IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17362

The Effectiveness of Teamwork for Student Academic Outcomes: Evidence from a Field Experiment

Ritwik Banerjee
Niels-Hugo Blunch
Daniele Cassese
Nabanita Datta Gupta
Paolo Pin

OCTOBER 2024

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17362

The Effectiveness of Teamwork for Student Academic Outcomes: Evidence from a Field Experiment

Ritwik Banerjee
Indian Institute of Management and IZA

Niels-Hugo Blunch
Washington and Lee University and IZA

Daniele Cassese
University of Cambridge

Nabanita Datta Gupta
Aarhus University and IZA

Paolo Pin
University of Siena and Università Bocconi

OCTOBER 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Effectiveness of Teamwork for Student Academic Outcomes: Evidence from a Field Experiment*

An enduring question in education is whether team-based peer learning methods help improve learning outcomes among students. We randomly assign around 10,000 middle school students in Karnataka, India, to alternative peer learning treatments in Math and English that vary the intensity of collaboration. Teamwork with co-coaching outperforms simple teamwork and incentive treatments by increasing the test scores by about 0.25 standard deviation, but only in Math. This is both statistically and economically significant for students at the bottom of the ability distribution. We develop theoretical conditions under which teamwork with co-coaching outperforms simple teamwork as a peer-learning method.

JEL Classification: I20, I24, C93
Keywords: cooperative learning methods, jigsaw, peer effects

Corresponding author:
Nabanita Datta Gupta
Department of Economics and Business Economics
Aarhus University
Fuglesangs Allé 4
8210 Aarhus V
Denmark
E-mail: ndg@econ.au.dk

* We thank Bertil Tungodden, Daniela di Cagno, Damiano Argan, Kartik Muralidharan, Gautam Rao, Nishith Prakash, Steven Haider, Gordon Dahl, Anna Piil Damm, Silke Anger, Malte Sander, Bart Golstyn, Andries de Grip, Raymond Montizaan, Michael Rosholm, Tarun Jain, seminar participants at University of Mastricht, DIW, Berlin, CSSS, Kolkata, and IAB Nuremberg for their comments during the course of this project. We would like to acknowledge the research assistance of Susnata Ganguly, Priyama Majumdar, Santosh Siwach, and Madhukari Mishra at various stages of the project. This study is registered at the randomized trail registry of the American Economic Association, see AEARCTR-0002567. We gratefully acknowledge the generous research support from the Danish Research Foundation (DFF) grant no. DFF – 1327-00037. P. Pin acknowledges funding from the Italian Ministry of Education Progetti di Rilevante Interesse Nazionale (PRIN) grants P20228SXNF and 2022389MRW.

1. Introduction

In recent years, research on education in developing countries has shifted from a focus on increasing school inputs and improving infrastructure (Glewwe, 1999) to enhancing the quality of instruction and interactions within the classroom (Muralidharan, 2019). A challenge in such settings is how to close the large achievement gaps that exist between children of different ability levels within the same classroom and at the same time improve overall learning levels within the remit of a resource-constrained public education system. The literature suggests that peer-based learning methods are promising candidates in this regard (Epple and Romano, 2011; Sacerdote, 2011).

While peer-based learning environments have been found to improve learning outcomes in general, Carrell et al. (2013) showed that low achievers do not necessarily benefit if they are randomly paired-up with high achievers. They surmise that a plausible reason for this is a lack of interaction between the two groups. Clearly, while institutional arrangements can help bring students from diverse backgrounds together, they may not result in actual inter-group interactions. One way to directly facilitate interactions between students is by employing cooperative learning methods. Cooperative learning in the classroom, involving different types of teamwork among students of diverse backgrounds, has been practiced since the 1970s (Slavin, 1989).

In this paper, we embed a peer-based cooperative learning method that facilitates interactions between students of different ability groups within the structure of a standard course curriculum. We conduct a randomized control trial in the state of Karnataka, India, at the middle school level in 37 schools within a common schooling system sharing syllabus, teaching objectives and methods. We introduce alternative team-based peer learning methods in the classroom and measure their impacts on learning outcomes in Math and English. We also report on whether teamwork benefits both high-achieving and low-achieving students alike. Finally, we derive the theoretical conditions under which teamwork can improve such outcomes.

The randomization is done at the school level and assigns nearly 10,000 students in grades 6, 7 and 8 in these 37 schools to three treatment arms and a control arm. Our treatments are nested and are denoted, respectively, Pair, Pair-Incentive, Pair-Incentive-Jigsaw. The control arm is the status quo with teacher-based instruction and usual, endogenously determined seating arrangement within the classroom. In the remaining treatments, pairs of students with different ability levels form bench-mates. Pair treatment introduces this mixed seating arrangement. Pair-Incentive, in addition to pairing by ability, offers a status reward to the pair that has the highest combined score in the endline. The final treatment, Pair-Incentive-Jigsaw, was inspired by the seminal work of Aronson et al. (1978). In addition to Pair-Incentive, this treatment facilitates a cooperative learning method, namely the Jigsaw method, where students develop expertise in parts of the day's lesson and subsequently co-teach each other. The motivation behind these alternative treatments is to vary the intensity of collaboration and test whether they have differential effects on outcomes. Thus, while paired seating captures the simplest type of teamwork that can arise between students of different ability levels, the Pair-Incentive-Jigsaw treatment requires intense collaboration with co-coaching. This nested structure of the experiment allows us to identify the mechanism behind why mixed-pair seating can produce positive effects, as has been found in the literature (see, for example, Li et al. (2014)).

Our findings show that mixed pair seating with Jigsaw-based learning techniques produces positive effects on student educational achievement, as measured by test scores. Further, this form of teamwork with co-coaching, outperforms simple teamwork and teamwork with incentive, by increasing the test scores by about 0.25 standard deviations, but only in Math. Further, the effect is both statistically and economically significant not only for all students but also for those at the bottom of the ability distribution. Our theoretical model predicts conditions under which teamwork with co-coaching outperforms simple teamwork as a peer-learning method and show that the mechanism depends on whether one's own effort improves one's own productivity more than the partner's effort does. The nature of Math, which requires one's own effort and practice in addition to being exposed to the concepts and techniques may thus be more amenable to Jigsaw-type cooperative learning techniques than English, in which exposure at home, for instance, may play a larger role.

In Section 2 we review the literature and in Section 3 we describe the experimental design. Section 4 presents and discusses results. Section 5 sketches a theoretical model with conditions under which (different forms of) teamwork can elicit more student effort, and Section 6 concludes.

2. Literature Review

For improving the quality of education further in developing countries, research needs to look beyond interventions focusing on increasing enrolment or increasing investments in inputs such as infrastructure, school materials etc. and focus instead on implementing learning interventions within the classroom that can improve students' basic skills in reading and numeracy (Glewwe and Muralidharan, 2016). Such pedagogical interventions are both low-cost and highly effective in raising test scores (Kremer and Holla, 2009). In many developing country settings, large class sizes make it difficult for teachers to provide individualized attention. Cooperative learning, which has been shown in meta-studies to reduce intergroup hostility and prejudice as well as improve student outcomes (Aronson, et al. 1978; Slavin, 1991; Johnson et al. 2000) is a potentially effective way to enhance an individual student's learning within a resource-constrained public education system.[1] These methods are usually practised at the school level in

[1] Jigsaw, Learning Together (LT), Student Team Achievement Divisions (STAD) are some prevalent cooperative learning methods.

developed countries, but they have also been introduced at the university level (Johnson et al. 2024), in teacher training programs, in on-the-job training and in workplaces.

A unique feature of cooperative learning methods is that the greater part of the class time is used to work together in small groups to achieve learning goals, i.e., it is a form of peer learning but with teacher facilitation and mentoring. Another feature is that student groups are generally mixed by ability. Such pedagogical practices have been examined in the education and social psychology literature and are generally associated with an improvement in academic and non-academic outcomes (see meta-analyses by Johnson et al. (1981), Johnson and Johnson (2002), Roseth et al. (2008), Slavin (1989), and Gillies (2016)). However, many of these studies on cooperative learning methods are affected by small samples, which are convenience/selected samples (rather than random samples), and often have non-random treatment assignments. Our study addresses these limitations by conducting a randomized control trial and carefully measuring effects on different parts of the ability distribution – issues that are often not addressed.

The economics literature examines peer effects in education, largely in high income settings, by exploiting the quasi-random assignment of students to their dormmates or roommates.[2] Peer effects are often found to be stronger for social outcomes than academic outcomes (Sacerdote, 2011). At the primary and secondary levels, which are the levels of the current study, peer effects have been found to be, at best, modest. A key finding is that peer effects are largest at the top and bottom and less at the middle and depend on peer group composition (Feld and Zölitz, 2017). Past literature has found that high-achieving peers gain from being matched to other high-achieving peers (Imberman, Kugler and Sacerdote, 2009). Some studies try to probe the conditions under which high-achieving peers can positively affect low-achieving peers' academic outcomes without hurting their own performance. A factor that seems to be important is whether there is sufficient interaction between different student groups (Carrell, 2013). A key contribution of our paper is that we test whether varying the intensity of inter-group interactions has different effects on the outcomes. Relatedly, unlike much of this literature, our paper investigates these questions in the context of public schools of an economically disadvantaged region, namely Karnataka, India.

The paper closest in spirit to ours is by Li et al. (2014). They randomly assign half of the bottom 20 low-achieving primary-level students within a classroom of migrant schools in Beijing to high-achieving bench mates. The remaining bottom students in the classroom are then assigned to the control group. Their results show that pairing across ability levels improves low-achiever combined (Math and Chinese) test scores by 0.265 SD without hurting the high-achievers. Incentives alone do not improve low-achieving student scores and neither does pure pairing alone. Thus, group incentives plus mixed pair seating together generate positive treatment effects. However, it remains unclear whether the treatment makes both high and low-achieving students expend more effort in coaching their bench-mates. Besides involving a risk of spillovers to other untreated students (although there is little evidence of that in their setting), their design relies on giving monetary incentives to only some students in the classroom – a feature that may be difficult to scale up in low-income environments. Further, they do not examine whether a change in the pedagogy makes any difference – something that becomes particularly relevant given that, like us, they do not find a pure bench-mate effect. Our paper contributes to this literature by addressing these issues, in addition to separately identifying effects by Math and Language. In doing so, our paper helps understand which subjects are most amenable to cooperative learning. We further add to this study by demonstrating that co-coaching is the mechanism that produces the overall positive effect of team-based learning.

