR is lower than the reported *prima facie* PTRs. High student absence rates of 31% (EdCil, 2008) and 28% (ASER, 2018) shown in Table A2, capture both fake enrolments as well as actual absence among genuine enrolees. Datta and Kingdon (2021) show that – in India's public elementary schools – the 'cost-conscious' PTR which adjusts for student absence rates was 15.8, and that the 'effective PTR' which adjusts for both student and teacher absence rates, was 20.8. However, for our cost-benefit analysis, we use the *prima facie* PTR of 22.8 (see Table A2)[xxi] even though it is known to be higher than the true PTR.

Our analysis has been for secondary schools. The impact of changes in class-size on learning levels, taken together with our analysis of the costs of teacher salaries presented in Tables 5(a, b) suggests that major cost-efficiencies can be achieved by maintaining larger than currently mandated class-sizes without compromising on student performance. Banerjee et. al.'s (2007) study also shows the lack of a relationship between class size and learning at the primary school level in India, which suggests that the findings at the secondary level in our current study may be true even at the elementary school level.

Tables 5(a, b) show the actual public expenditure on teacher salaries and the potential for absolute financial savings at different (hypothetical) levels of PTR, at the elementary and secondary levels respectively. Table 5(a) suggests that expenditure on public elementary school teachers' salary was around USD 37.25 billion (in 2017-18), and Table 5(b) suggests that public expenditure on secondary school teacher salaries was USD 11.37 billion (in 2016-17). If government had maintained a PTR of 40[xxii], it could save USD 19.4 billion (Rupees 145,000 crore in Indian currency) per annum taking the elementary and secondary savings together.

There is no strong consensus in the literature as to the educational interventions that are the most important for learning. The high-return interventions that raise student outcomes the most in Hattie's (2009) meta-analysis are changes to *process* or *pedagogy* in schools, which may require teacher training rather than inputs that require much expenditure. The political economy of education literature for developing countries suggests that decentralising educational decision-making, improving the governance environment and reform of accountability structures for schools/teachers may be good ways of improving schooling quality and student outcomes (Kingdon, et. al., 2014), but such reforms are typically not funding-intensive. Providing computers to schools and laptops/tablets to students have lately been politically popular reforms in some states of India. While the literature on the impact of technology on learning is often sceptical about its efficacy[xxiii], it is desirable for developing country schools to have computers so children can be taught basic word processing, excel, PowerPoint, etc. We examine some expenditure items within and outside the education sector to see how the USD 19.4 billion savings per year could be absorbed. The intention is not so much to cost what are the most impactful interventions in education (which in any case are not known with certainty), but rather to see to what extent a few popular interventions could absorb the large amount (USD 19 billion per annum) of savings from increasing PTR from 22.8 to 40:

a. Providing sixteen colourful story books, costing Rs. 50 each, free to all the below-poverty-line (BPL)[xxiv] pupils in public and private elementary schools (classes 1 to 8) each year, would cost only USD 0.44 billion per year. If these are provided to *all* the children rather than only poor children, that would still cost only USD 2.02 billion per year, i.e. only about 10% of the saved amount of USD 19.4 billion per annum.

b. 90.1% of public elementary schools in India do not have a single computer (DISE 2017-18 data[xxv]), and most rural children will never have seen one. If familiarity with basic tools such as word processing, excel tables and PowerPoint presentations, etc. is important for success in adult life, students need access to a computer and a trainer, preferably at school. Having a computer can also help the administrative processes of a school. If all public elementary schools with more than 50 pupils (and there were 6,08,549 such schools in 2017-18) were provided an IT professional, a computer-with-internet-connection and a printer, it would cost USD 0.28 billion (Rs. 27,000 for a computer, Rs. 8000 for a printer), and a recurring cost of USD 2.01 billion per annum for the remuneration of the IT professionals (at Rs. 20,000 per month), and an internet connection rate of Rs 600 per month. The total bill being USD 2.29 billion, which is under 12% of the saved amount of USD 19.4 billion per annum.

c. Providing a good tablet or smartphone for education costing Rs. 15,000 (approx. USD 200) to every single Below Poverty Line (BPL) child enrolled in class 1 to 8 would cost Rs. 61,800 crore, or USD 8.2 billion, once off, which would be only 42.6% of the saved USD 19.4 billion in one year alone (non-recurring).

d. There were 41.2 million BPL children enrolled in classes 1 to 8 in 2017-18 in India[xxvi]. With a total saved fund of USD 19.4 billion (obtained by maintaining a PTR of 40 rather than 22.8), the government could give a Direct Benefit Transfer for schooling, of USD 39 per month (Rs. 2943 per month) or USD 471 per annum, to each and every elementary-school enrolled BPL child of the country. Currently, the Indian central government gives a 'Child Education Allowance' of Rs. 2250 per month to the children of all its employees for the education of their children.

e. If the saved funds were to be used outside the education sector and government decides to spend the entire USD 19.4 billion in the National Rural Employment Guarantee Scheme, it can create additional employment of 100 days per year for 72.7 million workers at current wage rate[xxvii].

