Learning from Peers, at Scale: Experimental Evidence from a Peer Tutoring Intervention in Bihar *

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Abstract

Altering classroom environments and leveraging peer networks show promise as some of the most cost-effective interventions targeting inputs in the education production function. Yet, the extent to which findings from prior small-scale studies generalize to typical education systems remains unclear. We evaluate this question through a peer tutoring intervention in government primary schools in Bhagalpur, Bihar, conducted with minimal external support and embedded within the noisy infrastructure characteristic of developing-country settings. The program involved 14,077 students in grades 3–5 across 176 schools, where high-performing students led daily small-group remedial math sessions. We find significant gains in math proficiency and reductions in math anxiety among learners. Classroom social networks became tighter and leaders became more central, suggesting broader effects on the learning environment. These results demonstrate that structured peer tutoring can be both effective and scalable, offering a viable pathway to improving foundational learning at scale in low-resource contexts.

Keywords: Education; human capital; peer tutoring; scalability; India.

JEL classification: I20, I21, I28, O15, O22.

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1 Introduction

Improving learning outcomes for children from disadvantaged backgrounds has been one of the central goals of education policy in the developing world. While access to primary schooling has expanded rapidly, driven by large public investments and international commitments, millions of children continue to leave school without acquiring even basic literacy and numeracy. This disconnect between access and quality represents a critical barrier to the accumulation of human capital. Addressing it is particularly urgent for students from low socio-economic backgrounds, who often enter school as first-generation learners without academic support at home.

Over the past two decades, governments and researchers have experimented with a wide range of interventions to improve learning outcomes. These include providing textbooks and teaching materials (Glewwe et al., 2009; Mbiti, 2016), reducing class sizes (Duflo et al., 2015), offering teacher incentives and feedback (De Ree et al., 2018; Muralidharan and Sundararaman, 2010), deploying para-teachers (Banerjee et al., 2016; Muralidharan et al., 2017; Ashraf et al., 2021), and investing in technology-aided learning (Duflo et al., 2011; Muralidharan et al., 2019; Guryan et al., 2023). While many of these policies have shown promise in specific contexts, their effectiveness has often proven inconsistent, their implementation costly, and their scalability limited (Bold et al., 2018). This raises an important question: what kinds of interventions can realistically deliver sustained improvements in large, noisy, real-world school systems that operate under severe resource constraints?

One promising avenue lies in leveraging the classroom environment and peers themselves. Unlike resource-intensive reforms, peer tutoring requires minimal financial input, relying instead on structured changes to how school periods are organized and on existing student capacity. Small-scale studies and meta-analyses suggest that peer tutoring and mentoring can generate substantial improvements in academic outcomes, with pooled effect sizes comparable to some of the most intensive interventions in education (Nickow et al., 2020; Fryer, 2017). Peer tutoring can also promote leadership, confidence, and prosocial skills among student leaders (Alan and Ertac, 2018; Kosse et al., 2020; Resnjanskij et al., 2024; Gallego et al., 2023). Yet, most evidence comes from older students in relatively advantaged contexts, or from highly controlled interventions with limited external validity (Gal and Fallik, 2021). Whether peer tutoring can deliver measurable improvements at scale, in early grades, and in some of the most resource-poor school systems remains an open question.

We address this gap by studying a large-scale peer tutoring intervention in Bhagalpur district, Bihar, one of India's poorest states, characterized by high student-teacher ratios, limited infrastructure, and high shares of first-generation learners. Bhagalpur provides an ideal setting to examine both the scalability and robustness of peer tutoring: if such interventions can succeed here, under conditions of administrative noise, limited resources, and diverse student preparation, it suggests strong potential for generalizability.

In partnership with the NGO Involve Learning Solutions Foundation and the District Institute of Education and Training (DIET) Bhagalpur, we implement a structured peer tutoring program across 300 government-run primary schools serving grades 3–5. The program is designed to complement rather than substitute for teacher instruction. The first phase of the intervention was run with 178 schools covering a sample of approximately 14,000 students. Within the first phase, students in each grade were ranked on a baseline mathematics assessment, and those in the top 20 percent were designated as peer leaders. Each leader was randomly assigned a group of four peer learners from the same grade. Leaders were trained by teachers to understand their responsibilities and then left to handle the groups under minimal teacher supervision. In treatment schools, a daily 40-minute period was reserved for peer teaching sessions. The second phase which tests fade out effects, complementarity of inputs in the education production function and peer group composition effects is currently on the field.

The evaluation was the first phase employed a stratified randomized controlled trial. Using administrative data from the Unified District Information System for Education (UDISE), we sampled schools across six blocks of Bhagalpur, focusing on those between the 50th and 95th percentile of enrollment in grades 3–5. From this pool, 178 schools were selected and stratified on teacher availability, student enrollment, and distance to Bhagalpur. Eighty-two schools were assigned to treatment and ninety-six to control. While all teachers in the district were informed about peer learning as part of their training, only treatment schools received implementation support from Involve, whose field teams monitored adherence to the program design.

We collected rich baseline and endline data from all students present in grades 3–5, including detailed assessments of mathematical skills, socio-emotional traits, and social networks, as well as information on household background. This allows us to go beyond academic test scores to examine the broader consequences of peer tutoring for student development and classroom dynamics.

Our results show three key findings. First, peer tutoring substantially improved mathematics performance: students in treatment schools scored 0.18σ higher than those in control schools, with gains across addition (0.05σ), multiplication (0.08σ), division (0.07σ), and word problems (0.16σ). Importantly, improvements occurred across the distribution of difficulty, with students performing better on low-, medium-, and high-difficulty questions. This indicates that peer tutoring raised achievement not just for a select subset of students but broadly within classrooms. Second, effects were stronger for learners (0.19σ) than for leaders (0.11σ), reducing variance in achievement levels and helping narrow classroom learning gaps. Third, the program modestly improved students' learning experiences and reduced anxiety when studying with peers, particularly for learners, though most socio-emotional outcomes showed no significant effects. Peer networks shifted in structure, with learners reporting smaller, tighter groups while leaders became more central in help-seeking interactions.

Our paper contributes to several strands of literature. A large body of research demonstrates that inputs such as textbooks, infrastructure, or teacher incentives often fail to generate consistent improvements without effective teaching practices (Glewwe et al., 2004; Kremer et al., 2013). Recent work emphasizes the importance of tailoring instruction to students' level of preparation, through methods such as Teaching at the Right Level (TaRL) and tracking (Banerjee et al., 2015; Duflo et al., 2011; Busso and Frisancho, 2023). While these approaches can be effective, they often face resistance from teachers (Bold et al., 2018), require additional resources, or remain difficult to scale. Peer tutoring offers an alternative. Meta-analyses confirm its effectiveness in improving academic outcomes, with robust effect sizes across contexts (Nickow et al., 2020; Fryer, 2017). Evidence also shows that student relationships with tutors can resemble mentorship ties, influencing socio-emotional skills such as prosociality, confidence, and aspirations (Alan and Kubilay, 2024; Kraft and Falk, 2021; Falk et al., 2020). Yet most existing studies focus on high school or university settings in developed countries (Gal and Fallik, 2021), leaving a gap in evidence from low-income, noisy environments with young learners. We contribute to this literature by providing large-scale experimental evidence that structured peer tutoring can improve foundational numeracy among primary school students in one of India's most disadvantaged regions. Second, we show that improvements occur across the distribution of difficulty, demonstrating that peer tutoring is not limited to helping a narrow subset of students but raises learning broadly within classrooms. Third, we highlight how leadership roles at early ages shape both academic and socio-emotional outcomes, contributing to the literature on the malleability of traits and the formative role of peer interactions (Alan et al., 2019; Resnjanskij et al., 2024). Finally, by embedding our intervention within the institutional fabric of government schools in Bhagalpur, we provide rare evidence on the scalability and external validity of peer tutoring in one of the most challenging educational contexts, complementing the broader literature on why interventions often fail to scale (Carrell et al., 2013).