Thus, in this paper we ask: can team-based peer learning improve academic performance? Can such methods reduce achievement gaps such that low-ability children are helped without harming high-ability children? What level of collaboration – simple or with co-coaching is needed to produce positive effects? Does team-based learning work equally well in Math and in English? And finally, which theoretical conditions are consistent with the observed effects?

3. Experimental Design

3.1. The Randomized Trial: Background

The RCT was run in close association with *Kendriya Vidyalaya Sanghathan* (KVS). KVS is a system of schools under the administration of the Ministry of Education, Government of India, with about 1250 schools under its aegis. The stated aim of the *Sanghathan* is to impart knowledge and values through high quality educational endeavours, particularly for children of the often-transferred central government employees. While Kendriya Vidyalaya schools or KVs are public schools, they are much better managed, better funded, attract more qualified teachers and have different student profile than the public schools managed by the state governments. For this trial, we received permission to collaborate with the Karnataka chapter of KVS, which administers 50 KVs (including 5 KVs in Goa), from the KVS Headquarters, New Delhi.[3] Out of the 50 KVs in Karnataka & Goa, on grounds of feasibility, we had to exclude 13 KVs.[4] Eventually, we ran the RCT with students from grades 6, 7 and 8 in 37 schools, covering about 10,000 students in total. The schools are represented treatment-wise on a map of Karnataka and Goa, India in

[3] Karnataka is a large state in the southern part of India, with a population of 64 million. For a map of the geographic placement of KVS schools in Karnataka see Appendix Figure A2.

[4] Our project was on a tight timeline with respect to the funding, and as these 13 schools did not send their baseline information to us on time, they could not be included in the randomization and intervention. However, as they sent their information later, we were able to incorporate these schools in the analysis by running selection models and testing whether our results are driven by selection effects.

Figure A2. Our RCT was designed to examine the effect of the interventions on two subjects: English and Math. Every student participated in a baseline and an endline test, each of which comprised of standardized questions in Math and English, along with a short survey containing basic background questions. All tests were administered and invigilated by trained enumerators. The tests were carried out simultaneously across all schools to minimize leakage of questions. To avoid cheating, test questions were scrambled, and three different versions were handed out to the students (see Appendix E).

We randomized the 37 schools using the block randomization technique. We define blocks based on district income and school size to ensure that the treatments are broadly balanced. Post-randomization, we compare pre-treatment variables to ensure that certain observable characteristics of the schools and students are balanced across treatments (see Table A1). The pre-treatment variables are well-balanced and deviations from control group means are not statistically significant for any variable, except for class size, where Pair and Jigsaw classes are on average smaller. We use these pre-treatment variables as additional explanatory variables in regressions controlling for baseline scores for increasing the precision of the estimated treatment effects.

3.2. Treatments

Each school was randomly assigned one of the four treatments:

(i) Control Treatment: These schools are not offered any intervention. We simply conduct the baseline and endline tests. The seating pattern follows the status quo, where students sit according to endogenously formed pairs.[5]

(ii) Pair Treatment: In this treatment, students are grouped in pairs within each classroom and are assigned seats next to each other. How are the pairs determined? A baseline test is conducted. Students are ranked within their gender according to the scores in the test.[6] Pairing is done such that the top ranked student is paired with the student with the lowest rank (within the same gender). For example, if there are 50 students in a class, the rank 1 student is a girl, rank 2 is a boy, rank 49 and 50 are girls and boys, respectively, then rank 1 and rank 49 students are paired together, and rank 2 and rank 50 students are paired together. The paired students are assigned specific benches and

[5] Our field visits at the time of designing the RCT revealed that there was no rule describing how students should sit, and students endogenously formed groups to sit with friends.

[6] During our initial visits to the KVs, we had noticed that the seating arrangement of the children were gender segregated, with one column of desks assigned to boys and another to girls. One of the authors of this paper, a former KV student, recalls a similar norm in his school, located in a different state and belonging to a different era. We did not want to disrupt the widely held, deeply entrenched gender norms in the schools, so as not to confound our results with other social forces. Our visits also revealed that KVs follow a uniform classroom design across all schools, with mostly two students at a desk, and only rarely one student at a desk.

are required to sit together. This pairing scheme, consistent with that used in other studies (Li et al., 2014) paired students in the middle of the score distribution together and those in either end together. Notably, mixed ability pairing is a key feature of cooperative learning methods such as the jigsaw method described below.

(iii) Pair-Incentive Treatment: In this treatment, students are grouped in pairs, exactly as in the Pair Treatment. However, the top three groups, as per the highest combined scores in the endline test, are rewarded. The reward comes in the form of a prize, that is publicly given out in an award ceremony in the school assembly. This form of reward, a prize and public felicitation, is commonplace in KVs. Exceptional performance in major competitions such as Olympiads are routinely, publicly felicitated in school assemblies and such forms of social recognition are highly coveted among students. While the literature uses other forms of rewards, (e.g. cash awards (Li et al., 2014), scholarships (Kremer et al., 2009)), we choose not to use them to achieve scalability and consistency with local practices and norms.

(iv) Pair-Incentive-Jigsaw Treatment: In this treatment, students are grouped in pairs and are offered incentives, exactly as in the Pair-Incentive Treatment. Additionally, the jigsaw method of learning is implemented in the respective classes by the class teachers. We describe the jigsaw method in more detail below.

3.3. Jigsaw Method of Education

Cooperation, and not competition, forms the basis of the jigsaw method of education[7]. In a jigsaw classroom, students are allocated to their jigsaw groups, which are small groups of 2-4 students (2 in our case), who form the basis of the cooperative learning unit. The lesson for the day is then divided into two parts. Each student in the jigsaw group is assigned one of the two parts. Each student becomes an expert in their assigned part by going through the material themselves, and then meeting with a small group of students from other jigsaw groups who are assigned the same part of the material ("expert group"). In our case, the expert group size is 4, i.e., a student is matched with 3 other closely seated students who are assigned the same part of the lesson. The expert group studies that part together, till the point where each student can teach that part to their "non-expert" students. After specializing in their part of the lesson, the students get back to their jigsaw groups. A jigsaw group now has two students, each specializing in one of the two parts of the lesson. Each student now teaches their own part to the other student (i.e., co-coaching). This design necessarily demands cooperation among students, as each student specializes in one part of the whole. The role of the teacher is largely to introduce the lesson at the beginning of the class, manage the discussions in the expert and jigsaw groups, and finally, offer a summary at the end.

[7] See Aronson et al. (1978).

We needed the help of an education-consultant who had extensively researched and practiced the jigsaw method for implementing this. First, executing the jigsaw method of education in an Indian classroom needed some training. The teachers involved in teaching Mathematics and English in grades 6, 7 and 8 of the schools assigned to the Pair-Incentive-Jigsaw treatment were invited to a two-day special training session.[8] The training was given by the education-consultant. Second, the jigsaw method of education requires that the lesson of the day is appropriately divided into two parts, and that the key point of each part is explicitly laid out. Notice, that we did not introduce a different content, but simply helped transform the standard syllabus of the class into a jigsaw friendly format. The preparation of the lessons into a jigsaw friendly format was done by a team of education-consultants.

3.4. Implementation

We conducted the randomized trial in 2017-2018. The baseline test was conducted in August 2017 and had two parts, one each in English and Math. The randomization across the treatments was done within blocks defined based on district income and school characteristics. The study is powered to detect minimum effect sizes 0.25-0.29 SD with 80% power and a 5% significance threshold.[9] Teachers randomized to the jigsaw treatment were trained in the method by a team of educational consultants in October 2017. Overall, the interventions were in place for 4 months, November-February. The endline test was conducted in March 2018, before the final exam of the session. Different grades were administered separate, grade-appropriate tests prepared by our educational consultants. The awards were given out in the fall of 2019, when the new academic year had begun.

3.5. Description

We report the treatment-wise summary of the control variables for the full sample in Table A1 (N=9,838). The coefficients of 'Control' indicate sample mean for control treatment, while those of the treatments indicate the respective difference from the control treatment, as estimated by regressions that include block fixed effects and clusters the standard errors at school level. Table A1 shows that the pre-treatment characteristics are largely balanced, except for class size. We control for these variables in our regression specifications. Density distributions of baseline and endline test scores by subject and intervention type pooled across grades can be found in the Online Appendix, Figure A1.

[8] The entire program was implemented in close association with KVS Headquarters, which also issued the mandate of the training. Consequently, all the selected teachers were present.

[9] The power calculation initially assumed an intra-cluster correlation of 0.05 (MDE = 0.29) where a cluster is a school, but e.g. in Math, the intra-cluster correlation within control schools was ex post found to be 0.03, implying an MDE of 0.25.

4. Results

In this section we examine the effect of three alternative treatments (Pair, Incentive, and Jigsaw) on two outcomes: standardized Math and English test scores. To additionally estimate the pure effect of the Incentive and Jigsaw components, we compare Pair-Incentive with Pair and Pair-Incentive-Jigsaw with Pair-Incentive (see Appendix B for details of the empirical specifications). All specifications incorporate sampling weights (defined as the relative block shares) and clustered (at the school level) standard errors.[10] From these models, we estimate the treatment effects. Note that since the data originates from a randomized controlled trial, the estimates can be interpreted as causal treatment effects.

Table 1 presents our main results. The table consists of four columns, where the first two columns provide the results for Math and English test scores without control variables and the following two columns provide the results for Math and English test scores with the control variables added. Starting with the primary results, there appears to be a negative effect of the pure Incentive on Math test scores, both without and with controls, but statistically significant at the 10% level only. The pair treatment does not have any effect on Math. Further, none of the treatments have any effect on English test scores. Obtaining a negative effect of incentives is not a new result in the literature, for example, Fryer (2011) finds a negative (albeit non-statistically significant) effect of financial incentives on Math scores for 9th-grade students in Chicago schools. More recently, Jain and Tan (2023) find that there is no effect of individual level incentive on student performance in Kenya. Further, in our case the negative effect on Math does not survive randomization inference (Table A5 and Table A6). Overall, our primary results align with Fryer (2011). Turning next to the pure effect of Jigsaw, our estimates show that the effect on Math test scores is almost a quarter (0.239) of a standard deviation (SD) without any control variables (col(1)). This effect persists, and even slightly increases (to 0.251 SD), when the control variables are added (col(2)).

[10] For more details on the estimation strategy, see Appendix B.