7. Conclusion

Our paper used a pupil fixed effects method to examine the effect of class-size on pupils' learning outcomes. While earlier studies using pupil fixed effects (e.g. Altinok and Kingdon, 2012) could not control for subject-specific ability, the current study does so by including prior achievement of the student in various subjects. Our more refined estimates are thus an advance on previous studies and they help us to get closer to identifying the causal effect of class size on learning.

We could not reject the null of no relationship between class size and student achievement in the observed range of class sizes. This suggests that in the type of pedagogy that is practiced, children's learning does not suffer from larger class size. One explanation for this could be that children learn from peers too, and not only from the teacher, a hypothesis for which we found empirical support. It is not certain that these findings from a small sample of schools from one city can be generalized to the whole of India, but if they were true for the country, they suggest a scope for increasing class-sizes in India from their existing levels (a PTR of 22.8 in 2017-18) without hurting student learning.

Our estimates suggest that in secondary education, reducing class-size to 30 or below was not required for improve learning, and that the tacit assumption in policy makers' minds about there being a negative relationship between class-size and learning (which led them to mandate a maximum pupil teacher ratio of 30), was not empirically grounded. If our estimates are correct and are generalizable to the country as a whole, India spent a very substantial amount on reducing class size below the learning-maximizing level, which was not investment that would benefit children.

India spent an estimated US$ 3.6 billion in 2017-18 on the salaries of just the 0.40 million extra teachers it appointed between 2010 and 2017, which (when combined with falling enrolment) reduced pupil teacher ratio in elementary public schools from 31.2 (in 2010) to 22.8 (in 2017-18) and in secondary education, to 27.9. This increase in salary expenditure is a permanent liability. The reason for the appointments was the requirement of the *Right to Education Act* 2009 and the guidelines for India's secondary education program, which mandated a maximum pupil teacher ratio of 30. The National Education Policy (2019, 2020) states that there are one million teacher vacancies which must be urgently filled, and it reiterates the commitment to a maximum PTR of 30.

Our cost-benefit analysis results showed that if India increased the PTR from its current 22.8 in elementary and 27.9 in secondary schools, to 40 pupils per teacher in both, it would save USD 19.4 billion per annum in government's teacher salary expense, without reduction in learning outcomes. We showed how this money could allow investment in other educational items, such as internet-enabled computers and computer teachers to all public elementary schools; a smartphone to all 41.2 million below-poverty-line (BPL) children of the country; or a school voucher or Direct Benefit Transfer (DBT) for schooling, equal to Rs. 2943 per month, to every BPL child.

Since we used data on secondary age students, the question could arise whether the impact of class size could be different for a lower (e.g. elementary school) age group and, secondly, our analysis is based on data from private schools so the question arises whether individual attention by a teacher could matter more to children in public schools who have less learning support at home, with typically less educated parents. However, Banerjee et. al. (2007) in their RCT experiment study using data on 175 public primary schools of Mumbai and Vadodara found that reduction in class size[xxviii] had no effect on learning in government elementary schools in India. While this finding supports our conclusions, more research would strengthen the evidence base for the implied class-size policy direction for India.

While our results suggest that reducing class size does not raise test scores under current teaching practices, it could be an effective way to raise learning if it were combined with complementary inputs, such as increased teacher skills[xxix].

An important caveat is that our findings have been based on data from a small sample of schools from a single city. It is important to repeat this type of analysis at scale – with much bigger datasets nationally – to be confident about the stark conclusions reached here which challenge established class size policies.

Data availability: The data underlying this article will be shared on reasonable request to the corresponding author.

Appendix A

Insert Table A1 (here)

Insert Table A2 (here)

Appendix B

Insert Figure B (here)

Figure B: Histogram of marks in Maths (1st Row), Computing (2nd Row), English (3rd Row), Economics (4th Row).

Kingdon's (2019) opinion editorial on the 'moderation' practices of Indian exam boards states that in the class 10 (High School) CBSE board exam in maths, all students who actually got anywhere between 79 and 95 per cent mark on the exam script, got exactly 95% marks shown in their board mark-sheet and certificate.