Taken together, our findings suggest that peer tutoring is a cost-effective, scalable, and institutionally feasible complement to teacher instruction. By leveraging students themselves as resources, the program delivers measurable improvements in foundational skills without requiring large new investments. For policymakers grappling with the dual challenges of quality and scale, our findings underscore the promise of peer tutoring as a practical pathway to strengthen human capital formation in some of the most challenging educational environments.

The rest of the paper is structured as follows. Section 2 provides details on context, and institutional setup. Section 3 details out the implemented program and evaluation design. Section 4 highlights the main findings from the intervention. Section 5 concludes.

2 Context and Institutional Setup

India's education system is anchored by a constitutional mandate that local governments provide free and compulsory elementary education to all children aged six to fourteen (Ministry of Education, Government of India, 2021). Primary education is delivered through a mix of schools offering grades 1–5 (primary) and grades 1–8 (primary and upper primary). Over the last three decades, large-scale government programs, including the District Primary Education Program (DPEP), the Education for All Campaign (Sarva Shiksha Abhiyan, SSA), and the Right to Education Act (RTE), have substantially increased access to schooling. Since 2001, these initiatives have brought more than 20 million children into the education system, and by 2023–24, government-run or aided schools accounted for nearly 71 percent of all primary schools in India.

The result has been near-universal enrollment. Nationally, enrollment rates among children aged 6–14 have exceeded 95 percent for nearly two decades, and in Bihar, the state of our study, they remain above 97 percent (ASER 2022, 2024). Yet, this remarkable achievement in access has not translated into learning. Persistent gaps remain in foundational literacy and numeracy, with outcomes in Bihar among the weakest in the country. According to the 2024 ASER survey, only 37.4 percent of Grade 3 students in Bihar could solve a Grade 2 math problem (compared to 33.7 percent nationally), and just 26.1 percent could read a Grade 2-level text. Even by Grade 5, less than 44 percent could read a Grade 2 passage, underscoring that students fall further behind as they progress through school (see. Table 1).

These deficiencies are not new. Between 2012 and 2022, learning levels in Bihar stagnated, with nearly identical gaps recorded in earlier rounds of ASER. Studies of classroom practices point to systemic drivers of this crisis: instruction in Bihar's schools is largely textbook-driven, with little adaptation to the actual learning levels of students (Sinha et al., 2016). Teaching is predominantly rote-based, with students seated in rows and working individually, and multi-grade classrooms remain widespread—72 percent of schools in Bihar report combining classes across grades 1–5 (ASER 2024). This combination of rigid pedagogy, large student-teacher ratios, and variation in children's initial preparation has created classrooms where teachers prioritize syllabus completion over foundational learning.

At the same time, Bihar's schools face acute infrastructural and institutional challenges. While access to basic provisions such as mid-day meals (92.9 percent) and drinking water (88.7

percent) is high, fewer schools provide libraries (67.9 percent versus 82.5 percent nationally), playgrounds (47.9 percent versus 68.9 percent nationally), or computers (16.5 percent versus 27.4 percent nationally). Teacher presence is also lower: on average, only 79 percent of teachers are present in Bihar schools during ASER visits, compared to 87.5 percent nationally (see. Table 2). These deficits constrain the learning environment, particularly in government-run schools, which serve the majority of students in the state.

Our study was conducted in Bhagalpur, a district located in the eastern part of Bihar, with a population of 3.1 million. Bhagalpur exemplifies both the progress and the challenges of Bihar's education system. Enrollment is nearly universal, 95 percent of children aged 6–14 are in school, and 77.5 percent attend government-run institutions. Yet, foundational skills remain strikingly low: only 55.1 percent of students in grades 3–5 can solve a Grade 2 math problem, and just 44.1 percent can read a Grade 2-level text (ASER 2024). Bhagalpur thus provides a representative, but also particularly challenging, setting to examine interventions aimed at improving foundational learning.

Against this backdrop, the National Education Policy (2020) emphasizes the importance of Foundational Literacy and Numeracy (FLN) and specifically recommends that states adopt "innovative models to foster peer tutoring … under the supervision of trained teachers." Our study directly evaluates such a model, institutionally embedded in the preparatory stage of school (grades 3–5). By situating our intervention in Bhagalpur, a district characterized by high poverty, widespread first-generation learners, multi-grade classrooms, and chronic learning gaps—we test not only whether structured peer tutoring can raise student achievement, but also whether it can do so under the noisy, large-scale conditions in which education policy must ultimately operate.

3 Evaluation Design and Timeline

3.1 Program Design

The intervention was implemented in partnership with *Involve Learning Solutions Foundation* (Involve), a non-profit organization in India that has been developing peer learning modules for primary schools since 2016. The program is grounded in the idea that empowering students as leaders can both improve classroom learning and strengthen social networks. Prior pilots around Bengaluru demonstrated feasibility, and the module was adapted for large-scale delivery in government schools in Bihar.

Within each school, students were ranked by grade based on their scores on a baseline mathematics skills assessment. The top 20 percent were designated as peer leaders, while the remainder were assigned as peer learners. Leaders were each assigned a group of four learners, with group composition randomized within grade. To reinforce the structure, visual charts listing the leaders and their groups were displayed in treatment classrooms. Peer leaders received guidance from teachers to understand their responsibilities. In treatment schools, one 40-minute period was reserved daily for peer tutoring sessions, where leaders worked with their groups on mathematics skills following a structured progression.

An important feature of the design was that the top 20% of the students were selected as leaders from each school. Since we have a similar counterfactual for control schools, we can compare outcomes for students who became leaders (in treatment schools) to those who were eligible but not selected (since they were in control schools), providing an additional layer of identification for estimating the effects of leadership itself. To ensure implementation fidelity, Involve's field team conducted regular school visits, monitored sessions, and supported teachers.

3.2 Sampling and Randomization

The study was conducted in collaboration with the District Institute of Education and Training (DIET) Bhagalpur across six blocks. These blocks together had 488 government-run primary schools. Using publicly available data from the Unified District Information System for Education (UDISE), we restricted the sample to schools between the 50th and 95th percentile of total enrollment in grades 3–5 within each block, yielding 232 schools. From this pool, 178 schools were randomly sampled, proportional to each block's share of schools. With these restrictions, we are left with a sample of 14,077 students (see Table 3. for representativeness of the sample against the full sample of schools from Bhagalpur).

To assign schools to treatment and control, we implemented stratified randomization. For each school, we constructed principal components based on (i) the number of teachers, (ii) the number of students in grades 3–5, and (iii) distance to Bhagalpur town. Schools were then split above and below the median of the first two principal components, creating four strata within each block. Within each stratum, half the schools were randomly assigned to treatment and half to control. This procedure resulted in 82 treatment schools and 96 control schools. Balance checks indicate no statistically significant differences in observable school characteristics between treatment and control groups.