Table 1: Treatment effects on Math and English, with and without the control variables

	Math	*English*	*Math*	*English*
	(1)	*(2)*	*(3)*	*(4)*
Pair TE	0.014	0.267	0.021	0.223
	(0.09)	(0.167)	(0.097)	(0.152)
[p-value]	[0.879]	[0.11]	[0.828]	[0.141]
N		6,142		
Incentive TE	-0.192*	-0.081	-0.175*	-0.046
	(0.104)	(0.163)	(0.101)	(0.154)
[p-value]	[0.064]	[0.618]	[0.085]	[0.764]
N		4,979		
Jigsaw TE	0.239**	-0.184	0.251**	-0.163
	(0.11)	(0.131)	(0.106)	(0.136)
[p-value]	[0.03]	[0.159]	[0.018]	[0.23]
N		3,742		
Baseline characteristics	No	No	Yes	Yes

Notes: Columns (1) and (2) include the treatment variables, own baseline test scores and block FEs. Columns (3) and (4) additionally include the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses and p-values in square brackets.

Stratifying by ability (as defined by their baseline test scores) in Table 2 reveals that, starting with the primary results, the negative effect of the Incentive treatment on Math scores is not statistically significant any longer, except for the middle third of students (col(2)). Additionally, there appears to be a positive and statistically significant effect of the Pair treatment on English scores for the bottom third students (col(4)). The effect on English scores is not robust to randomization inference (see Table A5 and Table A6). Turning next to the effect of the pure Jigsaw treatment, we see that that the effect on standardized Math scores seen in the full-sample specification reported in Table 1 remains positive and statistically significant (at 5 percent) across all three ability groups. The magnitude of the effect is largest for the top third of students, at 0.249 SD (col(2)), and smallest for middle third, at 0.22 SD (col(3)). Hence, we can say that the main (statistically significant) effect of our treatments appears to be more effective at improving Math scores than language scores, which is consistent with the literature (Fryer 2017). One of the leading theories to explain this divergence between Math and English argues that when English is not the language spoken outside of the classroom it is particularly difficult to increase reading scores (Charity et. al., 2004) and this is likely to be the case for many students in our sample. Another study finds that when rich and poor students are exogenously mixed in private elite school classrooms in Delhi, learning outcomes are negatively affected in English but not in Math (Rao, 2019). Poor students in an Indian context are less likely to have been exposed to English at home, which is consistent with the theory above.

Table 2: Treatment effects on Math and English, stratified by ability

	Math			*English*		
	Bottom	*Middle*	*Top*	*Bottom*	*Middle*	*Top*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Pair TE	0.072	0.017	0.002	0.201*	0.241	0.221
	(0.088)	(0.099)	(0.121)	(0.118)	(0.164)	(0.178)
[p-value]	[0.413]	[0.864]	[0.121]	[0.089]	[0.142]	[0.215]
N	2,092	1,885	2,165	2,092	1,885	2,165
Incentive TE	-0.138	-0.229**	-0.18	-0.059	-0.044	-0.072
	(0.103)	(0.113)	(0.116)	(0.132)	(0.142)	(1.165)
[p-value]	[0.18]	[0.043]	[0.12]	[0.657]	[0.757]	[0.661]
N	1,706	1,522	1,751	1,706	1,522	1,751
Jigsaw TE	0.235**	0.225**	0.249**	-0.158	-0.184	-0.128
	(0.112)	(0.105)	(0.12)	(0.111)	(0.125)	(0.166)
[p-value]	[0.036]	[0.033]	[0.037]	[0.156]	[0.141]	[0.443]
N	1,280	1,136	1,326	1,280	1,136	1,326

Notes: All columns include the treatment variables, own baseline test scores, block FEs, and the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses and p-values in square brackets.

In Table 3 we add baseline Partner Test Scores to the specifications estimated in Table 2, and we find that the positive effect of Jigsaw on Math decreases only marginally in magnitude by 0.04 SD (col(1)). Partner Test Scores are negatively correlated with outcomes across all treatments, but none of these are statistically significant. As partner test scores capture, in part, partner's effort, this is evidence against imitation being the mechanism driving the findings.[11]

The pure Jigsaw effect for Math in the stratified model persists across the three ability strata after the introduction of Partner Test Scores, as can be seen in Table 4. The effect on the top third students is less precisely estimated than in the previous specification and is

[11] Note, that partner here refers to the jigsaw group partner only, as we did not collect data on the expert group composition.

now statistically significant at 10 percent (col(3)). The Jigsaw effect on the bottom and middle are 0.246 SD (col(1)) and 0.237 SD (col(2)), with p-values 0.025 and 0.023, respectively. In turn, this indicates the presence of a positive externality from being with better ability partners, especially when the student her or him -self is at the lower part of the ability distribution.

Table 3: Treatment effects on Math and English, adding partner test scores

	Math	*English*
	(1)	(2)
Pair TE	0.018	0.217
	(0.096)	(0.147)
[p-value]	[0.852]	[0.15]
Partner test score	-0.024	-0.034
	(0.017)	(0.025)
[p-value]	[0.161]	[0.18]
N	6,142	
Incentive TE	-0.175*	-0.061
	(0.103)	(0.146)
[p-value]	[0.088]	[0.678]
Partner test score	-0.019	-0.087**
	(0.025)	(0.005)
[p-value]	[0.431]	[0.031]
N	4,979	
Jigsaw TE	0.247**	-0.156
	(0.107)	(0.129)
[p-value]	[0.021]	[0.225]
Partner test score	-0.028	-0.029
	(0.031)	(0.037)
[p-value]	[0.357]	[0.434]
N	3,742	

Notes: Columns (1) and (2) include the treatment variables, own baseline test scores, block FEs, the control variables presented in Table A1, and partner test scores. The standard errors, clustered at the school level, are reported in parentheses and p-values in square brackets.

We can now summarize the above results into 3 main results, as follows:

Result 1. The Jigsaw treatment increases Math test scores between 0.24 SD and 0.25 SD compared to the control treatment.

Result 2. Stratifying by ability (as defined by students' baseline test scores) reveals that the Jigsaw treatment yields a positive, statistically significant effect on Math scores across the three ability strata, and this effect is marginally stronger for top ability students.

Result 3. The Jigsaw effect for Math across all ability strata persists after the introduction of Partner Test Scores.

We conduct several robustness checks, the results of which are presented in Appendix **A**. First, we estimate treatment effects for two model specifications (non-stratified, including control variables and stratified on ability) using inverse probability weights to account for a selection bias due to the excluded schools. The results Table A3 and Table A4 confirm our main results. Second, to take into account the intra-cluster correlation of the outcome variables, we conduct randomization inference as detailed in Appendix C. Table A5, Table A6 and Table A7 report the randomization inference p-values, as the share of 5,000 simulations in which the absolute value of the coefficient of interest is larger than the absolute value of the result from the true randomization. The positive effect of Jigsaw on Math scores is still statistically significant in all the models in Table A5, albeit at the 10 percent level. Table A6 and Table A7, which present the randomization inference p-values in the stratified model, with and without partner scores, confirm that Jigsaw has a positive effect on Math scores but significant at the 10% level, and only for bottom students.

Table 4: Treatment effects on Math and English, stratified by ability and adding partner test scores

	Math			*English*		
	Bottom	*Middle*	*Top*	*Bottom*	*Middle*	*Top*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Pair TE	0.051	0.011	0.006	0.2*	0.245	0.211
	(0.091)	(0.098)	(0.115)	(0.119)	(0.164)	(0.179)
[p-value]	[0.574]	[0.911]	[0.96]	[0.095]	[0.135]	[0.237]
Partner test score	0.038**	0.01	0.014	-0.006	0.025	0.001
	(0.018)	(0.028)	(0.034)	(0.02)	(0.032)	(0.024)
[p-value]	[0.031]	[0.715]	[0.683]	[0.766]	[0.44]	[0.96]
N	2,092	1,885	2,165	2,092	1,885	2,165
Incentive TE	-0.13	-0.225	-0.181	-0.062	-0.044	-0.081
	(0.1)	(0.11)	(0.117)	(0.132)	(0.142)	(1.162)

[p-value]	[0.195]	[0.041]	[0.124]	[0.639]	[0.757]	[0.615]
Partner test score	0.085***	0.069*	-0.033	-0.027	0.013	-0.067
	(0.026)	(0.038)	(0.057)	(0.027)	(0.026)	(0.052)
[p-value]	[0.001]	[0.066]	[0.561]	[0.321]	[0.614]	[0.052]
N	1,706	1,522	1,751	1,706	1,522	1,751
Jigsaw TE	0.246**	0.237**	0.239*	-0.168	-0.191	-0.12
	(0.11)	(0.104)	(0.124)	(0.105)	(0.125)	(0.163)
[p-value]	[0.025]	[0.023]	[0.053]	[0.11]	[0.127]	[0.46]
Partner test score	0.064*	0.083*	-0.09	0.041	0.046	-0.066
	(0.036)	(0.044)	(0.062)	(0.031)	(0.029)	(0.062)
[p-value]	[0.076]	[0.058]	[0.146]	[0.186]	[0.11]	[0.284]
N	1,280	1,136	1,326	1,280	1,136	1,326

Notes: All columns include the treatment variables, own baseline test scores, block FEs, the control variables presented in Table A1, and partner test scores. The standard errors, clustered at the school level, are reported in parentheses and p-values in square brackets.

The next section sketches a simple theoretical framework, with an aim to understand the mechanism behind the relative effectiveness of different team-based peer learning methods.

5. Theoretical Model

Here, we present sufficient conditions, based on a standard theoretical model, under which teamwork can serve as a more effective incentive for students to exert effort. Specifically, we demonstrate that when two students collaborate in a team and possess varying skill levels, with no capacity to influence each other's skills, the less skilled student may be inclined to rely on the efforts of the more skilled counterpart.

However, if they can coach each other, both the more skilled and less skilled students may be motivated to invest more effort, leading to an increase in overall productivity. Additionally, within the framework of our model, we find additional sufficient conditions for which this incentive for mutual coaching is amplified in the context of a jigsaw approach as opposed to simple teamwork.

So, the presence or not of those sufficient conditions may account for the disparate outcomes between Math and English, with regard to the type of teamwork that proves most effective.

We assume that each student i is characterized by a potential (or productivity) p_i, and that she can put effort e_i for achieving a certain grade. We model this with a production function $g(p_i, e_i)$ which is Cobb-Douglas of the form $g(p_i, e_i) = kp_i{}^{\alpha}e_i{}^{1-\alpha}$. She has a preference for grade and effort which is of the form $u(g, e) = v(g) - e$, and $v(g)$ is CARA with $-\frac{v'(g)}{v''(g)} = r$. In Appendix C we provide more details, the formal proofs, and a more general setup.