A *Times of India* report on 4th July 2018 stated that "A student who passed Central Board of Secondary Education's class XII exam this year is likely to have got 30 marks over the total in their exam scripts. Yes, CBSE did moderate the marks this year, granting nine additional marks in physics, chemistry, mathematics and accounts, eight marks in business studies and three in English Core"

Bhattacharji (2020) says: "It is okay if the exam board makes slight changes to the raw score assigned by a script-marker to a candidate, in a particular subject. Slight upscaling or downscaling of marks is fine - to take into account the fact that a question paper might be significantly harder than the previous years, or the fact that some script-markers might be more strict/liberal than the rest - which is why slight changes are permissible….But, what the scoring histograms suggest, is not minor or marginal changes, but gross distortions to the original scores - and a blatant misreporting of data, by inflation of pass-rates. Also, the score distributions are changing year to year, which reduces the reliability and repeatability of these examinations".

See https://www.thelearningpoint.net/home/examination-results-2013/cbse-2004-to-2014-bulls-in-china-shops

After observing that "the marks awarded to the students were not as one would expect in a public exam", Sanghi says: "what is clear is that unless boards come clean on their academic processes, they can't be trusted to the extent of using their mark sheets in the admission process for highly competitive colleges and universities…. There appears to be an extremely liberal policy on grace marks….are all boards trying to compete with each other in increasing the pass percentage (and making their political masters happy as a result of such a result)".

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Figure 1: Kernel density of scores in Mathematics, Computer Science, English and Economics, from the national Board Exam and the (within-school) Pre-Board Exam

Figure 2: Predictive margin plot of Pupil Fixed Effects estimation from Table 1.1
Note: The left panel shows the predictive margin plot of class size from the quadratic PFE estimation in column (d) of Table 1.1. The right panel shows the coefficient plot of the class-size dummy variables from the splines in column (e) of Table 1.1.

Figure 3: Marginal plots of Pupil Fixed Effects estimation by Gender and Subject Stream
Note: The left panel shows the Marginal plot of PFE estimation by gender in Table 2 (for males based on column (b) and for females based on column (c). The right panel shows the same by subject stream in Table 3 (for science subjects based on column (b); and for non-science subjects, based on column (c)). 95% confidence intervals shown in shaded colour.

Table 1.

OLS and Pupil Fixed Effects (PFE) Achievement Equations, Without and With a Value-Added Specification

Variables	**O L S**				**PUPIL FIXED EFFECTS**					
	Without Value-Added		**With Value-Added**		**Without Value-Added**		**With Value-Added**		**With Value-Added**	
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**	**(i)**	
Class Size	0.01315***	0.05218**	-0.00077	0.04684***	0.00500	0.04084	0.00475*	0.02469	1st Quantile	Base
	(0.00425)	(0.02545)	(0.00182)	(0.01307)	(0.00443)	(0.02709)	(0.00273)	(0.01799)		
Class Size Square		-0.00047		-0.00057***		-0.00048		-0.00026	2nd Quantile	0.07228
		(0.00031)		(0.00016)		(0.00037)		(0.00024)		(0.07012)
									3rd Quantile	0.11115
										(0.08046)
									4th Quantile	0.08065
										(0.07532)
									5th Quantile	0.19271*
										(0.11404)
									6th Quantile	0.07555
										(0.08734)
									7th Quantile	0.16719
										(0.14366)
Subject-Specific Ability			0.05534*** (0.00076)	0.05537*** (0.00075)			0.04287*** (0.00115)	0.04283*** (0.00116)		0.04279*** (0.00116)
Teacher's level control	✔	✔	✔	✔	✔	✔	✔	✔		✔
Subject Fixed Effect	✔	✔	✔	✔	✔	✔	✔	✔		✔
Pupil-Fixed Effect	No	No	No	No	✔	✔	✔	✔		✔
Observations	11,519	11,519	11,500	11,500	11,519	11,519	11,500	11,500		11,401
R-squared	0.07737	0.07876	0.69717	0.69924	0.66817	0.66863	0.78360	0.78374		0.78381

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard Errors are clustered at the **class** level.

Note: The 'With Value-Added' columns include prior subject-specific ability of the student, measured by their subject marks in a past exam within the school in the same academic year. The data section of the paper gives more details on this. STATA's xtreg command does not allow us to cluster at the class level, hence we have used OLS with subject fixed effects and pupil fixed effects. We have created seven quantiles of 'class size' using the "xtile" command in STATA 14. The 1st Quantile (class size 18 to 36), 2nd Quantile (class size 37 to 40), 3rd Quantile (class size 41 to 44), 4th Quantile (class size 45 to 47), 5th Quantile (class size 48), 6th Quantile (class size 49 to 53), 7th Quantile (class size 54 to 59). Roughly 14% of pupils observations are in each quantile. Teacher controls include teachers' general education, professional qualifications, gender, experience and experience square.

Table 2.