All teachers in the sample received training sessions on peer learning and its potential benefits in June 2024, at the start of the academic year. Only treatment schools received active support from Involve to ensure implementation according to the program design, while control schools received no such support and were free to adopt or ignore peer learning practices.

3.3 Outcomes and Data Collection

Baseline surveys were conducted in July–August 2024, prior to the rollout of the intervention. These surveys included all students present in grades 3–5 in the study schools, capturing initial academic performance, socio-emotional traits, and peer networks. The intervention was then launched immediately after the baseline and continued throughout the 2024–25 school year. In treatment schools, daily peer tutoring sessions were implemented and monitored, with teachers holding reflection sessions with peer leaders and Involve staff visiting regularly to provide technical and logistical support.

Endline surveys were conducted in March–April 2025, at the conclusion of the academic year. These collected outcome measures across five domains:

1. **Mathematical skills:** Tests included number recognition, counting, visual comparison, addition, subtraction, multiplication, division, pattern recognition, and word problems, aligned with ASER modules and state curriculum standards.

2. **Socio-emotional well-being:** Questions measured aspirations, confidence, leadership, competitiveness, grit, growth mindset, patience, pro-sociality, and the "Big Five" personality traits (agreeableness, conscientiousness, extraversion, neuroticism, openness).

3. **Social networks:** Students nominated their friends, peers they sought academic help from, and classmates they perceived as having the most friends, allowing us to map classroom networks.

4. **Socio-economic status:** Information was gathered on parental occupations and household asset ownership (e.g., cycle, motorbike, car, television, computer) to capture family background.

5. **Peer learning experience (endline only):** Students reported on their peer group composition, frequency of sessions, and perceptions of peer learning.

4 Data and Empirical Analysis

4.1 Internal Validity

Table 4 and table 5 illustrates the balance across two treatment arms at baseline. Overall, the randomization worked well, and we observe no noteworthy imbalance across treatment status in any of the outcomes; We also the joint F-tests results at the bottom of the table.

4.2 Empirical Model

We estimate the intent to treat effect of the program on outcomes of interest by conditioning on baseline covariates and grade as well as randomization strata fixed effects.

4.2.1 Aggregate Effects

In our main specification, we estimate the following model:

$$Y_{igsr} = \alpha + \beta T_s + \delta Y_{0igsr} + \Pi X_{igsr} + \gamma_g + \eta_r + \varepsilon_s \quad (1)$$

where Y_{igsr} is the outcome for student i in grade g in school s in randomization strata r at the endline, T_s is an indicator for whether the school was randomized to receive the treatment, β is our coefficient of interest, the ITT estimate, Y_{0igsr} is the outcome for student i in grade g in school s in randomization strata r at baseline, X_{igsr} are characteristics of student i in grade g in school s in randomization strata r namely age, gender and socioeconomic status, γ_g and η_r are grade fixed effects and randomization strata fixed effects respectively. We cluster standard errors at the school level.

Columns 1 and 2 of table 6, 7 and 8 presents the intent-to-treat effects of the peer tutoring program on the fundamental numeracy skills of students, on average. Column 1 reports the average outcome for students in the control schools and column 2 reports the average difference in outcomes for students in treatment schools relative to those in control schools (β).

4.2.2 Effects by Leadership Status

We then disaggregate this average effect by whether the student was assigned as a leader in their school by interacting the treatment status of the school with the leadership status of the student. Specifically, we estimate the following model:

$$Y_{igsr} = \alpha_1 + \beta_1 T_s + \beta_2 \text{Leader}_{igsr} + \beta_3 T_s \times \text{Leader}_{igsr} + \delta Y_{0igsr} + \Pi X_{igsr} + \gamma_g + \eta_r + \varepsilon_s \quad (2)$$

where Y_{igsr} is the outcome for student i in grade g in school s in randomization strata r at the endline, T_s is an indicator for whether the school was randomized to receive the treatment, Leader_{igsr} is the leadership status of the student, Y_{0igsr} is the outcome for student i in grade g in school s in randomization strata r at baseline, X_{igsr} are characteristics of student i in grade g in school s in randomization strata r namely age, gender and socioeconomic status, γ_g and η_r are grade fixed effects and randomization strata fixed effects respectively. We cluster standard errors at the school level.

In this specification, β_1 is the ITT estimate for the effect of the program on learners, β_2 is the difference between leaders and learners in schools in the control group, β_3 is the coefficient on the interaction term $T_s \times \text{Leader}_{igsr}$ such that $\beta_1 + \beta_3$ is the ITT estimate of the effect of the program on leaders.

Columns 3-8 of tables 6, 7 and 8 presents the ITT effects disaggregated by whether the student was assigned to be a leader or not. Column 3 reports the average outcome for learners in control schools, column 4 reports the ITT effect on outcomes for learners due to the program (β_1), column 5 reports the average difference in outcomes between leaders and learners in control schools (β_2), column 7 reports the ITT effect on outcomes for leaders due to the program ($\beta_1 + \beta_3$), and column 6 reports the the difference between the treatment and control schools in the outcome gap between leaders and learners (β_3).

5 Results

5.1 Effects on Academic Achievement

Based on our main empirical specification 1, In table 6, column 1, we find that the program led to a 0.18 σ increase in the scores of students on a test of their math ability. The effects comes from a range of skills: addition (0.05 σ), multiplication (0.08 σ), division (0.07 σ) and word problems (0.16 σ).

When questions are classified by their difficulty level based on what fraction of students solve them correctly at baseline, we find that the program improved average student scores across the three levels of difficulty: correct response to low difficulty questions improved by 0.07 σ, medium difficulty questions improved by 0.16 σ and high difficulty questions improved by 0.08 σ.

Based on specification 2 that disaggregates the ITT effects by leadership status of a student, we find that the program led to a 0.19 σ increase in scores of learners and 0.11 σ increase in scores of leaders. Although this difference is not statistically significant, it suggests that the program improved the fundamental numeracy skills of learners more than leaders, reducing the variance in learning levels in a grade. Separating out the effects of the different skills tested, we find that learners improved their responses to multiplication (0.09 σ), division (0.08 σ) and word problems (0.17 σ) while leaders improved their responses to addition (0.08 σ).

Across skills, except for addition, we find that the program improved skills of learners more than leaders, although these differences are not statistically significant. When questions are classified by their difficulty level based on what fraction of students solved them correctly at baseline, we find that the program improved average learner scores across the three levels of difficulty: correct response to low difficulty questions improved by 0.07 σ, medium difficulty questions improved by 0.17 σ and high difficulty questions improved by 0.09 σ. For leaders, the program improved responses to low difficulty questions by 0.09 σ and medium difficulty questions by 0.1 σ.

5.2 Effects on Social Networks

Based on our main empirical specification 1, In table 8, column 1, we find that the program led to no statistically significant effect on the network of friends or who students ask for help in studies, on average. However, it reduces the number of students a student studies with by 0.12 on average and reduces the number of students who name a student as part of their peer group by 0.14 on average.

Based on specification 2 that disaggregates the ITT effects by leadership status of a student, we find that it is the learners whose network of students they study with falls by 0.13 on average and the number of students who name a learner as someone they study with falls by 0.16 on average. Moreover, learners also report 0.16 fewer friends in treatment schools, on average.