We show that if a student is alone, or in the *simple teamwork* treatment (because our model is not based on pure imitation and peer effects), then the function from the potential of a student to her achieved grade is increasing and concave, meaning that the marginal effect of the potential is positive but decreasing in the potential (Proposition 2 in Appendix C). From an empirical point of view, this means that if we observe that student i has a better grade than student j, we infer that $p_i > p_j$.

Next, we model two types of incentivized teamwork. Under *pair-incentive teamwork*, the two students have to prepare separate parts of the project, and the grade is the sum of the two outputs, so that the payoff function for the two students is $v_i(g_i + g_j^*) - e_i$ for student i and $v_j(g_i^* + g_j) - e_j$ for student j.

Instead, under *teamwork with co-coaching* or *Pair-Incentive Jigsaw teamwork*, both have to work on predefined separated parts of the project (the experts' part). We model the payoff functions for the two students as $v(g_i) - e_i + \beta v(g_j^*)$ for student i and $v(g_j) - e_j + \beta v(g_i^*)$ for student i, where $\beta \in (0,1)$ is a constant. Under Jigsaw, the output of student j cannot be changed by student i, and this induces free riding from the weakest student, unless we assume a preliminary form of coaching/teaching between the two students.

So, we assume that students can coach/teach each other before the teamwork commences, and that this activity will increase their productivity. In our model the diffusion of skills is not based on passive diffusion, but work only to the extent to which students put effort in teaching to each other and learning from each other. Let us assume that the coaching function is a function of the following form:

$$t(p_i^0, \tau_i, p_j^0, \tau_j) = (\Delta p_i, \Delta p_j)\,.$$

Depending on initial productivity and effort τ_i and τ_j, they increase their productivity. Students still care only about their grade, and not about their increase in productivity (that is, we assume that they are myopic). In Appendix B we formalize other properties of this coaching function.

One possible assumption on the externalities of these effects that we consider in the model (

Assumption **2** in Appendix C) is that $\frac{\partial t_i}{\partial \tau_i} > \frac{\partial t_i}{\partial \tau_j}$, and symmetrically $\frac{\partial t_j}{\partial \tau_i} < \frac{\partial t_j}{\partial \tau_j}$. This means that the effect of one student's effort is more beneficial for her productivity than for the productivity of the other student.

In the following, we assume without loss of generality that $p_i > p_j$, so that we can assume that students i and j are matched together and i is has a higher potential than j, and then, as discussed above, also $g_i > g_j$ (which is what we can observe empirically). In the context of this model, we show (Proposition 3 in Appendix C) that under the above assumption (and additional conditions at the margins for the initial effect on productivity) that both students will put in effort in both types of teamwork. This means that both will improve their potential. This is what we observe empirically for Math.

For English, we do not observe an impact of Jigsaw on the improvement of students in any part of the grades' distribution. As we discuss in the end of Appendix C, the reason could be that

Assumption **2** does not hold for English. Indeed, we find empirically (see Table A10, commented also at the end of Appendix C) that own effort has a statistically significant, positive association on own score, but only for math.

6. Conclusion

Teamwork among diverse groups of students is the cornerstone of cooperative learning methods. Such team-based peer learning methods have been shown to improve student academic outcomes and reduce bias and stereotyping. However, economists may be concerned about the potential for free riding. Under what theoretical conditions can mixed teamwork improve academic outcomes among low-ability students without harming their high-ability team-mates? Previous literature has been largely based on small samples and incomplete randomization.

This paper reports the findings of a randomized intervention among 10,000 middle school children in Karnataka, India, who are assigned to alternative team-based peer learning treatments in Math and English in different ability groupings. The treatments vary the amount of co-coaching of the study material. We find that teamwork with co-coaching outperforms simple teamwork and incentive treatments.

The teamwork with co-coaching treatment alone produces statistically significant effects, but only in Math. The effect is substantial - an almost 0.25 standard deviation increase relative to the baseline, which is approximately the same as that found in Li et al. (2014) in their intervention, and therefore, points to co-coaching as a possible mechanism producing the effect of pairing students of different ability together as benchmates. Furthermore, we find that an effect of this size is found across all ability thirds of the baseline score distribution but is statistically significant only for bottom students. Thus, low-ability students in the intervention are helped without hurting their high-ability team-mates.

We also find that the statistically significant increase in Math scores at the bottom arises despite the inclusion of partner baseline scores in the model. This indicates that it is the treatment itself and not the partner's skill or effort level or imitation of the partner's work habits that matters for the enhanced performance effect.

Why does teamwork with co-coaching work—and why only in Math? We elaborate the theoretical conditions under which collaborative teamwork outperforms simple teamwork as a peer-learning method and the mechanism that may produce a larger effect in Math than in English. The effectiveness of collaborative learning, such as co-coaching, depends significantly on whether an individual's effort enhances their own productivity more than their partner's effort does. In Mathematics, where mastery requires substantial individual effort and practice beyond initial concept comprehension, co-coaching is particularly effective. This subject's demands align well with the active engagement co-coaching fosters. In contrast, English relies more on external exposure, such as at home, which plays a larger role in language acquisition. As a result, co-coaching may have a stronger impact on Math outcomes than on English, where external factors complement formal learning more heavily.

Our study thus corroborates the earlier educational literature on the positive effects of cooperative learning methods involving co-coaching. It goes beyond the previous literature by imposing a stringent randomization design and exploring the theoretical channels that produce these effects. A limitation is that we report on only the short-run effects of the intervention and the evidence therefore cannot speak to the existence of a longer-term effect. That would require following up on the children's academic performance over time. Furthermore, this paper only investigates effects on academic performance. In ongoing work, we are exploring effects of the intervention on secondary outcomes such as social behavior.

References

Aronson, E., Blaney, N., Stephin, C., Sikes, J., & Snapp, M. (1978). The Jigsaw Classroom. Beverly Hills.

Barker, N., Bryan, G., Karlan, D., Ofori-Atta, A., & Udry, C. (2022). Cognitive Behavioral Therapy among Ghana's Rural Poor is Effective Regardless of Baseline Mental Distress. American Economic Review: Insights, 4(4), 527-545.

Carrell, S. E., Sacerdote, B. I., & West, J. E. (2013). From Natural Variation to Optimal Policy? The Importance of Endogenous Peer Group Formation. Econometrica, 81(3), 855-882.

Charity, A. H., Scarborough, H. S., & Griffin, D. M. (2004). Familiarity with School English in African American Children and its Relation to Early Reading Achievement. Child Development, 75(5), 1340-1356.

Epple, D., & Romano, R. E. (2011). Peer Effects in Education: A Survey of the Theory and Evidence. In Handbook of Social Economics (Vol. 1, pp. 1053-1163). North-Holland.

Feld, J., & Zölitz, U. (2017). Understanding Peer Effects: On the Nature, Estimation, and Channels of Peer Effects. Journal of Labor Economics, 35(2), 387-428.

Fryer Jr, R. G. (2011). Financial Incentives and Student Achievement: Evidence from Randomized Trials. The Quarterly Journal of Economics, 126(4), 1755-1798.

Fryer Jr, R. G. (2017). The Production of Human Capital in Developed Countries: Evidence from 196 Randomized Field Experiments. In Handbook of Economic Field Experiments (Vol. 2, pp. 95-322). North-Holland.

Gillies, R. M. (2016). Cooperative Learning: Review of Research and Practice. Australian Journal of Teacher Education (Online), 41(3), 39-54.

Glewwe, P., & Glewwe, P. (1999). The Impact of Investments in School Quality on Cognitive Skills. The Economics of School Quality Investments in Developing Countries: An Empirical Study of Ghana, MacMillan Press, U.K., 100-166.

Glewwe, P., & Muralidharan, K. (2016). Improving Education Outcomes in Developing Countries: Evidence, Knowledge Gaps, and Policy Implications. In Handbook of the Economics of Education, (Vol. 5, pp. 653-743). Elsevier.

Imberman, S. A., Kugler, A. D., & Sacerdote, B. I. (2012). Katrina's Children: Evidence on the Structure of Peer effects from Hurricane Evacuees. American Economic Review, 102(5), 2048-2082.

Jain, R., & Tan, B. J. (2023). The Effects of Classroom Incentives: Experimental Evidence from Kenya. Harvard University Department of Economics. Mimeo.

Johnson, D. W., Maruyama, G., Johnson, R., Nelson, D., & Skon, L. (1981). Effects of Cooperative, Competitive, and Individualistic Goal Structures on Achievement: A Meta-Analysis. Psychological Bulletin, 89(1), 47.

Johnson, D. W., Johnson, R. T., & Stanne, M. B. (2000). Cooperative Learning Methods: A Meta-Analysis.

Johnson, D. W., & Johnson, R. T. (2002). Learning Together and Alone: Overview and Meta-Analysis. Asia Pacific Journal of Education, 22(1), 95-105.

Johnson, D. W., Johnson, R. T., & Smith, K. A. (2024). Cooperative Learning: Improving University Instruction by Basing Practice on Validated Theory.

Kremer, M., & Holla, A. (2009). Improving Education in the Developing World: What Have We Learned from Randomized Evaluations? Annu. Rev. Econ., 1(1), 513-542.

Kremer, M., Miguel, E., & Thornton, R. (2009). Incentives to Learn. The Review of Economics and Statistics, 91(3), 437-456.

Li, T., Han, L., Zhang, L., & Rozelle, S. (2014). Encouraging Classroom Peer Interactions: Evidence from Chinese Migrant Schools. Journal of Public Economics, 111, 29-45.

Muralidharan, K. (2019) "Reforming the Indian School Education System" in What the Economy Needs Now, edited by Abhijit Banerjee, Gita Gopinath, Raghuram Rajan, and Mihir Sharma, Juggernaut.

Rao, G. (2019). Familiarity Does Not Breed Contempt: Generosity, Discrimination, and Diversity in Delhi Schools. American Economic Review, 109(3), 774-809.

Roseth, C. J., Johnson, D. W., & Johnson, R. T. (2008). Promoting Early Adolescents' Achievement and Peer Relationships: The Effects of Cooperative, Competitive, and Individualistic Goal Structures. Psychological Bulletin, 134(2), 223.

Sacerdote, B. (2011). Peer Effects in Education: How Might they Work, How Big are They and How Much Do We Know Thus Far? In Handbook of the Economics of Education (Vol. 3, pp. 249-277). Elsevier.