Pupil Fixed Effects (PFE) achievement equation, by gender

Variables	Male		Female	
	Linear	Quadratic	Linear	Quadratic
	(a)	(b)	(c)	(d)
Class Size	0.00204	0.02839	0.00695**	0.01981
	(0.00308)	(0.02034)	(0.00329)	(0.02155)
Class Size Square		-0.00035		-0.00017
		(0.00027)		(0.00028)
Teacher's level control	✓	✓	✓	✓
Subject Fixed Effect	✓	✓	✓	✓
Pupil-Fixed Effect	✓	✓	✓	✓
Observations	6,278	6,278	5,222	5,222
R-squared	0.78424	0.78443	0.77756	0.77764

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard Errors are clustered at the class level.

Note: Student's subject-specific ability is included, but not shown. The turning point in column (b) is at a class size of 40.5, and the turning point in column (d) is at a class size of 58.3, though neither is based on a statistically significant relationship. For girls we have created the z-score of achievement in each subject with reference to the mean score of the girls in that subject, and similarly for boys with reference to the mean score of boys in that subject. The same strategy was followed for creating the z-scores for science and non-science subject streams in Table 3 below.

Table 3.

Pupil Fixed Effect (PFE) achievement equation, by subject stream (Science and Non-Science)

Variables	Science		Non-science	
	Linear	Quadratic	Linear	Quadratic
	(a)	(b)	(c)	(d)
Class Size	0.00270	0.02968	0.00567	0.00579
	(0.00358)	(0.02262)	(0.00452)	(0.02777)
Class Size Square		-0.00036		-0.00000
		(0.00029)		(0.00038)
Teacher's level control	✓	✓	✓	✓
Subject Fixed Effect	✓	✓	✓	✓
Pupil-Fixed Effect	✓	✓	✓	✓
Observations	7,581	7,581	3,919	3,919
R-squared	0.76792	0.76813	0.78562	0.78562

Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard Errors are clustered at the class level.

Note: Student's subject-specific ability included, but not shown. The turning point in column (b) is at a class size of 41.2, and the turning point in column (d) effectively does not exist, since the coefficient on the quadratic term of class size is virtually zero, i.e. the relationship is effectively linear. However, in actual fact, neither is based on a statistically significant relationship.

Table 4.

Pupil Fixed Effects achievement equation, with peer group variables

VARIABLES	**Full Sample**	**Science**	**Non-Science**	**Male**	**Female**
	1	**2**	**3**	**4**	**5**
Class Size	0.02003	0.03313	0.00774	0.02327	0.00250
	(0.01833)	(0.02445)	(0.00480)	(0.02091)	(0.00352)
Class Size Square	-0.00025	-0.00041		-0.00033	
	(0.00024)	(0.00030)		(0.00027)	
Subject Specific Ability+	0.04040***	0.04519***	0.03572***	0.03812***	0.04357***
	(0.00155)	(0.00200)	(0.00294)	(0.00183)	(0.00262)
Peer group variables					
Class-Peer Mean Score (Except Index Student)	0.00523**	0.00015	0.01061*	0.00498	0.00657**
	(0.00261)	(0.00380)	(0.00544)	(0.00309)	(0.00288)
Ability-Peer Mean Score (Except Index Student)	0.00164	0.00058	0.00339	0.00276*	-0.00076
	(0.00124)	(0.00154)	(0.00255)	(0.00157)	(0.00235)
Variation in class ability (SD of class score)++	-0.00954	-0.02263*	0.00791	-0.00484	-0.01472
	(0.00982)	(0.01323)	(0.01771)	(0.01111)	(0.01012)
Constant	-2.7805***	-3.4666***	-1.3584**	-2.5822***	-2.4006***
	(0.65860)	(0.88886)	(0.52617)	(0.71798)	(0.58808)
Teacher's level control	✓	✓	✓	✓	✓
Subject Fixed Effect	✓	✓	✓	✓	✓
Pupil-Fixed Effect	✓	✓	✓	✓	✓
Observations	11,500	7,581	3,322	6,278	5,222
R-squared	0.78451	0.76915	0.79341	0.78505	0.77891

Note: Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Std. Errs. are clustered at the class level.

+ Subject specific ability is the student's score in each subject in his/her past within-school exam. It is the average of the student's marks in a subject over the first and second comparative exams.

++ Variation in class ability is measured by the Standard Deviation of score in the class, in the previous exam.

Table 5(a).

