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Haste Makes No Waste: Positive Peer Effects of Classroom Speed Competition on Learning

HIKARU KAWARAZAKI,†,‡ MINHAJ MAHMUD,§,¶
YASUYUKI SAWADA# and MAI SEKI††

†Department of Economics, University College London, 30 Gordon Street, Kings Cross London, WC1H 0AX, UK (e-mail: hikaru.kawarazaki.20@ucl.ac.uk)
‡Institute for Fiscal Studies, 7 Ridgmount Street London, United Kingdom (e-mail: hikaru.kawarazaki.20@ucl.ac.uk)
§Economic Research and Regional Cooperation Department, Asian Development Bank, 6 ADB Avenue Mandaluyong City, 1550 Metro Manila, Philippines (e-mail: mmahmud@adb.org)
¶Bangladesh Institute of Development Studies, E-17 Agargaon, Sher-e-Bangla Nagar Dhaka 1207, Bangladesh (e-mail: mmahmud@adb.org)
#Faculty of Economics, University of Tokyo, 7 Chome-3- 1 Hongo, Bunkyo Tokyo 113 8654, Japan (e-mail: sawada@e.u-tokyo.ac.jp)
††Faculty of Economics, Ritsumeikan University, 1-1-1 Nojihigarhi Kusatsu, Shiga 525-8577, Japan (e-mail: maiseki@fc.ritsumei.ac.jp)

Abstract

This study investigates the effects of speed competition in classrooms on young pupils' learning outcomes. To examine how faster peers' speed affects slower pupils' speed and learning, we employ students' daily progress data in a self-learning programme at BRAC primary schools in Bangladesh. The programme's unique setting allows us to address the reflection problem reasonably well. While speed competition could generate negative consequences, our results show overall positive peer effects on problem-solving time and scores. The effects are stronger among peers with similar abilities, without negatively affecting others. Our results show efficiency gains from non-market competition in education and learning.

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I. Introduction

Competitive markets are the focus of modern economics research, but competition also arises from non-market mechanisms. The Tiebout model highlights the role of non-price competition in efficiently using public resources in the case of local governments (Tiebout, 1956). In addition, in the case of firms, the rank-order tournament provides a competitive mechanism to enhance overall productivity (Lazear and Rosen, 1981). However, efficiency gains from non-market competition are not always warranted. For example, political competition may not result in a socially optimal outcome (Arrow, 1950). As pointed out by Keynes (1936), a beauty contest may result in a suboptimal outcome. This result can be attributed to herding behaviour (Banerjee, 1992). In the real world, non-market competition often takes place under time pressure in a form of speed competition, especially in sports (Jane, 2015; Yamane and Hayashi, 2015) and the workplace (Mas and Moretti, 2009; Kilduff, 2014; Park, 2019).[1]

In educational setting, many studies witness peer effects in different non-market contexts. Most papers focus on spillover effects of other schoolmates, classmates, or flat mates on academic outcomes (Hoxby, 2000; Sacerdote, 2001; Zimmerman, 2003; Ding and Lehrer, 2007; Figlio, 2007; Kang, 2007; Ammermueller and Pischke, 2009; Carrell, Fullerton, and West, 2009; Carrell and Hoekstra, 2010; Duflo, Dupas, and Kremer, 2011; Arcidiacono *et al.*, 2012; Lavy, Silva, and Weinhardt, 2012; Burke and Sass, 2013; Angrist, 2014; Lu and Anderson, 2015; Feld and Zölitz, 2017; Murphy and Weinhardt, 2020), while some investigate competition-orientation and gender difference (Gneezy, Niederle, and Rustichini, 2003; Gneezy and Rustichini, 2004; Gneezy, Leonard, and List, 2009) as well as peer pressure and behavioural changes when their choices on competition-participation are revealed (Bursztyn and Jensen, 2015; Bursztyn, Egorov, and Jensen, 2019).[2] However, to our knowledge, real-time non-market competition in an educational setting is under-investigated.[3][4]

This study attempts to bridge this gap in the existing literature at least partially by investigating the impact of contemporaneous speed competition on human capital investment. Especially, we focus on real-time non-market competition in an educational setting whereby problem-solving speed is a signal of competitiveness. To our knowledge, this study is the first to examine this. Speed in general is an important aspect of thinking about the efficiency of completing a task, regardless of in an educational or labour-market setting.

[1]In the literature of experimental economics and psychology, researchers have begun investigating the role of time (Diederich, 1997; Kocher and Sutter, 2006; Voyer, 2011; Rubinstein, 2016; Spiliopoulos and Ortmann, 2018).