Slavin, R. E. (2013). Cooperative Learning and Student Achievement. School and Classroom Organization, 129-156.

Slavin, R. E. (1991). Synthesis of Research of Cooperative Learning. Educational Leadership, 48(5), 71-82.

Slavin, R. E. (1989). Research on Cooperative Learning: An International Perspective. Scandinavian Journal of Educational Research, 33(4), 231-243.

Young, A. (2019). Channeling Fisher: Randomization Tests and the Statistical Insignificance of Seemingly Significant Experimental Results. The Quarterly Journal of Economics, 134(2), 557-598.

ONLINE APPENDIX

A: Additional Tables and Figures

Figure A1: Density distributions of baseline and endline test scores

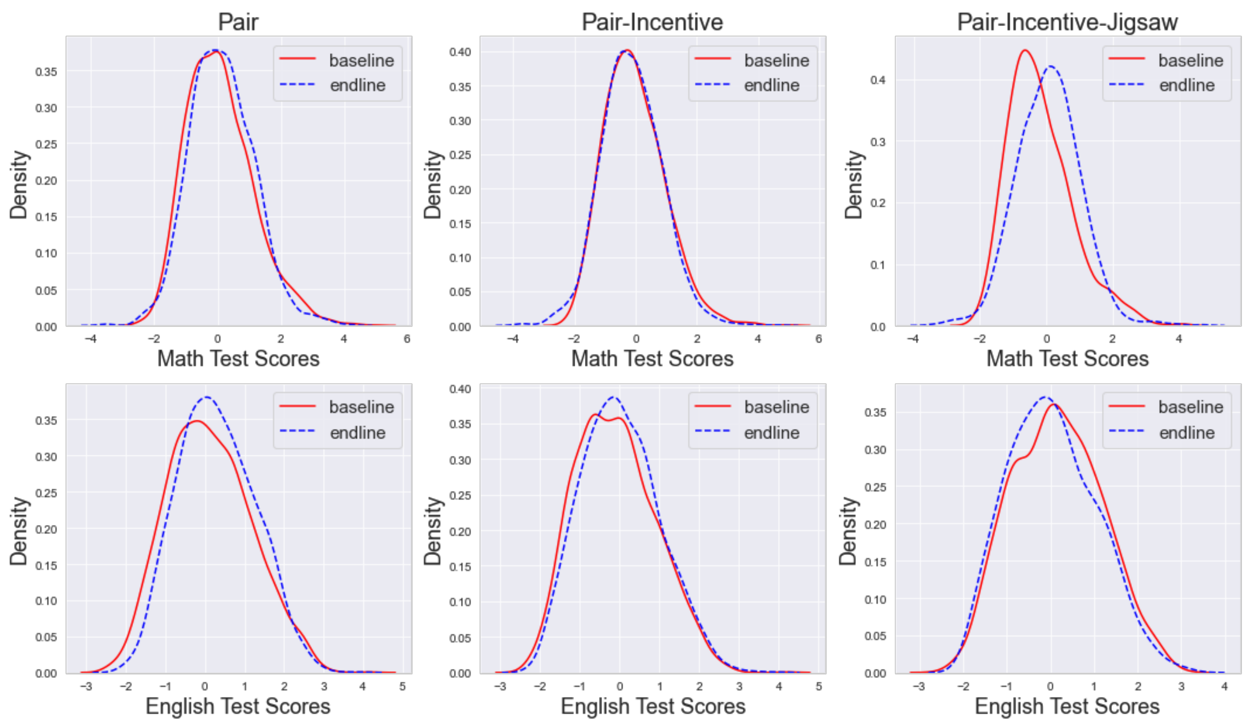
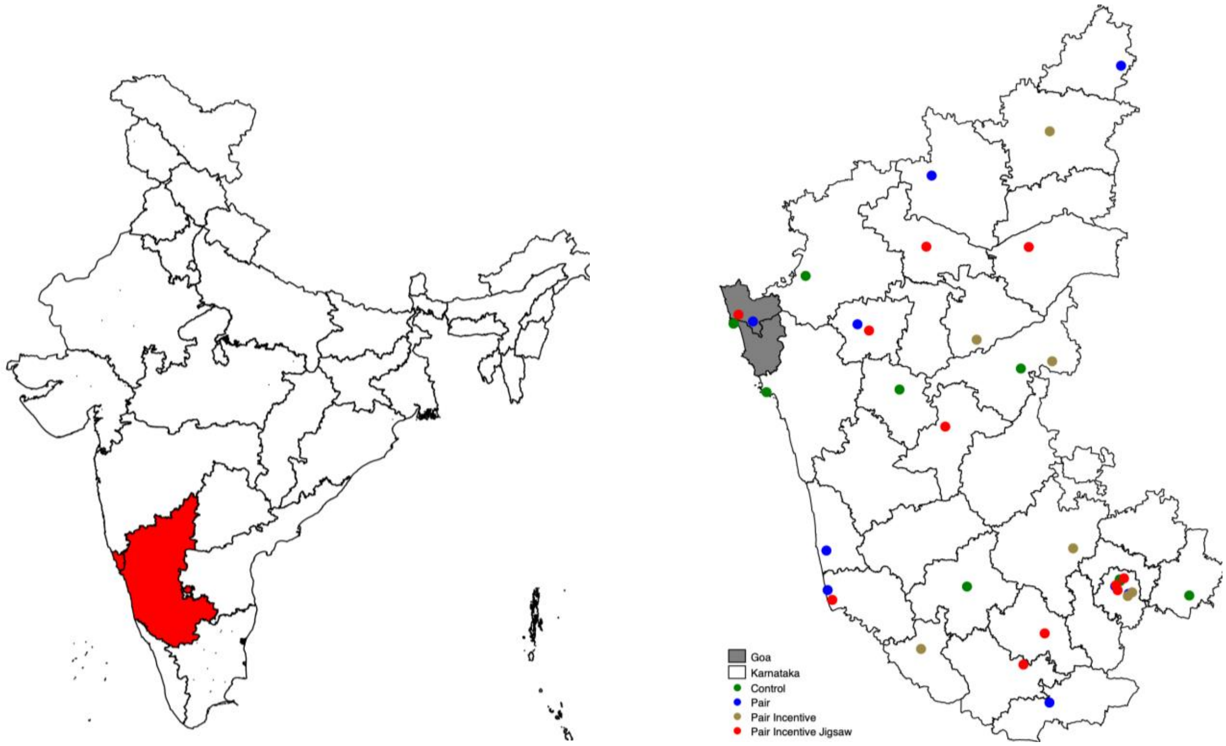


Figure A2: Maps of Karnataka and Goa and the selected schools under different treatments



(a) Map of Goa and Karnataka in India

(b) Treatment-wise locations of the 37 schools in Karnataka and Goa, India

Table A1: Control group means and tests for statistical significance of differences of means between the control and treatment groups for explanatory variables

Explanatory variables:	Age	First Language Kannada	Hindu	High Caste	Father High Education	Number of HH Members
Control	12.488	0.587	0.852	0.319	0.702	4.493
	(0.057)	(0.061)	(0.014)	(0.034)	(0.025)	(0.123)
Pair	-0.056	-0.022	0.006	0.042	0.012	-0.087
	(0.065)	(0.092)	(0.013)	(0.054)	(0.025)	(0.118)
Incentive	0.041	0.017	-0.007	-0.002	-0.011	0.042
	(0.078)	(0.080)	(0.010)	(0.05)	(0.025)	(0.09)
Jigsaw	-0.013	0.087	-0.013	-0.002	-0.002	0.099
	(0.020)	(0.106)	(0.020)	(0.061)	(0.021)	(0.146)

	Mother Works	Class Size	Female
Control	0.289	41.83	0.459
	(0.028)	(1.751)	(0.014)
Pair	0.01	-3.85***	0.028
	(0.036)	(1.391)	(0.017)
Incentive	0.03	-2.642	0.007
	(0.034)	(1.644)	(0.015)
Jigsaw	0.066*	-3.948**	0.024
	(0.036)	(1.658)	(0.02)

Notes: The total number of observations is 9,838. The descriptive statistics in Table A1 have been estimated from regressions including block fixed effects, incorporating weights, and also clustering the standard errors at the school level (similar to the main estimations in Tables 1-4). The numbers for the Control column are the sample means (with standard errors in parentheses), while the numbers for the treatment groups are the deviations from the means of the Control group (with standard errors in parentheses).

Table A2: Control group means and tests for statistical significance of differences of means between the control and treatment groups for the explanatory variables, non-test takers

Explanatory variables:

	Age	First Language Kannada	Hindu	High Caste	Father High Education	Number of HH Members
Control	13.71	-0.371	0.775	0.158	0.907	5.76
	(0.742)	(0.294)	(0.151)	(0.282)	(0.187)	(1.043)
Pair	-0.056	0.059	0.008	0.032	-0.042	-0.167
	(0.16)	(0.107)	(0.038)	(0.066)	(0.039)	(0.231)
Incentive	0.062	0.048	-0.039	-0.025	-0.039	0.015
	(0.148)	(0.072)	(0.033)	(0.055)	(0.033)	(0.247)
Jigsaw	0.086	0.019	-0.072**	0.057	0.006	0.267
	(0.175)	(0.88)	(0.037)	(0.067)	(0.036)	(0.321)

	Mother Works	Class Size	Female
Control	0.937	45.014	0.686
	(0.254)	(2.35)	(0.251)
Pair	0.036	-5.111***	0.009
	(0.047)	(1.565)	(0.045)
Incentive	0.014	-3.446*	-0.092
	(0.051)	(1.795)	(0.046)
Jigsaw	0.061	-3.926**	-0.11**
	(0.061)	(1.828)	(0.054)

Notes: The total number of observations is 941 (70 who did not show for the baseline test, 871 for the endline test). The descriptive statistics in Table A2 have been estimated from regressions including block fixed effects, incorporating weights, and also clustering the standard errors at the school level (similar to the main estimations in Tables 1-4). The numbers for the Control column are the sample means (with standard errors in parentheses), while the numbers for the treatment groups are the deviations from the means of the Control group (with standard errors in parentheses).