Cost-Benefit analysis at different PTR levels in Primary and Upper primary level in 2017-18

	Student Enrolment	**Number of Teachers**	**Actual PTR (Enrolment/ teachers)**	**Teacher salary rate per month (Rupees)**	**Total teacher salary cost (billion US$)**	**Govt. Savings (billon US$)**
1	102321358	4486966	22.80	51,887	37.25*	
		Number of teachers implied by the hypothetical PTR	**Hypothetical PTR**			
2	102321358	3410712	**30.00**	51,887	28.32	8.93
3	102321358	2923467	**35.00**	51,887	24.27	12.98
4	102321358	2558034	**40.00**	51,887	21.24	16.01
5	102321358	2273808	**45.00**	51,887	18.88	18.37
6	102321358	2046427	**50.00**	51,887	16.99	20.26

Note: *-Actual Cost. Row 1 represents actual data of 2017-18 for 21 major states and it shows the Pupil Teacher Ratio as 22.8 in these states. The government's uDISE data for 2017-18 shows a PTR of 21.0 for India as a whole (not only 21 major states, see http://udise.schooleduinfo.in/dashboard/elementary#/). Total yearly cost of teachers' salary is calculated based on an estimated average salary rate of an elementary teacher of Rs. 51,887 per month in 2017-18. From row 2 and onwards, we present estimates of the total salary cost and government savings at different supposed levels of PTR (in a hypothetical scenario). An exchange rate of 75 rupees to the dollar has been used. Monthly salary data are obtained from the note to Table 4 in Kingdon (2020) who estimates them as follows.

1. Monthly salary data at the India level is obtained by taking the simple average of state-wise salary of primary school teachers with 15 years' experience from Ramachandran (2015) at the National University of Educational Planning and Administration (NUEPA), who had salary data from six major states of India.

2. In the above calculation, the average salary of upper primary level teachers is ignored even though one-third of all public elementary schools are upper primary schools, whose teachers receive a significantly higher salary rate. If we were to include upper primary school teachers' salary, it would come to a weighted average monthly elementary school teacher salary of Rs. 53996, in which case the estimated actual cost would be USD 38.76 billion instead of USD 37.25 billion.

Table 5(b).

Cost-Benefit analysis at different PTR levels in Secondary & Higher secondary schools, 2016-17

	Enrolment	**Teacher**	**Actual PTR**	**Teacher's salary per month**	**Total teacher salary cost (billion US $)**	**Govt. Savings (billon US$)**
1	26,276,072	941,725	27.90	Rs. 74,001	11.15*	
		Number of teachers implied by the hypothetical PTR	**Hypothetical PTR**			
2	26,276,072	875,869	**30.00**	Rs. 74,001	10.37	0.78
3	26,276,072	750,745	**35.00**	Rs. 74,001	8.89	2.26
4	26,276,072	656,902	**40.00**	Rs. 74,001	7.78	3.37
5	26,,276,072	583,913	**45.00**	Rs. 74,001	6.91	4.24
6	26,276,072	525,521	**50.00**	Rs. 74,001	6.22	4.93

Note: Similar as Table 5. The data of row 1 is for 2016-17. Monthly salary data is obtained from Kingdon (2020) which is based on averaging of salary data of secondary school teachers (15 years' experience) from across six major Indian states in Ramachandran (2015), and this data for 2014 is extrapolated to 2016-17 using the Consumer Price Index. *-Actual Cost.

Table A1.

Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Marks and class size				
Z-score (Full Sample)	0	0.9994	-4.50	2.85
Actual absolute score**	46.61	18.38	0	100
Mean Score of previous 2 internal exams (1st & 2nd Comparative)	45.67	18.33	0	100
Class Size	44.21	8.06	18	59
Teacher' Highest Education Level				
Bachelor	0.10	0.31	0	1
Masters	0.78	0.41	0	1
M. Phil and More	0.12	0.32	0	1
Teachers' Highest Professional Qualification				
No-Training	0.11	0.31	0	1
B. Ed	0.79	0.41	0	1
M. Ed	0.10	0.30	0	1
Teacher's Gender (Male=1)	0.52	0.50	0	1
Teacher's Experience*	21.69	8.28	1	43
Student's Gender (Male=1)	0.58	0.49	0	1
Muslim	0.12	0.32	0	1

Note: As explained in the data section, we take the students' marks in the pre-board exam as our main measure of pupil achievement. There are many sections of a class of a particular subject in each sample school. So, there are 283 class observations. * Experience = (Actual Age – 24). We have assumed that everybody joined the job market at the age of 24. ** This is the absolute average mark of a student, averaged across all subjects in which the student took the pre-board exam.

Table A2.

Pupil teacher ratio and pupils per grade, in Government Elementary Schools, DISE data (sorted by column 'e'), 2017-18