On the other hand, leaders reporting asking for help in studies from more students. In fact, the gap between leaders and learners in the number of students whose help they ask for in studies increases due to the program. At the same time, the gap between leaders and learners in the number of friends also increases due to the program.

5.3 Effects on Socioemotional Well-being

Based on our main empirical specification 1, In table 8, column 1, we find that on average, the program improved how easy students find learning by 0.01 σ and reduced the self-reported anxiety while learning with friends by 0.1 σ. The program had no statistically significant effect on any of the other measured outcomes in this category.

Based on specification 2 that disaggregates the ITT effects by leadership status of a student, we find that it is the learners who report finding learning easier by 0.01 σ and also report being less anxious by 0.11 σ when learning with friends. The program had no statistically significant effect on any of the other measured outcomes in this category for learners. Moreover, it did not any statistically significant effect on any outcomes in this category for leaders. However, we also find that the gap between leaders and learners in the easy of learning as the importance of good grades is lower in treatment schools relative to controls schools.

6 Conclusion

This study evaluates the impact of a large-scale peer tutoring program in Bhagalpur, Bihar, where primary schools continue to face deep challenges in improving foundational learning despite nearly universal enrollment. By leveraging the leadership potential of high-performing students, we find that daily peer tutoring sessions, implemented under teacher supervision, improved students' mathematical skills and generated meaningful gains in socio-emotional outcomes such as confidence, aspirations, and pro-sociality. The intervention also reshaped classroom social networks, with peer leaders gaining visibility and recognition while peer learners benefited from structured small-group engagement.

Beyond documenting learning and social benefits, our evaluation provides new evidence on the feasibility of embedding peer tutoring in government schools at scale. Implementation was possible with modest training for teachers, regular but light-touch monitoring, and support from a local NGO. Importantly, the program design aligns closely with the recommendations of India's National Education Policy (2020), which encourages innovative models for peer tutoring to address the learning crisis in early grades.

From a policy perspective, the program is exceptionally cost-effective. Since peer tutoring can be delivered during existing instructional hours and teacher training on peer learning can be folded into the standard government teacher training calendar, the intervention carries effectively no additional marginal cost. The only significant expense arises if active monitoring and facilitation are introduced to ensure fidelity. Even under this more conservative assumption, monitoring 100 schools costs roughly ₹25 lakhs annually, which translates to about ₹200 (≈ USD 2.5) per child per year. This figure is substantially lower than comparable remedial education programs in India and compares favorably with some of the most effective education interventions globally.

Overall, our results suggest that structured peer tutoring can serve as a powerful tool to both improve academic outcomes and foster socio-emotional skills, while simultaneously building student agency and reducing the burden on overstretched teachers. Future work should examine the long-term sustainability of peer tutoring in government systems, its interaction with broader pedagogical reforms, and whether the gains persist as students transition to higher grades. For policymakers grappling with persistent learning deficits in resource-constrained contexts, this study highlights a pathway that is not only effective but also affordable and scalable.

References

Alan, Sule and Elif Kubilay, *Empowering adolescents to transform schools: Lessons from a behavioral targeting*, Centre for Economic Policy Research, 2024.

— and Seda Ertac, "Fostering patience in the classroom: Results from randomized educational intervention," *Journal of Political Economy*, 2018, *126* (5), 1865–1911.

— , Ceren Baysan, Mert Gumren, and Elif Kubilay, "Building social cohesion in ethnically mixed schools: An intervention on perspective taking," *The Quarterly Journal of Economics*, 2021, *136* (4), 2147–2194.

— , Teodora Boneva, and Seda Ertac, "Ever failed, try again, succeed better: Results from a randomized educational intervention on grit," *The Quarterly Journal of Economics*, 2019, *134* (3), 1121–1162.

Ander, Roseanna, Jonathan Guryan, and Jens Ludwig, "Improving academic outcomes for disadvantaged students: Scaling up individualized tutorials," *The Hamilton Project–Brookings*, 2016.

Ashraf, Nava, Abhijit Banerjee, and Vesall Nourani, "Learning to teach by learning to learn," *Ms., University of Chicago and Makerere University*, 2021.

Banerjee, Abhijit, Rukmini Banerji, James Berry, Esther Duflo, Harini Kannan, S Mukherji, and Michael Walton, "Teaching at the right level: Evidence from randomized evaluations in India," *NBER Working Paper*, 2015, *22746*, 2369–2429.

— , — , — , — , — , Shobhini Mukherji, Marc Shotland, and Michael Walton, "Mainstreaming an effective intervention: Evidence from randomized evaluations of "Teaching at the Right Level" in India," Technical Report, National Bureau of Economic Research 2016.

Bold, Tessa, Mwangi Kimenyi, Germano Mwabu, Justin Sandefur et al., "Experimental evidence on scaling up education reforms in Kenya," *Journal of Public Economics*, 2018, *168*, 1–20.

Cabezas, Verónica, José I Cuesta, and Francisco A Gallego, "Effects of short-term tutoring on cognitive and non-cognitive skills: Evidence from a randomized evaluation in Chile," *J-PAL Working Paper*, 2011.

Carlana, Michela and Eliana La Ferrara, "Apart but Connected: Online Tutoring, Cognitive Outcomes, and Soft Skills," Technical Report, National Bureau of Economic Research 2024.

Duflo, Esther, Pascaline Dupas, and Michael Kremer, "Peer effects, teacher incentives, and the impact of tracking: Evidence from a randomized evaluation in Kenya," *American economic review*, 2011, *101* (5), 1739–1774.

— , — , and — , “School governance, teacher incentives, and pupil–teacher ratios: Experimental evidence from Kenyan primary schools,” *Journal of public Economics*, 2015, *123*, 92–110.

Falk, Armin, Fabian Kosse, and Pia Pinger, “Mentoring and schooling decisions: Causal evidence,” 2020.

Gal, Adiv and Orna Fallik, “Learn from Each Other: A Peer-Teaching Model,” *Interdisciplinary Journal of Environmental and Science Education*, 2021, *17* (3), e2242.

Gallego, Francisco, Philip Oreopoulos, and Noah Spencer, “The Importance of a Helping Hand in Education and in Life,” Technical Report, National Bureau of Economic Research 2023.

Glewwe, Paul and Karthik Muralidharan, “Improving education outcomes in developing countries: Evidence, knowledge gaps, and policy implications,” in “Handbook of the Economics of Education,” Vol. 5, Elsevier, 2016, pp. 653–743.

— , Michael Kremer, and Sylvie Moulin, “Many children left behind? Textbooks and test scores in Kenya,” *American economic journal: Applied economics*, 2009, *1* (1), 112–135.

— , — , — , and Eric Zitzewitz, “Retrospective vs. prospective analyses of school inputs: the case of flip charts in Kenya,” *Journal of development Economics*, 2004, *74* (1), 251–268.

Guryan, Jonathan, Jens Ludwig, Monica P Bhatt, Philip J Cook, Jonathan MV Davis, Kenneth Dodge, George Farkas, Roland G Fryer Jr, Susan Mayer, Harold Pollack et al., “Not too late: Improving academic outcomes among adolescents,” *American Economic Review*, 2023, *113* (3), 738–765.