Table A3: Treatment effects on Math and English, IPW, including basic controls

	Math	English
	(1)	(2)
Pair TE	0.028	0.236
	(0.099)	(0.136)
[p-value]	[0.776]	[0.131]
N	6,142	
Incentive TE	-0.157	-0.083
	(0.108)	(0.165)
[p-value]	[0.146]	[0.613]
N	4,979	
Jigsaw TE	0.243**	-0.145
	(0.118)	(0.143)
[p-value]	[0.04]	[0.304]
N	3,742	

Notes: Columns (1) and (2) include the treatment variables, own baseline test scores, block FEs, and the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses and p-values in square brackets.

Table A4: Treatment effects on Math and English, IPW, stratified by ability

	Math			*English*		
	Bottom	*Middle*	*Top*	*Bottom*	*Middle*	*Top*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Pair TE	0.064	0.016	0.003	0.203	0.229	0.261
	(0.094)	(0.097)	(0.123)	(0.114)	(0.172)	(0.173)
[p-value]	[0.497]	[0.873]	[0.805]	[0.128]	[0.183]	[0.173]
N	2,092	1,885	2,165	2,092	1,885	2,165
Incentive TE	-0.119	-0.196*	-0.184	-0.095	-0.066	-0.122
	(0.11)	(0.114)	(0.122)	(0.139)	(0.153)	(1.178)
[p-value]	[0.279]	[0.085]	[0.131]	[0.493]	[0.664]	[0.493]
N	1,706	1,522	1,751	1,706	1,522	1,751
Jigsaw TE	0.237**	0.207*	0.247*	-0.14	-0.184	-0.087
	(0.119)	(0.115)	(0.134)	(0.116)	(0.131)	(0.173)
[p-value]	[0.047]	[0.07]	[0.066]	[0.228]	[0.159]	[0.617]
N	1,280	1,136	1,326	1,280	1,136	1,326

Notes: All columns include the treatment variables, own baseline test scores, block FEs, and the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses and p-values in square brackets.

Table A5: Treatment effects on Math and English, randomization inference, with and without the control variables

	Math	*English*	*Math*	*English*
	(1)	*(2)*	*(3)*	*(4)*
Pair TE	0.014	0.267	0.021	0.223
	(0.09)	(0.167)	(0.097)	(0.152)
[RI p-value]	[0.916]	[0.183]	[0.870]	[0.248]
N		6,142		
Incentive TE	-0.192	-0.081	-0.175	-0.046
	(0.104)	(0.163)	(0.101)	(0.154)
[RI p-value]	[0.150]	[0.711]	[0.193]	[0.826]
N		4,979		
Jigsaw TE	0.239*	-0.184	0.251*	-0.163
	(0.11)	(0.131)	(0.106)	(0.136)
[RI p-value]	[0.097]	[0.415]	[0.073]	[0.463]
N		3,742		
Baseline characteristics	No	No	Yes	Yes

Notes: Columns (1) and (2) include the treatment variables, own baseline test scores, and block FEs. Columns (3) and (4) add the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses. Randomization inference p-values (in square brackets) are based on 5,000 permutations inside each block.

Table A6: Treatment effects on Math and English, randomization inference, stratified by ability

	Math			*English*		
	Bottom	*Middle*	*Top*	*Bottom*	*Middle*	*Top*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Pair TE	0.072	0.017	0.002	0.201	0.241	0.221
	(0.088)	(0.099)	(0.121)	(0.118)	(0.164)	(0.178)
[RI p-value]	[0.576]	[0.906]	[0.992]	[0.212]	[0.228]	[0.31]
N	2,092	1,885	2,165	2,092	1,885	2,165
Incentive TE	-0.138	-0.229	-0.18	-0.059	-0.044	-0.072
	(0.103)	(0.113)	(0.116)	(0.132)	(0.142)	(1.165)
[RI p-value]	[0.295]	[0.111]	[0.263]	[0.73]	[0.838]	[0.753]
N	1,706	1,522	1,751	1,706	1,522	1,751
Jigsaw TE	0.235*	0.225	0.249	-0.158	-0.184	-0.128
	(0.112)	(0.105)	(0.12)	(0.111)	(0.125)	(0.166)
[RI p-value]	[0.096]	[0.152]	[0.137]	[0.39]	[0.42]	[0.617]
N	1,280	1,136	1,326	1,280	1,136	1,326

Notes: All columns include the treatment variables, own baseline test scores, block FEs, and the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses. Randomization inference p-values (in square brackets) are based on 5,000 permutations inside each block.

Table A7: Treatment effects on Math and English, randomization inference, stratified by ability, adding partner test scores

	Math			*English*		
	Bottom	*Middle*	*Top*	*Bottom*	*Middle*	*Top*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Pair TE	0.051	0.011	0.006	0.2	0.245	0.211
	(0.091)	(0.098)	(0.115)	(0.119)	(0.164)	(0.179)
[RI p-value]	[0.69]	[0.94]	[0.971]	[0.219]	[0.221]	[0.339]
Partner test scores	0.038	0.01	0.014	-0.006	0.025	0.001
	(0.018)	(0.028)	(0.034)	(0.02)	(0.032)	(0.024)
[RI p-value]	[0.521]	[0.773]	[0.727]	[0.791]	[0.635]	[0.997]
N	2,092	1,885	2,165	2,092	1,885	2,165
Incentive TE	-0.13	-0.225	-0.181	-0.062	-0.044	-0.081
	(0.1)	(0.11)	(0.117)	(0.132)	(0.142)	(1.162)
[RI p-value]	[0.324]	[0.118]	[0.263]	[0.723]	[0.839]	[0.72]
Partner test scores	0.085**	0.069*	-0.033	-0.027	0.013	-0.067
	(0.026)	(0.038)	(0.057)	(0.027)	(0.026)	(0.052)
[RI p-value]	[0.011]	[0.025]	[0.417]	[0.760]	[0.211]	[0.345]
N	1,706	1,522	1,751	1,706	1,522	1,751
Jigsaw TE	0.246*	0.237	0.239	-0.168	-0.191	-0.12
	(0.11)	(0.104)	(0.124)	(0.105)	(0.125)	(0.163)
[RI p-value]	[0.077]	[0.131]	[0.158]	[0.369]	[0.403]	[0.643]
Partner test scores	0.064*	0.083*	-0.09	0.041	0.046	-0.066
	(0.036)	(0.044)	(0.062)	(0.031)	(0.029)	(0.062)
[RI p-value]	[0.159]	[0.010]	[0.104]	[0.126]	[0.222]	[0.335]
N	1,280	1,136	1,326	1,280	1,136	1,326

Notes: All columns include the treatment variables, own baseline test scores, block FEs, and the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses. Randomization inference p-values (in square brackets) are based on 5,000 permutations inside each block.

Table A8: Treatment effects on Math and English, by gender

	Math		*English*	
	Male	*Female*	*Male*	*Female*
	(1)	*(2)*	*(3)*	*(4)*
Pair TE	0.078	-0.039	0.243*	0.2
	(0.106)	(0.095)	(0.136)	(0.172)
[p-value]	[0.461]	[0.683]	[0.074]	[0.243]
N	3,258	2,884	3,258	2,884
Incentive TE	-0.223**	-0.125	-0.052	-0.029
	(0.107)	(0.098)	(0.148)	(0.161)
[p-value]	[0.037]	[0.203]	[0.724]	[0.856]
N	2,623	2,356	2,623	2,356
Jigsaw TE	0.315***	0.191*	-0.196	-0.133
	(0.011)	(0.104)	(0.128)	(0.145)
[p-value]	[0.004]	[0.067]	[0.127]	[0.358]
N	1,988	1,754	1,988	1,754

Notes: All columns include the treatment variables, own baseline test scores, block FEs, and the control variables presented in Table A1. The standard errors, clustered at the school level, are reported in parentheses and p-values in square brackets.

Table A9: Treatment effects on attendance, by gender

	Male	*Female*
	(1)	*(2)*
Pair TE	-0.041	-0.074
	(0.057)	(0.077)
Incentive TE	-0.068	-0.085
	(0.048)	(0.078)
Jigsaw TE	0.012	0.094
	(0.085)	(0.075)
Absent sometimes	0.66	0.731
	(0.06)	(0.094)
Absent often	0.516	0.635
	(0.02)	(0.022)
N	4,335	3,919

Notes: Ordered probit model of reported attendance post intervention: no significant difference in attendance emerges between treatments and control. Both specifications include baseline reported attendance and block fixed effects. Clustered standard errors (at the school level) are shown in parentheses.

Table A10: Effect of own effort and partner effort on Math and English

	Math	*English*
	(1)	*(2)*
Own effort change	0.033**	0.003
	(0.015)	(0.12)
[p-value]	[0.024]	[0.798]
Partner effort change	0.003	-0.018
	(0.013)	(0.013)
[p-value]	[0.822]	[0.156]
N	4,722	

Notes: All specifications here include own baseline test scores, block FEs, and all the additional explanatory variables shown in Table A1. Clustered standard errors (at the school level) are shown in parentheses. These specifications include Pair Treatment, Pair-Incentive Treatment and Pair-Incentive Jigsaw Treatment schools, for a total of 6,314 students. After dropping missing values in the effort variable, we are left with 4,722 students.

B: Estimation Equations

For student *i* in school *j* in community *k*, test scores *TS* at time 1 are regressed on test scores at time 0 (baseline), plus other controls (i.e. a value-added model).

$$TS_{ijk}^{1} = \alpha + \beta_b TS_{ijk}^{0} + \delta_1 Pair_{ijk} + \delta_2 Pair\_Incentive_{ijk} + \delta_3 Pair\_Incentive\_Jigsaw_{ijk} + \beta_x X_{ijk}^{0} + \psi_k + \varepsilon_{ijk}$$

where *Pair* is a binary indicator for the pairing treatment, *Incentive* is a binary indicator for the financial incentive treatment and *Jigsaw* is a binary indicator for the main teaching innovation treatment; X are a set of controls at the level of the student and school; ψ are a set of block fixed effects; and where standard errors are clustered at the level of the school.

Since *Jigsaw* and *Incentive* are combined into one, joint "combination-treatment," we tease out the "pure" (i.e., marginal) *Jigsaw* effect using the following two-step method. First, we restrict the estimation sample to the *Pair* and *Pair_Incentive* groups, only; hence, estimating the following equation:

$$TS_{ijk}^{1} = \alpha + \beta_b TS_{ijk}^{0} + \delta_1 Pair_{ijk} + \delta_2 Pair\_Incentive_{ijk} + \beta_x X_{ijk}^{0} + \psi_k + \varepsilon_{ijk}$$

We then subtract the estimated treatment effect for *Pair_Incentive*, $\hat{\delta}_2$, from the test scores for the *Pair_Incentive_Jigsaw* group (only). In the second step of the procedure we then restrict the estimation sample to the *Pair_Incentive_Jigsaw* and Control groups, only; hence, now estimating the following equation regression:

$$TS_{ijk}^{1} = \alpha + \beta_b TS_{ijk}^{0} + \delta_3 Pair\_Incentive\_Jigsaw_{ijk} + \beta_x X_{ijk}^{0} + \psi_k + \varepsilon_{ijk}$$

The estimated treatment effect for *Pair_Incentive_Jigsaw*, $\hat{\delta}_3$, then, yields the "pure" (i.e., marginal) treatment effect for *Jigsaw*, only.