S. No.	State	Total Students (Reported)	Total Teachers (Regular)	Total Teachers (Contractual)	Total Teachers (Reported)	Pupil Teacher Ratio (Reported) ('prima-facie' PTR)	Student Attendance Rate$	Teacher Attendance Rate$	Effective Pupil Teacher Ratio (PTR)	Cost-Conscious Pupil-Teacher Ratio (CPTR)	PTR at Secondary + H. Secondary School level (Reported)#
		(a)	(b)	(c)	(d)	(e=a/d)	(f)	(g)	h=(a*f)/(e*g)	i=(a*f)/d	(j)
1	Himachal Pradesh	5,33,388	47,246	20,676	67,922	7.9	0.95	0.69	10.73	7.5	14.45
2	Jammu-Kashmir*	9,37,825	89,093	10,117	99,210	9.5	0.79	0.81	9.18	7.5	16.46
3	Uttaranchal	6,81,848	57,010	3,458	60,468	11.3	0.80	0.79	11.42	9.0	13.20
4	Kerala	8,44,947	62,500	2,225	64,725	13.1	0.91	0.84	14.17	11.9	19.60
5	Tamil Nadu	31,40,559	2,09,070	29,924	2,38,994	13.1	0.88	0.87	13.32	11.6	22.21
6	Punjab	16,52,599	82,727	34,753	1,17,480	14.1	0.82	0.63	18.14	11.5	19.11
7	Andhra Pradesh*	50,72,962	3,18,028	14,029	3,32,057	15.3	0.73	0.79	14.15	11.2	21.36
8	Haryana	15,42,191	83,471	13,759	97,230	15.9	0.82	0.82	15.85	13.0	14.68
9	Assam	38,28,109	1,89,614	32,992	2,22,606	17.2	0.81	0.74	18.96	13.9	16.37
10	Rajasthan	62,24,446	3,38,550	4,503	3,43,053	18.1	0.63	0.75	15.19	11.4	21.90
11	Chhattisgarh	30,82,746	1,50,035	835	1,50,870	20.4	0.68	0.86	16.12	13.9	32.51
12	Maharashtra	54,99,126	2,57,155	4,464	2,61,619	21.0	0.89	0.86	21.78	18.7	26.89
13	West Bengal	1,04,24,158	3,76,865	1,01,912	4,78,777	21.8	0.74	0.79	20.44	16.1	46.36
14	Karnataka	38,16,438	1,73,895	703	1,74,598	21.9	0.86	0.76	24.77	18.8	25.95
15	Odisha	46,90,160	1,18,796	94,299	2,13,095	22.0	0.67	0.86	17.14	14.7	24.00
16	Madhya Pradesh	72,17,655	2,79,654	1,115	2,80,769	25.7	0.72	0.74	25.16	18.5	37.01
17	Gujarat	54,56,424	2,04,309	1,223	2,05,532	26.5	0.75	0.84	23.74	19.9	26.58
18	Uttar Pradesh	1,57,23,078	5,04,125	73,395	5,77,520	27.2	0.57	0.69	22.72	15.5	43.43
19	Jharkhand	41,64,893	46,261	69,831	1,16,092	35.9	NA	0.54	NA	NA	63.69
20	Bihar	1,77,87,806	3,22,262	62,087	3,84,349	46.3	0.42	0.71	27.39	19.4	53.07
	Major 21 States	**10,23,20,384**	**39,05,678**	**5,76,300**	**44,81,978**	**22.8**	**0.69**	**0.77**	**20.40**	**15.8**	**27.33**

Note: The data for student and teacher attendance rate is for 2006.
$ We have assumed that this proportion remains same over the years. There may be a slight change over time, but it is unlikely to have changed very substantially.
# The PTRs in Secondary and Higher Secondary schools are based on DISE data for the year 2016-17.
Source: For student enrolment and teacher numbers, authors' calculations on official DISE data (www.dise.in). Compared with our calculation of a PTR of 22.8, he government's published national pupil teacher ratio in government elementary schools in 2017-18 is 20.0 (see http://udise.schooleduinfo.in/dashboard/elementary#/). The source for official data on Student and Teacher attendance rates is the EdCil Survey, commissioned by Ministry of Human Resource Development (MHRD) https://www.educationforallinindia.com/study-on-students-attendance.pdf Recent data from (non-official) ASER survey of 2018 show a student attendance rate of 72% and a teacher attendance rate of 85% http://img.asercentre.org/docs/ASER%202018/Release%20Material/schoolreportcardenglish.pdf

[i] A Ministry of Human Resource Development document (MHRD, undated) which lays down norms for the funding of secondary schools under the RMSA secondary education programme states that "for every incremental enrolment of 30 students, 1 additional teacher may be provided as per the RMSA norm of PTR of 30:1". https://www.education.gov.in/en/sites/upload_files/mhrd/files/upload_document/FAQ_0.pdf

[ii] Data on govt. school teachers' salary for 2014-15 is available from Ramachandran (2015) where mean govt. primary school teacher salary (averaged across new and experienced teachers) was 40,623 per month. For 2017-18, this has been inflated by 8.5% per year (based on salary escalation in Uttar Pradesh, see Annex Table 2 in Kingdon, 2017). Thus, mean primary teacher salary is taken as Rs. 51,887 per month (or Rs. 6,22,644 for 12 months) in 2017-18. Thus, the teacher salary bill of 404,883 extra teachers in 2017-18 is Rupees 252,097,970,652 or US $ 3,601,399,581, i.e. $3601 million or $ 3.6 billion in 2017-18.