[2]In general, peer pressure works in a complicated manner: either to improve a positive norm or to hide effort (Bursztyn and Jensen, 2015; Bursztyn *et al.*, 2019)

[3]For example, we frequently see a 'racing'-type environment in the high-stake screening mechanism for entry into high-tier educational institutions.

[4]Furthermore, we relate our study to the viewpoint of efficiency in the standard economic theory of market competition, namely, applications of the celebrated general equilibrium model of monopolistic competition by Dixit and Stiglitz (1977) that shows the inefficiencies of the lack of perfect competition in a general equilibrium. The model has been applied in a variety of economic fields, including macroeconomics, growth literature (Blanchard and Kiyotaki, 1987; Romer, 1990), international trade theory (Krugman, 1979; Krugman, 1980) and economic geography (Krugman, 1991; Krugman, 1992). Also, the new industrial organization field emerged in 1990s that studies on market competition in a strategic context (Tirole, 1988).

Furthermore, this study is the first to analyse the potential trade-off between learning and speed. Theoretically, in a learning environment, speed competition among peers can either positively or negatively affect one's own learning. While speed competition among peers may incentivize them to invest more effort and maintain high motivation to achieve better learning outcomes, it could also have negative impacts by inducing careless errors owing to excessive time pressures as well as anxiety. Peer effects in educational settings have been of great interest to educators, parents and researchers. Although there is extensive literature on peer effects via learning outcomes, such as test scores and grades, to the best of our knowledge, no study has focused on the peer effects of speed on learning.[5] Using a unique competitive classroom setting of an individualized self-learning programme, we focus on the potential compatibility or trade-off between problem-solving speed and learning measured by mathematics test scores. In particular, we examine the peer effects of a classroom speed competition by leveraging the treatment sample of a randomized controlled trial (RCT) study that investigated the effectiveness of self-learning at the right-level programme (the Kumon method of learning) (Sawada *et al.*, 2022).[6]

In the Kumon programme, students work on their individualized worksheets and submit them to the grading assistants who sit in the front row of the classroom.[7] Students can observe who finishes the daily classroom assignment faster than others. This unique setting allows us to examine the peer effects of problem-solving speed on students' learning outcomes across two dimensions: their own speed and score. In our setting, when solving individualized worksheets, students might compete along the lines of speed, which may affect their learning outcomes.[8] Problem-solving speed is measured based on the time of submission, which becomes visible to others when someone stands up and submits the completed worksheets to the graders. Therefore, the speed of a student who finishes faster can work as an exogenous shock to other slower students. Furthermore, the faster students' speed measured by their submission time can affect slower students, but not vice versa, that is, one-directional peer effects. This unique setup helps us to identify the causal effects of a faster peer's behaviour on the rest of the classmates still working on their worksheets. This also allows us to address the reflection problem reasonably well.

A potential mechanism behind this competition is a sense of rivalry, which can instil the motivation to perform beyond the ordinary competitive spirit and/or objective stakes (Kilduff, Elfenbein, and Staw, 2010). This rivalry can motivate students to work harder, smarter and longer (Grant and Shandell, 2022).[9] Students speed up so

[5] See (Epple and Romano, 2011; Sacerdote, 2011; Paloyo, 2020) for reviews of the literature on peer effects.

[6] The intervention comprised daily sessions of the Kumon method of learning (hereafter, Kumon) over 8 months, introduced to non-formal primary schools operated by BRAC in Bangladesh. In a companion paper on the impact of the Kumon programme, Sawada *et al.* (2022) found substantial improvements in students' cognitive abilities as measured by mathematics test scores.

[7] Ten worksheets are assigned as daily assignments during the 30 minutes of a Kumon session, and students submit them upon completion of all 10 worksheets.

[8] One might argue that students do not know that they are in a time-competition, but students generally face a time limit to complete their task and seeing someone submitting the worksheets early can potentially encourage competition in terms of speed. Also, students have no other incentive to speed up, such as finishing early to play outside because they are not allowed to leave the classroom, and even if they finish early, must wait to join the regular BPS class.

[9] See Grant and Shandell (2022) for a review on the literature about competition in psychology.

that they are not slower than their peers, while they do not necessarily compete for grade because they cannot observe others' grades or compare them directly as they apparently solve different problem sets, but potentially taking the risk of making careless errors (To *et al.*, 2018).[10,11]

Our result shows positive peer effects on speed – the faster the peers, the faster a student. We also find positive peer effects on scores of students who perform similarly in terms of speed – the faster the peers with similar speeds, the better a student performs. However, the scores of students who are slower than the class median are not affected by the speed of the fastest peers. Rather, these slower students' scores improve when the median speed of the class increases.