C: Theoretical model

In the following, we model the incentives of students in a classical effort setup, adding the characteristics of teamwork.

Imagine that a student i is characterized by a potential (or productivity) p_i, and that she can put effort e_i for achieving a certain grade. In the model, we assume that a student cannot affect her p_i by herself.

We model this with a production function $g(p_i, e_i)$, which is increasing in p_i and increasing and concave in e_i. We also assume that $\frac{\partial^2 g}{\partial e \partial p} > 0$, meaning that effort and potential are complements.
The student has preferences for effort and grade that are shaped by a quasi-concave utility function $u(g, e)$, which is decreasing in effort and increasing in grade.
The solution for this problem is obtained when marginal utilities are equal to marginal rate of substitution:

$$-\frac{\partial u}{\partial g} \Big/ \frac{\partial u}{\partial e} = \frac{\partial g}{\partial e},$$

or equivalently, when the student satisfies first order conditions

$$\frac{\partial}{\partial e} u(g(p,e), e) = \frac{\partial u}{\partial e} + \frac{\partial u}{\partial g}\frac{\partial g}{\partial e} = 0 .$$

Let us call g^* the bliss point of this optimization. By the envelope theorem

$$\frac{dg^*}{dp} = -\frac{\dfrac{\partial\left(\frac{\partial u}{\partial e} + \frac{\partial u}{\partial g}\frac{\partial g}{\partial e}\right)}{\partial p}}{\dfrac{\partial\left(\frac{\partial u}{\partial e} + \frac{\partial u}{\partial g}\frac{\partial g}{\partial e}\right)}{\partial g}} = -\frac{\frac{\partial^2 u}{\partial g \partial e}\frac{\partial g}{\partial p} + \frac{\partial u}{\partial g}\frac{\partial^2 g}{\partial e \partial p}}{\frac{\partial^2 u}{\partial g \partial e} + \frac{\partial^2 u}{\partial g^2}\frac{\partial g}{\partial e}}.$$

In the following we will assume quasilinear preferences.

Assumption 1:

$u(g, e)$ is quasilinear in effort, that is $u(g, e) = v(g) - e$.

Under Assumption 1, the condition for an optimum is that $v'(g)\frac{\partial g}{\partial e} = 1$. In this case, $\frac{dg^*}{dp}$ will be positive, and its magnitude is

$$-\frac{v'(g)}{v''(g)}\frac{\frac{\partial^2 g}{\partial e \partial p}}{\frac{\partial g}{\partial e}}.$$

We assume that the same mechanism described above model also the behavior of students in the simple pair teamwork treatment, where they just sit next to each other when performing the task. Their incentives remain unchanged because they are graded separately, and we assume no imitation effect.
Let us consider now that two students are matched to work jointly on a project with common incentives. We call them student i and student j, and we assume without loss of generality that $p_i > p_j$.

We model this teamwork incentives in two ways, which differ in the way grades are provided, that is, finally, in the form of the functions $v_i(g_i, g_j)$ and $v_j(g_i, g_j)$.

First teamwork type: Pair-Incentive Treatment

The students have to work on separate parts of the project, and the grade is the sum of the two outputs, so that the payoff functions for the two students are $v_i(g_i + g_j^*) - e_i$ for student i and $v_j(g_i^* + g_j) - e_j$ for student j.

In this case, student j has no incentive to put in any effort, as the bliss point of student i alone is higher than her bliss point.

Second teamwork type: Pair-Incentive-Jigsaw Treatment

In this case, the payoff function changes, as both have to work on predefined separated parts of the project (the experts' part).

We can consider the payoff functions for the two students are $v(g_i) - e_i + \beta v(g_j^*)$ for student i and $v(g_j) - e_j + \beta v(g_i^*)$ for student i, where v Is homogeneous for both students, with the form from Assumption 1, and $\beta \in (0,1)$ is a constant.

As the last term is not under their control, that will not affect their choice from the single student case.

Coaching/teaching

Let us assume that, before students decide on their effort for the schoolwork, they have the possibility to do some coaching/teaching activity in which they also can decide how much effort to put in.

This activity will increase their productivity. Let us assume that it is a function of the following form:

$$t(p_i^0, \tau_i, p_j^0, \tau_j) = (\Delta p_i, \Delta p_j)\,.$$

Depending on initial productivity and effort τ_i and τ_j, they increase their productivity. We call t_i and t_j the two unidimensional functions derived from t. However, students still care only about their grade, and not about their increase in productivity (that is, we assume that they are myopic).

τ_i and τ_j enter in preferences exactly as e_i and e_j, we can think about both as efforts measured in the time spent by the students. We assume that both t_i and t_j are increasing and concave in τ_i and τ_j. We assume also that efforts are complementary, meaning that both $\frac{\partial^2 t_i}{\partial \tau_i \partial \tau_j} > 0$ and $\frac{\partial^2 t_j}{\partial \tau_i \partial \tau_j} > 0$.

We assume that $t(\cdot\,, 0, \cdot, \cdot) = (0,0)$, meaning that if the best student does not put some effort, then their productivity remains unchanged. However, if $\tau_i > 0$, then $t_i(\cdot, \cdot, \cdot\,, 0) > 0$, meaning that if the best student puts some effort in coaching/teaching, she will improve her potential even if the worst student does not put any effort.

We assume that in any case, it cannot be the case that $p_i^0 + \Delta p_i < p_j^0 + \Delta p_j$, meaning that the productivity of the two students cannot revert in order.

A first result that we provide is related to who will put any effort in the teaching/coaching activity. We find that in both Pair-Incentive teamwork and Jigsaw the best student is more likely to put any effort.

Proposition 1- Under Assumption 1, both in the Pair-Incentive teamwork, and in the Jigsaw mechanism, when there is coaching/teaching, the worst student will put some effort if the best student puts any effort.

Proof: Let us consider first the pair-incentive teamwork with coaching/teaching. With quasi-linear preferences, student j has an incentive to put some effort if

$$\frac{\partial}{\partial \tau_j}\left(v(g_i^*) - \tau_j\right) > 0\,,$$

which is to say that

$$-\frac{v'(g_i^*)}{v''(g_i^*)}\frac{\frac{\partial^2 g}{\partial e \partial p}}{\frac{\partial g}{\partial e}}\left(\frac{\partial}{\partial \tau_j} t_i\left(p_i^0, \tau_i, p_j^0, \tau_j\right)\Big|_{\tau_j=0}\right) > 1. \qquad (1)$$

Then student i will indeed put effort if

$$-\frac{v'(g_i^*)}{v''(g_i^*)}\frac{\frac{\partial^2 g}{\partial e \partial p}}{\frac{\partial g}{\partial e}}\left(\frac{\partial}{\partial \tau_i} t_i\left(p_i^0, \tau_i, p_j^0, \tau_j\right)\Big|_{\tau_i=0}\right) > 1\,.$$

Since $\frac{\partial t_i}{\partial \tau_i} > \frac{\partial t_i}{\partial \tau_j}$, this condition is stronger than the previous one, meaning that we could have cases where no student put any effort, only student i does, or both do.

In the cases where only student i does, we have

$$-\frac{v'(g_i^*)}{v''(g_i^*)}\frac{\frac{\partial^2 g}{\partial e \partial p}}{\frac{\partial g}{\partial e}}\left(\frac{\partial}{\partial \tau_i} t_i\left(p_i^0, \tau_i, p_j^0, 0\right)\Big|_{\tau_i=0}\right) > 1\,. \qquad (2)$$

Let us now consider Jigsaw with coaching/teaching. In this case, the problem of putting effort in the first coaching stage is separable from the second problem.

In the second stage, they will behave as if they were in the individual student schoolwork. In the first stage the two students must choose τ_i and τ_j in order to maximize $\beta v\left(g_j^*\right)$, for student i, and $\beta v(g_i^*)$, for student j.

As before, assuming that student i puts some positive effort τ_i, student j, then, will put effort if

$$-\frac{v'\left(g_j^*\right)}{v''\left(g_j^*\right)}\frac{\frac{\partial^2 g}{\partial e \partial p}}{\frac{\partial g}{\partial e}}\left(\frac{\partial}{\partial \tau_j} t_j\left(p_i^0, \tau_i, p_j^0, \tau_j\right)\Big|_{\tau_j=0}\right) - \beta\frac{v'(g_i^*)}{v''(g_i^*)}\frac{\frac{\partial^2 g}{\partial e \partial p}}{\frac{\partial g}{\partial e}}\left(\frac{\partial}{\partial \tau_j} t_i\left(p_i^0, \tau_i, p_j^0, \tau_j\right)\Big|_{\tau_j=0}\right) > 1\,.$$

(3)

The analogous condition for student i will be

$$-\frac{v'(g_i^*)}{v''(g_i^*)}\frac{\frac{\partial^2 g}{\partial e\partial p}}{\frac{\partial g}{\partial e}}\left(\frac{\partial}{\partial\tau_i}t_i(p_i^0,\tau_i,p_j^0,\tau_j)\Big|_{\tau_i=0}\right)-\beta\frac{v'(g_j^*)}{v''(g_j^*)}\frac{\frac{\partial^2 g}{\partial e\partial p}}{\frac{\partial g}{\partial e}}\left(\frac{\partial}{\partial\tau_i}t_j(p_i^0,\tau_i,p_j^0,\tau_j)\Big|_{\tau_i=0}\right)>1\,.$$

(4)

Since $\frac{\partial t_i}{\partial \tau_i} > \frac{\partial t_i}{\partial \tau_j}$ and $\frac{\partial t_j}{\partial \tau_i} < \frac{\partial t_j}{\partial \tau_j}$, condition (3) implies condition (4), and as in the previous case we cannot have that only student i puts any effort. □

This result implies that there are 3 possible cases, once a couple is formed: (i) no one puts effort, (ii) only the best student puts effort and the other free rides, (iii) both put effort. Clearly, we are assuming a one-shot interaction (or, which is the same, we model our students as myopic), but in reality, the student who puts effort will improve her skills also for future activities in the school.