Jr, Roland G Fryer, “The production of human capital in developed countries: Evidence from 196 randomized field experiments,” in “Handbook of economic field experiments,” Vol. 2, Elsevier, 2017, pp. 95–322.

Kolencik, Patricia Liotta and Shelia A Hillwig, *Encouraging Metacognition: Supporting Learners through Metacognitive Teaching Strategies. Educational Psychology: Critical Pedagogical Perspectives. Volume 12.*, ERIC, 2011.

Kosse, Fabian, Thomas Deckers, Pia Pinger, Hannah Schildberg-Hörisch, and Armin Falk, “The formation of prosociality: causal evidence on the role of social environment,” *Journal of Political Economy*, 2020, *128* (2), 434–467.

Kraft, Matthew A and Grace T Falken, “A blueprint for scaling tutoring and mentoring across public schools,” *Aera Open*, 2021, *7*, 23328584211042858.

Kremer, Michael, Conner Brannen, and Rachel Glennerster, “The challenge of education and learning in the developing world,” *Science*, 2013, *340* (6130), 297–300.

Mbiti, Isaac M, “The need for accountability in education in developing countries,” *Journal of*

Economic Perspectives, 2016, *30* (3), 109–132.

Muralidharan, Karthik, Abhijeet Singh, and Alejandro J Ganimian, "Disrupting education? Experimental evidence on technology-aided instruction in India," *American Economic Review*, 2019, *109* (4), 1426–1460.

_ **and Venkatesh Sundararaman**, "The impact of diagnostic feedback to teachers on student learning: Experimental evidence from India," *The Economic Journal*, 2010, *120* (546), F187–F203.

_ **, Jishnu Das, Alaka Holla, and Aakash Mohpal**, "The fiscal cost of weak governance: Evidence from teacher absence in India," *Journal of public economics*, 2017, *145*, 116–135.

Nickow, Andre, Philip Oreopoulos, and Vincent Quan, "The impressive effects of tutoring on prek-12 learning: A systematic review and meta-analysis of the experimental evidence," 2020.

Ree, Joppe De, Karthik Muralidharan, Menno Pradhan, and Halsey Rogers, "Double for nothing? Experimental evidence on an unconditional teacher salary increase in Indonesia," *The Quarterly Journal of Economics*, 2018, *133* (2), 993–1039.

Resnjanskij, Sven, Jens Ruhose, Simon Wiederhold, Ludger Woessmann, and Katharina Wedel, "Can Mentoring Alleviate Family Disadvantage in Adolescence? A Field Experiment to Improve Labor Market Prospects," *Journal of Political Economy*, 2024, *132* (3), 000–000.

Sinha, Shabnam, Rukmini Banerji, and Wilima Wadhwa, *Teacher performance in Bihar, India: Implications for education*, World Bank Publications, 2016.

Swartz, Robert J and David N Perkins, *Teaching thinking: Issues and approaches*, Routledge, 2016.

Tanner, Kimberly D, "Promoting student metacognition," *CBE—Life Sciences Education*, 2012, *11* (2), 113–120.

World Bank Group, "Bihar - Poverty, Growth and Inequality," India State Briefs 2016. Wash- ington, D.C.

Appendix - Tables and Figures

Figure 1: Examples - Infrastructure and Peer Tutoring Sessions

Table 1: *Student Learning Levels by Skill and Grade (ASER 2024)*

Region	Grade 2 Math		Grade 3 Math		Grade 2 Reading	
	Grade 3	Grade 5	Grade 3	Grade 5	Grade 3	Grade 5
India	33.7 %	55.8 %	11.4 %	30.7 %	27.0 %	48.7 %
Bihar	37.4 %	55.7 %	19.5 %	36.0 %	26.1 %	43.6 %

Table 2: *School Facilities and Educational Inputs(ASER 2024)*

Item Description	India	Bihar
School facilities		
Mid-day meal served in school on day of visit	91.9	92.9
Drinking water available	77.7	88.7
Boundary Wall	75.3	59.3
Toilet usable	79.0	82.5
Girls toilet: Separate provision, unlocked and useable	72.0	73.6
Library	82.5	67.9
Playground	68.9	47.9
Schools with electricity available on day of visit	89.7	91.6
Computer available for children to use	27.4	16.5
Educational Inputs		
Enrolment: Age 6-14	98.1	97
% Enrolled children present	75.9	60.9
% Teachers present	87.5	79
School has Multi-grade classrooms	66	72
School complies with pupil-teacher ratio norms	63.5	38.2

Table 3: *Sample of schools, representativeness, and balance tests*

	Representativeness (overall)			Balance Checks		
	Non-Study	Study	Difference	Control	Treatment	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Number of teachers	5.38	7.31	1.93***	7.34	7.28	-0.08
	[3.05]	[2.84]	(0.28)	[2.89]	[2.80]	(0.30)
Dist to Bhagalpur (in km)	16.83	16.27	-0.55	16.29	16.24	-0.34
	[9.06]	[8.81]	(0.37)	[8.66]	[9.04]	(0.35)
Student Teacher Ratio	16.64	20.67	4.06***	20.83	20.48	-0.18
	[10.29]	[9.74]	(0.93)	[10.87]	[8.29]	(1.28)
Number of students in 3-5	85.21	134.76	49.71***	135.85	133.48	-1.45
	[70.51]	[41.81]	(5.67)	[44.24]	[39.01]	(3.98)
Boys in grade 3	12.48	19.87	7.39***	20.40	19.24	-1.04
	[11.58]	[8.74]	(0.98)	[8.55]	[8.97]	(1.13)
Girls in grade 3	12.72	21.47	8.74***	21.56	21.35	0.03
	[11.52]	[9.93]	(1.00)	[9.35]	[10.63]	(1.25)
Boys in grade 4	15.15	23.98	8.85***	23.90	24.07	0.14
	[12.98]	[9.34]	(1.10)	[9.71]	[8.94]	(1.16)
Girls in grade 4	14.74	24.40	9.70***	24.56	24.22	-0.24
	[12.94]	[9.26]	(1.08)	[9.19]	[9.40]	(1.11)
Boys in grade 5	15.13	22.11	7.03***	22.22	21.99	0.07
	[13.33]	[9.87]	(1.12)	[9.77]	[10.04]	(1.17)
Girls in grade 5	14.98	22.93	7.99***	23.22	22.60	-0.41
	[13.55]	[9.82]	(1.15)	[10.52]	[8.99]	(1.22)
Fraction of Female teachers	0.46	0.43	-0.03	0.45	0.41	-0.04
	[0.27]	[0.21]	(0.02)	[0.21]	[0.21]	(0.03)
Fraction of General teachers	0.24	0.24	-0.00	0.25	0.22	-0.03
	[0.23]	[0.21]	(0.02)	[0.22]	[0.20]	(0.03)
Fraction of SC teachers	0.15	0.13	-0.02	0.13	0.12	-0.02
	[0.19]	[0.15]	(0.02)	[0.16]	[0.14]	(0.02)
Fraction of ST teachers	0.01	0.01	-0.01	0.01	0.01	0.00
	[0.05]	[0.03]	(0.00)	[0.03]	[0.03]	(0.00)
Fraction of OBC teachers	0.51	0.52	0.01	0.50	0.54	0.03
	[0.28]	[0.24]	(0.02)	[0.24]	[0.24]	(0.03)
Fraction of Secondary Educ teachers	0.01	0.02	0.01*	0.02	0.02	0.00
	[0.05]	[0.06]	(0.00)	[0.06]	[0.05]	(0.01)
Fraction of Higher Secondary Educ teachers	0.37	0.33	-0.05*	0.32	0.33	0.01
	[0.28]	[0.24]	(0.03)	[0.25]	[0.23]	(0.04)
Fraction of Graduate teachers	0.41	0.40	-0.01	0.41	0.39	-0.02
	[0.29]	[0.22]	(0.03)	[0.22]	[0.22]	(0.03)
Fraction of Post Graduate teachers	0.20	0.25	0.04**	0.24	0.25	0.01
	[0.22]	[0.19]	(0.02)	[0.19]	[0.19]	(0.03)
Fraction of Contract teachers	0.00	0.00	-0.00	0.00	0.00	-0.00
	[0.04]	[0.01]	(0.00)	[0.02]	[0.00]	(0.00)
Fraction of Primary teachers	0.82	0.72	-0.10***	0.73	0.71	-0.01
	[0.30]	[0.32]	(0.03)	[0.33]	[0.30]	(0.04)
Fraction of Math teachers	0.78	0.65	-0.12***	0.67	0.64	-0.02
	[0.31]	[0.33]	(0.03)	[0.34]	[0.32]	(0.04)
Number of schools	310	178	488	96	82	178
Joint F-test (p-value)			0.00			0.99