[iii] In December 2017, India's education minister Prakash Javadekar informed parliament that at the elementary level, 17.5% and at secondary level 14.8% of government school teacher posts were vacant https://www.ndtv.com/education/indias-teachers-crisis-country-falls-short-of-1-million-school-teachers-1778220 ; "Of the 6 million teaching positions in government schools nationwide….about 1 million–were vacant" (IndiaSpend, December 12, 2016); "No Funds, No Policy, Few Teachers: Former NCERT Director Says Budget Should Increase for Education", Krishna Kumar (30-01-2018) http://www.indianews-today.com/news/no-funds-no-policy-few-teachers-former-ncert-director-says-budget-should-increase-for-education ; "We have a shortage of teachers across the state and, over the years the number of vacancies has increased," said Deepak Joshi, minister of state for school education", *Times of India* (Jul 3, 2017) https://timesofindia.indiatimes.com/city/bhopal/teachers-shortage-hits-edu-in-govt-schools/articleshow/59415617.cms; "74 countries face an acute teacher shortage…India is second in terms of teacher recruitment required to meet the current education demand. Talking in absolute terms, India needs close to 370 thousand new teachers to meet its demand for primary education", UNESCO (October 2016) http://unesdoc.unesco.org/images/0024/002461/246124e.pdf

[iv] Appendix A1.4.4 of the draft New Education Policy 2019 recommends increasing the total (not just education) budget by 0.5 percentage points to fill teacher vacancies. The Indian central government's budget in 2020-21 is Rupees 30,422 billion or USD 435 billion (Parliamentary Research Services, 2020), and 0.5% of that is Rs 152 billion or USD 2.2. However, based on the prevailing mean teacher salary of primary teachers (Rs. 61,083 per month or Rs. 7,33,000 in

2019-20), the actual cost of 1 million teachers in 2020 would be Rs. 733 billion (USD 10.5 billion), which is 2.4% of the central government budget, not 0.5%.

[v] Pupil teacher ratio (PTR) in public elementary schools fell dramatically over the 7 year period, partly due to a large number of fresh teacher appointments (of 0.40 million teachers), and partly due to falling student numbers (24 million fewer students) due to the abandonment of government schools (DISE, 2017-18). A decomposition of the temporal fall in PTR shows that if total enrolment in public schools had remained unchanged (i.e. had there been no abandonment of government schools), PTR would have fallen from 31.2 to 28.4 just on account of the increase in the total stock of teachers. Equally, if there had been no fresh teacher appointments, PTR would have fallen from 31.2 to 25.3 just on account of the fall in student enrolments in public schools. Part of the reason for the low PTR is the stipulation of the Right to Education Act that up to a total enrolment of 60 pupils, a school must have a minimum of two teachers, and a very high proportion of India's public schools are tiny: in 2017-18, 41% of all public elementary schools had fewer than 50 students and about 16% schools had fewer than 20 students. Data on enrolment and teachers in 2010-11 are obtained from DISE Elementary State Report Card http://udise.in/src.htm accessed in April 2020.

[vi] Class-size and pupil teacher ratio (PTR) are not the same thing. In a school where there are teachers other than class-teachers – for example say art, dance, sports, etc. teachers in addition to class teachers – there, class size will be higher than the PTR. However, in public elementary schools in India, there are hardly any such teachers appointed. Mean public school size is 97 students per elementary school (DISE, 2017-18) but in 68% of schools total enrolment is less than 100 and mean enrolment per school is 45 students. Given that schools are mandated to have at least two teachers, the mean PTR in a school with an enrolment of 45 is 22.5 if the school has two teachers, or PTR is 15 if there are three teachers. If say three teachers teach 5 classes separately, then (given 5 classes and 45 students), mean class size is 9 students, i.e. lower than the PTR. But if 3 teachers means that two of the five classes run as multi-grade classes, then class size would be 15, i.e. still lower than the PTR.

[vii] For example, in Krueger (1999), the most well-known study and that used the RCT approach, a reduction of 8 students per class increased learning score statistically significantly but by only 0.2 SD and this only in the first year of school.

[viii] In Israel, maximum class size is 40. Consequently, when student increases from 40 to 41, a new section has to be formed and average class size exogenously becomes 20.5, i.e. the change is class size is not because of the choice of pupil or school.

[ix] All students take 6 subjects. English is a compulsory subject for all students. Science-stream students take English, Physics and Chemistry as compulsory subjects and must choose between Mathematics or Biology, and also choose two optional subjects from among Hindi, Biology, Bio-Technology, Computers, and Physical-Education. Commerce-stream students take English, Economics, Commerce and Accountancy as compulsory subjects, along with two optional subjects from among Hindi, Psychology, History, Geography, Computers and Physical-Education. The Humanities subject combination is taken by fewer students and students can combine compulsory English with a range of the above subjects, such as psychology, History, Geography, Hindi, etc.