We can now ask ourselves in which mechanism are both students more likely to put effort, in the coaching/teaching preliminary activity.

Since, because of Proposition 1, student j putting effort implies student i putting effort in both mechanisms, it is enough to focus on the former student. However, we need to make assumptions on the production function g and on the utility v for grades. We focus on pair-incentive sufficient conditions which, we will see, guarantee that under Jigsaw both students are more likely to put effort.

Assumption 2:

We assume that $\frac{\partial t_i}{\partial \tau_i} > \frac{\partial t_i}{\partial \tau_j}$, and symmetrically $\frac{\partial t_j}{\partial \tau_i} < \frac{\partial t_j}{\partial \tau_j}$, meaning that the effect of one student's effort is more beneficial for her productivity than for the productivity of the other student.

Assumption 3:

The grade function is Cobb-Douglas

$$g(p_i, e_i) = k{p_i}^{\alpha}{e_i}^{1-\alpha}$$

and $v(g)$ is CARA with $-\frac{v'(g)}{v''(g)} = r$. □

Proposition 2- Under Assumptions 1 and 2, the grade that a single student, working on her own, will achieve is increasing in the potential of that student. This function from potential to obtained grade is concave, meaning that the marginal effect of potential is decreasing in the potential.

Proof: If we assume that the grade function is Cobb-Douglas

$$g(p_i, e_i) = k{p_i}^{\alpha}{e_i}^{1-\alpha}$$

and that $v(g)$ is CARA with $-\frac{v'(g)}{v''(g)} = r$, then

$$\frac{dg^*}{dp} = \frac{rk\alpha}{p_i}.$$

The higher the potential, the less positive effect on the grade of increasing the potential. □

Proposition 3- Under Assumptions 1, 2 and 3, if both students put effort in the coaching/teaching activity under Pair-Incentive teamwork, they will also do under Jigsaw.

Proof: Under CARA value for grade, and Cobb-Douglas production function, student j will put effort in teamwork if condition (1) holds, which then becomes

$$rk\alpha\left(\frac{1}{p_i^0}\left(\frac{\partial}{\partial\tau_j}t_i(p_i^0,\tau_i,p_j^0,\tau_j)\Big|_{\tau_j=0}\right)\right) > 1\,.$$

and in Jigsaw if condition (3) holds, which then becomes

$$rk\alpha\left(\frac{1}{p_j^0}\left(\frac{\partial}{\partial\tau_j}t_j(p_i^0,\tau_i,p_j^0,\tau_j)\Big|_{\tau_j=0}\right)+\frac{\beta}{p_i^0}\left(\frac{\partial}{\partial\tau_j}t_i(p_i^0,\tau_i,p_j^0,\tau_j)\Big|_{\tau_j=0}\right)\right) > 1\,.$$

The first condition implies the second one, because $\frac{\partial t_i}{\partial\tau_i} > \frac{\partial t_i}{\partial\tau_j}$. □

Proposition 2 implies that, under Assumptions 1, 2 and 3, a couple of students may put effort under jigsaw, but not in pair-incentive teamwork.

If we call $\sigma_{ji} = \frac{\partial}{\partial\tau_j}t_i(p_i^0,\tau_i,p_j^0,\tau_j)\Big|_{\tau_j=0}$ the initial marginal effect of the worst student, as she starts putting some effort, on the productivity of the best student. This quantity turns out to be important, because we show in **Proposition 3** in Appendix C that if

$$rk\alpha > \frac{p_i^0}{\sigma_{ji}},$$

then both students will put in effort in both types of teamwork. This means that both will improve their potential and, as a consequence, the grade of the worst student is likely to improve more, because of the concavity of the achieved grade with respect to the potential. This is what we observe empirically for Math.

It is worth noticing that this condition depends on the left side, only on simple parameters of the production function and of the preferences, homogeneous across students, and on the right side on the potential of the best student and on the effect that the worst student has on improving it.

If instead

$$rk\alpha < \frac{p_i^0}{\sigma_{ji}},$$

then only the best student will put in effort, and more so under Jigsaw than under pair-incentive teamwork (Proposition 1). If that is the case, only the grades of the best students will improve under teamwork, more frequently under Jigsaw.[12]

However, in the data we do not observe this either for English. In the context of the model, one difference between Math and English could be in the validity of Assumptions 2 or 3, which could hold only for Math, as we discuss in the paper.

In particular, Assumption 2 is about the externality in marginal effects of productivity, saying that the effect of one student's effort is more beneficial for her productivity than for the productivity of the other student. We have indeed evidence suggesting that Assumption 2 holds for Math: the effect of a student's effort (the difference between endline and baseline effort) on grade is larger than the effect of partner's effort. For English none of the two effects is statistically significant (Table A10).

D: Description of Randomization Inference Procedure

We adapt the randomization procedure outlined by Young (2019) to our specific setting. The randomization is done to preserve our original block randomization, by keeping the number of schools inside each block that is assigned to a specific treatment. The randomization is done as follows:

1. For each block i, we randomly assign C_i schools assigned to Control, P_i (of the non-extracted) schools to Pair, PI_i to Pair-Incentive, and PIJ_i to Pair-Incentive-Jigsaw treatment, where C_i, P_i, PI_i, PIJ_i denote the number of schools assigned to each treatment in block i in our true randomization.
2. We compute the new sample weights for each student based on the placebo assignment of their school.
3. We run the respective models' regressions for the placebo treatments and store the estimates of the coefficients (i.e., the treatment effects).

We repeat the above procedure 5,000 times (Young (2019)) reports no change in rejection rates above 2,000 draws) and we compare the true treatment effect estimate with the empirical distribution of coefficients obtained from our 5,000 simulations, as in Barker et. al (2022). The *RI p-value* in Table A5 and Table A6 reports the share of the 5,000 simulations for which the absolute value of the coefficient is larger than the absolute value of the coefficient estimated for the true randomization.

[12] An alternative explanation regarding the magnitude of $rk\alpha$ with respect to $1/\sigma_{ji}$ is that it is smaller in Math and greater in English, and, therefore, the two above inequalities could be different for the two topics. However, we discard this explanation based on the empirical evidence from the data.

E: First page of exam questions

END LINE TEST

Class VIII Subject: Mathematics

Total Marks: 40 **Total Time: 30 minutes**

Name of the student ______________________________________

Name of the school _______________________________________

Section ______ **Roll No.** ___________

Relevant rough work must be shown next to the answers in the space provided.

Rough work

1. Each question carries 1 mark, tick the correct option. (4M)

a) 100 to the power of 0 is equal to

(i) 0 (ii) 1 (iii) 10 (iv) 100

b) A tree 14m tall casts a shadow of 10m. Under similar conditions, a tree of what height will cast a shadow of 15m?

(i) 15 (ii) 18 (iii) 21 (iv) 24

c) Generally while factorizing algebraic expressions of the type x^2+px+q, we try to find two factors *a* and *b* of q (the constant term) such that

(i) a/b=q, a+b=p (ii) ab=p, a+b=q (iii) ab=q, a-b=p (iv) ab=q, a+b=p

d) A type of bar graph that shows data in intervals is called a

(i) Histogram (ii) grouped bar graph (iii) stacked bar graph (iv) none of these

2. Complete the following statements: (3M)

(a) The independent variable is usually plotted along the __________ axis of a graph.

(b) __________ is a factor of every term.

(c) The distance travelled by a car and the amount of fuel left in the tank are __________related.

3. Write the following numbers in the expanded form using exponents. (3M)

i) 159.36

ii) 100.01

iii) 48.698

4. You are trying to list the following data in separate charts. What kind of graphs/charts will you choose in each case to represent them? (4M)

(i) The percentage of people using different brands of toothpaste. ___________

(ii) The comparative monthly readership figures of Times of India and Deccan Herald in Karnataka over the first 6 months of 2017. ___________

(iii) The distribution of heights of students in a school. ___________

1

END LINE TEST

Class VIII Subject: Mathematics

Total Marks: 40 **Total Time: 30 minutes**

Name of the student ______________________________

Name of the school ______________________________

Section ______ **Roll No.** __________

Relevant rough work must be shown next to the answers in the space provided.

Rough work

1. Complete the following statements: (3M)

(a) The independent variable is usually plotted along the _________ axis of a graph.

(b) _________ is a factor of every term.

(c) The distance travelled by a car and the amount of fuel left in the tank are _________related.

2. The table shows the times 4 elevators take to travel various distances. Look at the table and answer the questions that follow: (4M)

	Distance (m)	Time (sec)
Elevator A	435	29
Elevator B	448	28
Elevator C	130	10
Elevator D	85	5

(i) Which is the fastest elevator? __________

(ii) Which is the slowest elevator? __________

(iii) How much will be travelled by elevator D in 2 minutes? __________

(iv) By how much is that distance more than the distance travelled by elevator C in the same time? __________

3. If 15 workers can build a wall in 48 hours, how many workers will be required to do the same work in 30 hours? (2M)

(i) 22 (ii) 24 (iii) 28

4. The given graph describes the distances of a car from a city P at different times when it is travelling from City P to City Q, which are 350 km apart. Study the graph and answer the following: (3M)

END LINE TEST

Class VIII   Subject: Mathematics

Total Marks: 40   **Total Time: 30 minutes**

Name of the student ____

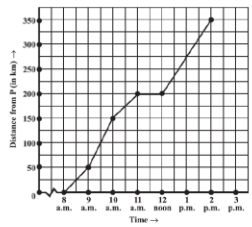
Name of the school ____

Section ______ **Roll No.** ___________

Rough work

Relevant rough work must be shown next to the answers in the space provided.

1. The given graph describes the distances of a car from a city P at different times when it is travelling from City P to City Q, which are 350 km apart. Study the graph and answer the following: (3M)



i) The distance from Q at 11 a.m. was _________ km

ii) Before halting at 11a.m. the car moved fastest between ___ a.m. and ___ a.m.

iii) They covered the first half of the distance at _______ a.m.

2. If 15 workers can build a wall in 48 hours, how many workers will be required to do the same work in 30 hours? (2M)

(i) 22   (ii) 24   (iii) 28

3. Complete the following statements: (3M)

(a) The independent variable is usually plotted along the __________ axis of a graph.

(b) __________ is a factor of every term.

(c) The distance travelled by a car and the amount of fuel left in the tank are __________related.

1