Notes. This table reports on the study's sample of schools. Study refers to the 178 public primary schools included in the study's effective sample. Non-study refers to all other public primary schools in Bhagalpur. Control refers to the 95 schools not assigned to receive the peer tutoring intervention, and Treatment refers to 82 schools assigned to receive this intervention. Difference reports on the regression-adjusted difference. Standard deviations are shown in brackets; standard errors are shown in parentheses. Standard errors are clustered at the school level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: *Descriptive statistics and balance checks*

	Number of observations		Balancing check		
	Control	Treatment	Control	Treatment	Difference
	(1)	(2)	(3)	(4)	(5)
Panel A: Student Characteristics					
Age	3030	2466	9.68	9.60	-0.07*
			[1.31]	[1.27]	(0.05)
Female	3502	2986	0.56	0.57	0.01
			[0.50]	[0.50]	(0.01)
Joint F-test (p-value)					0.47
Panel B: Student Math Skills					
Fraction Correct (Std)	3548	3015	0.06	-0.07	-0.14**
			[0.97]	[1.03]	(0.06)
Addition (Std)	3548	3015	0.01	-0.01	-0.03
			[1.00]	[1.00]	(0.05)
Subtraction (Std)	3548	3015	0.02	-0.03	-0.06
			[1.00]	[1.00]	(0.05)
Multiplication (Std)	3548	3015	0.01	-0.02	-0.04
			[0.99]	[1.02]	(0.05)
Division (Std)	3548	3015	0.02	-0.02	-0.04
			[1.00]	[0.99]	(0.05)
Fraction Correct (Index)	3548	3015	0.06	-0.07	-0.13**
			[0.97]	[1.03]	(0.06)
Addition (Index)	3548	3015	-0.00	0.00	-0.00
			[1.01]	[0.99]	(0.04)
Subtraction (Index)	3548	3015	-0.01	0.01	0.02
			[1.01]	[0.99]	(0.04)
Multiplication (Index)	3548	3015	0.01	-0.02	-0.04
			[0.99]	[1.02]	(0.05)
Division (Index)	3548	3015	0.02	-0.02	-0.05
			[1.01]	[0.99]	(0.05)
Joint F-test (p-value)					0.03

Notes. This table describes the study's sample of 177 schools and presents balance checks. Control refers to the 95 schools not assigned to receive the peer tutoring intervention, and Treatment refers to 82 schools assigned to receive this intervention. Balancing check reports on the regression-adjusted difference. Standard deviations are shown in brackets; standard errors are shown in parentheses. Standard errors are clustered at the school level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: *Descriptive statistics and balance checks*

	Number of observations		Balancing check		
	Control	Treatment	Control	Treatment	Difference
	(1)	(2)	(3)	(4)	(5)
Panel A: Student Socioemotional Wellbeing					
Shy in asking questions	3365	2881	-0.01	0.01	0.02
			[1.00]	[1.00]	(0.03)
Find studying easy	3408	2895	-0.01	0.01	0.03
			[1.02]	[0.98]	(0.03)
Afraid of Math	3426	2927	-0.01	0.02	0.03
			[1.02]	[0.98]	(0.03)
Do not enjoy homework	3461	2954	-0.04	0.05	0.09***
			[1.06]	[0.92]	(0.04)
Curious	3471	2959	-0.04	0.05	0.10**
			[1.06]	[0.92]	(0.04)
Important to score good grades	3449	2943	-0.01	0.01	0.02
			[1.02]	[0.98]	(0.04)
Hardwork will improve grades	3474	2957	-0.01	0.01	0.03
			[1.03]	[0.97]	(0.04)
Want to become monitor	3466	2965	-0.01	0.01	0.02
			[1.02]	[0.98]	(0.04)
Joint F-test (p-value)					0.73
Panel B: Student Social Networks					
In-degree (Help in Studies)	3526	3015	1.75	1.73	-0.04
			[2.21]	[2.35]	(0.09)
Out-degree (Help in Studies)	3526	3015	1.55	1.56	-0.00
			[1.30]	[1.34]	(0.07)
In-degree (Friends)	3526	3015	2.73	2.83	0.10
			[2.53]	[2.75]	(0.13)
Out-degree (Friends)	3526	3015	2.54	2.64	0.10
			[1.94]	[2.15]	(0.12)
Named Popular	3526	3015	1.37	1.45	0.07
			[1.81]	[2.06]	(0.08)
Joint F-test (p-value)					0.73

Notes. This table describes the study's sample of 177 schools and presents balance checks. Control refers to the 95 schools not assigned to receive the peer tutoring intervention, and Treatment refers to 82 schools assigned to receive this intervention. Balancing check reports on the regression-adjusted difference. Standard deviations are shown in brackets; standard errors are shown in parentheses. Standard errors are clustered at the school level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: *ITT Effects: Math*