[x] Physical Education is a non-academic subject, an outlier (with all students obtaining a very high mark in PEd) and scoring well in PEd does not need much effort, special training or ability, nor is it a high stakes subject since performance in PEd does not get counted for admission to university

[xi] For the Pre-board exam, the sample school chain centrally prepares a grade 12 internal examination paper in each subject, which is taken by the students at all ten schools in the chain. Scripts are marked by the teachers in each school, but on a pre-agreed mark-scheme. The pre-board exam takes place in December when the syllabus is complete. Prior to that, grade 12 students take the First Comparative exam in June and the Second comparative exam in September.

[xii] OLS estimation without either pupil fixed effects or prior achievement controls shows a positive linear statistically significant relationship between class size and student achievement, but adding pupil fixed effects reduces the point estimates and also renders the class size coefficient statistically insignificant. The OLS value-added estimation i.e. with prior ability term included, shows a strongly concave relationship between class size and achievement, with both the linear and quadratic terms of class size being highly statistically significant, with a turning point at a (hypothetical) class size of 82, suggesting that learning achievement *increases* with class size, but at a decreasing rate. But again, adding pupil fixed effects reduces the size of both the linear and quadratic class size terms and also renders them both statistically insignificant.

[xiii] In each school, there are several sections (classes) of grade 12.

[xiv] When we cluster standard errors at the pupil level (not shown), we get statistically highly significant coefficients. Clustering at the class level raises the SEs and renders the results statistically insignificant in most cases. Though after clustering SEs at the class level we can no longer talk about the turning point with confidence, we conclude that student learning is non-decreasing in class size over the whole observed range of class sizes.

[xv] The science subjects' group consists of physics, chemistry, biology, biotechnology and maths.

[xvi] We consider a student as studying in the science stream if his/her core subject combination has Physics, Chemistry and Mathematics (PCM) or Physics, Chemistry and Biology (PCB) out of 6 subjects. Students without PCM or PCB combinations are categorized as non-science students.

[xvii] 1 SD of achievement in the school's (pre-board) exam is 18.38 per cent mark. This is the mark used throughout the analysis.

[xviii] There are some inexplicable variations in published official statistics on the pupil teacher ratio in public elementary schools. For example, in 2019-20, DISE data show the PTR to be 25.1 (Table 8a in Datta & Kingdon, 2021). However, all official sources put PTR at between 21.5 to 25.

[xix] Enrolment and total number of teachers at secondary and higher secondary level are 26276072 and 941725 respectively in 2016-17. Source: http://udise.schooleduinfo.in/

[xx] For a detailed explanation on fake enrolments, see section IV of Datta and Kingdon (2021).

[xxi] We are unable to compute the effective pupil teacher ratio (EPTR) at secondary and higher secondary school levels due to lack of any survey data on pupil and teacher absence rates for these levels.

[xxii] A PTR of 40 is roughly in the middle of the flat range of the relationship, i.e. 40 is roughly half way between class-sizes 27 and 51, where the relationship between class-size and achievement score is approximately flat/non-decreasing.

[xxiii] Rodriguez-Segura, D. (2021); Cristia, J. et. al. (2017); Snilstveit, B. et. al. (2016); Evans, D. K., & Mendez Acosta, A. (2021); Cilliers, J. et. al. (2020); Castro, J. F. et. al. (2021); Lee, S. M. et. al. (2009).

[xxiv] https://web.archive.org/web/20140407102043/http://www.rbi.org.in/scripts/PublicationsView.aspx?id=15283 (The proportion of BPL population in India was 21.92% as per 2011-12 NSS survey

[xxv] http://udise.schooleduinfo.in/dashboard/elementary#/

[xxvi] The total number of children enrolled in classes 1 to 8 in all school types in India in 2017-18 was 187,826,622, as per UDISE 2017-18 data (http://udise.schooleduinfo.in/dashboard/elementary#/). Since 21.92% of the population were Below Poverty Line (http://mospi.nic.in/sites/default/files/publication_reports/India_in_figures-2018_rev.pdf) as per the latest available NSS 2011-12 data estimates, and we presume this percentage remained the same in 2017-18, this means that 41,171,595 elementary school children were BPL in 2017-18.

[xxvii] Average MGNREGA wages was Rs. 201 in 2017-18. Source: https://nrega.nic.in/netnrega/writereaddata/Circulars/2058Notification_wage_rate_2017-2018.pdf

[xxviii] For the non-remedial children who were left behind in the class when the academically weaker children were taken out for a remedial class by the teacher-aide (Balsakhi).

[xxix] For example, Cilliers et. al. (2020) find that a teacher coaching programme was effective only for moderate class sizes.