	ITT: All			ITT: Learners	Leaders Vs Learners (Control)	ITT:Leaders Vs ITT:Learners	ITT: Leaders	Leaders Vs Learners (Treatment)
	Control Mean (All)	Treat (β)	Control Mean (Learners)	Treat (β_1)	Leader (β_2)	TreatXLeader (β_3)	($\beta_1 + \beta_3$)	($\beta_2 + \beta_3$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Score (Standardized)	0.709	0.187***	0.682	0.195***	0.192***	-0.056	0.139**	0.135***
	[0.195]	(0.058)	[0.197]	(0.065)	(0.045)	(0.057)	(0.054)	(0.043)
Weighted Score (Standardized)	0.714	0.179***	0.686	0.188***	0.174***	-0.060	0.128**	0.114***
	[0.205]	(0.054)	[0.208]	(0.061)	(0.044)	(0.055)	(0.052)	(0.043)
Addition (Standardized)	0.886	0.052**	0.874	0.043	0.110***	0.035	0.077**	0.145***
	[0.193]	(0.025)	[0.202]	(0.031)	(0.033)	(0.042)	(0.033)	(0.026)
Subtraction (Standardized)	0.736	0.042	0.711	0.036	0.262***	0.013	0.049	0.275***
	[0.267]	(0.039)	[0.269]	(0.044)	(0.036)	(0.051)	(0.046)	(0.037)
Multiplication (Standardized)	0.604	0.083*	0.569	0.091*	0.266***	-0.042	0.049	0.224***
	[0.342]	(0.046)	[0.343]	(0.052)	(0.041)	(0.055)	(0.055)	(0.041)
Division (Standardized)	0.619	0.088**	0.576	0.097**	0.232***	-0.047	0.050	0.185***
	[0.373]	(0.039)	[0.377]	(0.045)	(0.038)	(0.052)	(0.044)	(0.039)
Pictorial (Standardized)	0.832	0.071*	0.813	0.070	0.180***	-0.005	0.064	0.175***
	[0.312]	(0.038)	[0.324]	(0.044)	(0.038)	(0.050)	(0.042)	(0.034)
Counting (Standardized)	0.611	0.124	0.586	0.102	0.401***	0.040	0.142	0.441***
	[0.320]	(0.087)	[0.321]	(0.095)	(0.063)	(0.084)	(0.092)	(0.058)
Word Problems (Standardized)	0.717	0.170**	0.689	0.198**	0.354***	-0.142*	0.055	0.211***
	[0.337]	(0.081)	[0.348]	(0.088)	(0.054)	(0.079)	(0.085)	(0.057)
Easy (Standardized)	0.890	0.075**	0.877	0.069*	0.124***	0.022	0.091**	0.146***
	[0.172]	(0.032)	[0.180]	(0.038)	(0.036)	(0.046)	(0.037)	(0.028)
Medium (Standardized)	0.690	0.167***	0.665	0.160***	0.244***	-0.011	0.149***	0.233***
	[0.256]	(0.050)	[0.258]	(0.055)	(0.038)	(0.049)	(0.053)	(0.036)
Hard (Standardized)	0.567	0.086**	0.526	0.097**	0.234***	-0.055	0.042	0.179***
	[0.295]	(0.040)	[0.292]	(0.045)	(0.037)	(0.047)	(0.044)	(0.036)
Score (Index)	0.689	0.198***	0.521	0.203**	0.260***	-0.055	0.149**	0.206***
	[1.214]	(0.073)	[1.216]	(0.082)	(0.051)	(0.067)	(0.068)	(0.052)
Addition (Index)	0.262	0.025	0.233	0.015	0.070***	0.043	0.057*	0.113***
	[0.614]	(0.022)	[0.635]	(0.026)	(0.027)	(0.035)	(0.029)	(0.022)
Subtraction (Index)	0.114	0.025	0.041	0.022	0.235***	0.011	0.033	0.246***
	[0.843]	(0.036)	[0.853]	(0.041)	(0.032)	(0.047)	(0.044)	(0.035)
Multiplication (Index)	0.026	0.085*	-0.076	0.092*	0.271***	-0.039	0.053	0.232***
	[0.934]	(0.047)	[0.935]	(0.052)	(0.042)	(0.056)	(0.056)	(0.042)
Division (Index)	0.590	0.088**	0.482	0.097**	0.236***	-0.046	0.051	0.190***
	[0.900]	(0.039)	[0.909]	(0.045)	(0.038)	(0.052)	(0.045)	(0.039)
Pictorial (Index)	0.333	0.079**	0.270	0.078*	0.189***	-0.008	0.070	0.181***
	[0.980]	(0.039)	[1.023]	(0.045)	(0.040)	(0.052)	(0.042)	(0.035)
Counting (Index)	2.028	0.122	1.805	0.116	0.837***	0.003	0.120	0.840***
	[2.936]	(0.167)	[2.909]	(0.183)	(0.109)	(0.162)	(0.177)	(0.119)
Word Problems (Index)	-0.227	0.125**	-0.309	0.148**	0.282***	-0.110*	0.038	0.172***
	[0.971]	(0.060)	[1.003]	(0.066)	(0.041)	(0.059)	(0.063)	(0.042)
Easy (Index)	0.240	0.074**	0.174	0.068*	0.129***	0.021	0.089**	0.150***
	[0.846]	(0.033)	[0.887]	(0.040)	(0.036)	(0.047)	(0.037)	(0.029)
Medium (Index)	0.422	0.164***	0.328	0.157***	0.243***	-0.010	0.147***	0.233***
	[0.914]	(0.049)	[0.924]	(0.055)	(0.037)	(0.049)	(0.052)	(0.036)
Hard (Index)	0.148	0.088**	0.036	0.095**	0.223***	-0.037	0.058	0.185***
	[0.774]	(0.041)	[0.772]	(0.046)	(0.036)	(0.046)	(0.043)	(0.035)

Notes. Standard deviations are shown in brackets; standard errors are shown in parentheses. Standard errors are clustered at the school level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure 2: *Quantile regression to evaluate treatment effects on standardized math test scores across the baseline distribution*

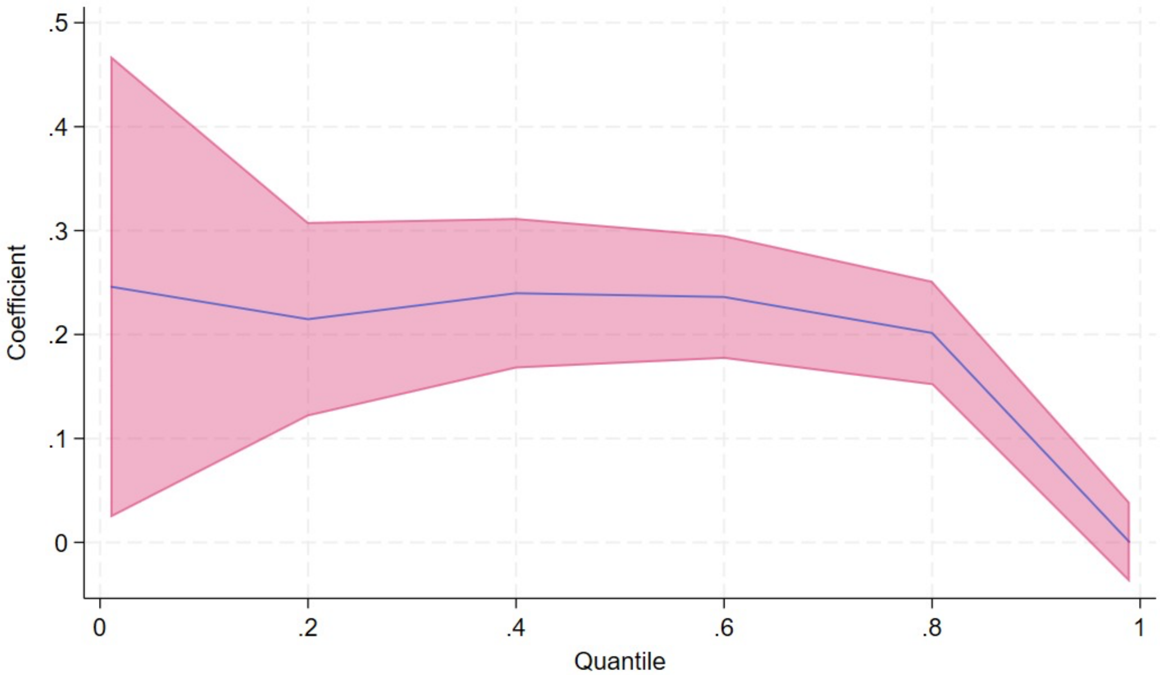

Table 7: *ITT Effects: Socioemotional Wellbeing*

	ITT: All			ITT: Learners	Leaders Vs Learners (Control)	ITT:Leaders Vs ITT:Learners	ITT: Leaders	Leaders Vs Learners (Treatment)
	Control Mean (All)	Treat (β)	Control Mean (Learners)	Treat (β_1)	Leader (β_2)	TreatXLeader (β_3)	($\beta_1 + \beta_3$)	($\beta_2 + \beta_3$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shy in Asking Qs	1.980	-0.002	2.046	-0.002	-0.015***	-0.001	-0.003	-0.016***
	[1.569]	(0.005)	[1.598]	(0.005)	(0.003)	(0.005)	(0.006)	(0.004)
Studying is Easy	4.157	0.006**	4.130	0.008**	0.006*	-0.006	0.002	-0.000
	[1.451]	(0.003)	[1.459]	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)
Afraid of Math	1.922	-0.001	1.979	0.000	-0.010***	-0.004	-0.004	-0.014***
	[1.545]	(0.003)	[1.569]	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Don't Enjoy HW	1.926	0.002	1.996	0.002	-0.010***	0.000	0.002	-0.010***
	[1.541]	(0.003)	[1.574]	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)
Want to Learn Magic	3.709	-0.001	3.674	0.000	0.005**	-0.004	-0.004	0.001
	[1.692]	(0.003)	[1.700]	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Good Grades Important	4.539	0.002	4.476	0.004*	0.012***	-0.007**	-0.003	0.005**
	[1.127]	(0.002)	[1.194]	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Harwork Improves Grades	4.669	0.002	4.628	0.002	0.008***	-0.002	0.000	0.006***
	[0.924]	(0.002)	[0.972]	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Want to Become Monitor	4.505	0.002	4.448	0.003	0.010***	-0.004	-0.001	0.006***
	[1.132]	(0.002)	[1.187]	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Best Grades Important	4.574	0.001	4.517	0.002	0.009***	-0.003	-0.001	0.006***
	[1.067]	(0.002)	[1.126]	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Quit Game if Lose	2.442	0.000	2.529	-0.001	-0.012***	0.003	0.002	-0.009***
	[1.796]	(0.003)	[1.811]	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Monitor if Friend is	4.369	0.003	4.347	0.002	0.003	0.003	0.005**	0.006***
	[1.304]	(0.002)	[1.313]	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Sharing Laddoo	2.804	0.003	2.807	0.003	-0.001	0.000	0.004	-0.001
	[1.231]	(0.005)	[1.239]	(0.005)	(0.003)	(0.005)	(0.006)	(0.004)
Khokho Vs Kabaddi	1.750	0.001	1.768	0.001	-0.002**	-0.000	0.001	-0.002**
	[0.660]	(0.001)	[0.658]	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Play Alone	4.212	-0.001	4.181	-0.001	0.004**	0.001	0.000	0.005***
	[1.091]	(0.002)	[1.106]	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Enjoy Friends Teaching	4.634	0.007	4.614	-0.008	0.075*	0.059	0.052	0.134***
	[0.985]	(0.040)	[0.997]	(0.046)	(0.042)	(0.064)	(0.057)	(0.048)
Anxious Learning with Friends	2.211	-0.097**	2.302	-0.106**	-0.203***	0.033	-0.073	-0.171***
	[1.730]	(0.047)	[1.756]	(0.052)	(0.041)	(0.060)	(0.059)	(0.043)
Exclude Poor Performer	2.878	0.083*	2.895	0.092*	-0.045	-0.035	0.057	-0.080
	[1.829]	(0.050)	[1.821]	(0.052)	(0.045)	(0.068)	(0.072)	(0.052)
Befriend Better Performer	4.086	0.059	4.064	0.074	0.043	-0.058	0.016	-0.015
	[1.537]	(0.058)	[1.540]	(0.059)	(0.044)	(0.069)	(0.080)	(0.053)
Less Shy in Groups	2.725	0.020	2.786	0.019	-0.131**	0.003	0.022	-0.128***
	[1.832]	(0.048)	[1.822]	(0.051)	(0.051)	(0.067)	(0.068)	(0.046)
Like Group Study	1.437	-0.023	1.467	-0.013	-0.123***	-0.033	-0.046	-0.157***
	[0.965]	(0.052)	[0.997]	(0.058)	(0.042)	(0.061)	(0.061)	(0.045)
Frequency of Groups	2.559	-0.017	2.574	-0.041	-0.044	0.087	0.047	0.043
	[1.157]	(0.050)	[1.175]	(0.054)	(0.040)	(0.060)	(0.063)	(0.043)

Notes. Standard deviations are shown in brackets; standard errors are shown in parentheses. Standard errors are clustered at the school level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 8: *ITT Effects: Social Networks*

	ITT: All		ITT: Learners		Leaders Vs Learners (Control)	ITT:Leaders Vs ITT:Learners	ITT: Leaders	Leaders Vs Learners (Treatment)
	Control Mean (All)	Treat (β)	Control Mean (Learners)	Treat (β_1)	Leader (β_2)	TreatXLeader (β_3)	($\beta_1 + \beta_3$)	($\beta_2 + \beta_3$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In Degree (Help in Studies)	1.343	0.054	1.157	0.045	0.512***	0.030	0.074	0.542***
	[1.893]	(0.063)	[1.687]	(0.058)	(0.083)	(0.130)	(0.137)	(0.096)
Out Degree (Help in Studies)	1.254	0.020	1.218	-0.018	0.080	0.150*	0.133	0.231***
	[1.425]	(0.055)	[1.400]	(0.060)	(0.056)	(0.091)	(0.088)	(0.073)
In Degree (Friends)	1.652	-0.056	1.549	-0.064	0.210**	0.034	-0.030	0.244**
	[1.958]	(0.085)	[1.844]	(0.086)	(0.081)	(0.127)	(0.138)	(0.096)
Out Degree (Friends)	1.568	-0.055	1.519	-0.102	0.080	0.197*	0.094	0.277***
	[1.983]	(0.085)	[1.926]	(0.088)	(0.084)	(0.115)	(0.126)	(0.077)
In Degree (Peer Group)	1.399	-0.119*	1.277	-0.087	0.473***	-0.136	-0.223*	0.337***
	[1.819]	(0.071)	[1.729]	(0.072)	(0.074)	(0.106)	(0.116)	(0.078)
Out Degree (Peer Group)	1.326	-0.114	1.272	-0.146**	0.190***	0.126	-0.020	0.316***
	[1.559]	(0.070)	[1.523]	(0.072)	(0.055)	(0.083)	(0.098)	(0.063)
Named Popular	1.130	0.019	1.002	0.020	0.363***	-0.005	0.015	0.358***
	[1.757]	(0.055)	[1.518]	(0.055)	(0.075)	(0.106)	(0.107)	(0.070)

Notes. Standard deviations are shown in brackets; standard errors are shown in parentheses. Standard errors are clustered at the school level. * p < 0.10, ** p < 0.05, *** p < 0.01.