These results suggest that competition is most likely to occur sequentially: students in the fastest group compete with each other, while slower students only compete against their peers who are slightly faster than them but not necessarily the fastest. We do not observe any negative peer pressure. Our findings suggest that competing with others leads to better performance, consistent with previous studies (Vroom, 1964; Van Eerde and Thierry, 1996; Tran and Zeckhauser, 2012; Kilduff, 2014).

The remainder of the paper is organized as follows. Sections II and III outline the setting and data, respectively. Section IV presents the empirical approach, Section V discusses the results, and Section VI concludes the paper.

II. Setting

We use data from an RCT that investigated Kumon's impact on the cognitive and non-cognitive abilities (Sawada *et al.*, 2022) of students of 34 BRAC Primary Schools (BPS) in Bangladesh, with support from the Kumon Institute of Education Co., Ltd., which provided an intervention package comprising mathematics materials and an instructor's manual with recording sheets for the teachers.[12] The intervention entailed a 30-minute session on the Kumon study prior to regular lessons. The starting level of each student was adjusted to the student's ability determined by the initial diagnostic test, regardless of their age or grade, so that the students could solve all problems correctly by themselves within a

[10] By conceptualizing 'rivalry as a relationship that magnifies the subjective valence of competitive outcomes', Kilduff *et al.* (2010) suggest that the individual similarities, repeated competitive interactions, and past competitiveness can lead to rivalry.

[11] In the psychology and pedagogy literature, there seems to be a consensus that cooperation leads to a considerably better outcome (Johnson *et al.*, 1981; Qin, Johnson, and Johnson, 1995). However, the definition of a competitive environment in the literature is a situation in which there is a negative correlation between each participant's goal attainment, and not everyone can achieve their goals (Deutsch, 1949; Johnson *et al.*, 1981). In our setting, however, the students' focus is essentially on obtaining a full score in each worksheet and not winning a race against others – everyone can achieve her goal. Therefore, the competition in our setting is more implicit and indirect, and students might enjoy it as a game with others. In the literature on gamification in education, defined as an educational programme or setting with a game or a game-like element, a lot of evidence on the positive effects of gamification (Lee and Hammer, 2011; Dicheva *et al.*, 2015). Therefore, another potential mechanism through which we could have observed positive peer effects is the gamification aspect of speed competition.

[12] The full material set comprised (i) mathematics worksheets with questions of varying difficulty levels (Table A1 and Figure A1 in Data S1) and (ii) a record book to note daily progress, including the level of the student's worksheet, time spent until submission, any repetition required before achieving a full score, and the number of worksheets finally completed (Figure A2 in Data S1). Table A2 in Data S1 explains how the difficulty level of the worksheet is converted into numerical values.

certain time. We studied the detailed daily records of students' problem solving in Kumon sessions running 8 months (August 2015 to April 2016) from the 17 intervention schools. In a particular school intervention is either offered in grade 3 or grade 4 classroom.

During the daily Kumon session, each student solved 10 worksheets in an ascending order of difficulty level, starting with worksheet No.1. Once they completed all 10 worksheets, the students brought their sheets for grading to the marking assistant/grader sitting in the front row. The session ended either when students achieved a full score (when all the answers are correct), or when 30 minutes had passed; the students are allowed to correct their mistakes to obtain the full score until the end of the session. During the sessions, the BPS teachers did not provide lectures; they simply observed the students' progress. They only intervened when students were stuck on the same worksheet or could not solve a problem after many attempts, and adjusted the level of the worksheets. However, they provided guidance when advanced students proceeded to entirely new material beyond the regular curriculum.

In our setting, students solve individualized worksheets, and they submit to the grader once all the 10 worksheets are solved. After the first submission, if the grader finds any mistake, then the relevant worksheet is returned for correction. It is possible for someone to notice if a peer's worksheet(s) is returned for correction, indicating that they did not obtain full mark in the first submission, which would make others to pay attention to both their speed and score. However, no student would know for certain the exact number of correctly solved worksheets or grade obtained by the faster peers. Furthermore, as the grading is done manually one by one, they could not know the result immediately. In our analysis, we only considered the time and score of the first submission to avoid any such complication.

III. Data

We used the daily student record of the time taken to submit 10 worksheets, along with their scores, and whether any repetitions were required before achieving a full score on a given worksheet. We focused on the first 3 months of daily records for the analysis because the number of worksheets solved by students during these Kumon sessions is universally measured at 10 worksheets during this time.[13]

Table 1 shows the summary statistics of the variables used in the analysis. Panel A highlights the key demographics of the sample of 335 students. More than one third of the students are female (38.2%) and about 40% of them are studying in grade four. We also show the statistics of the baseline cognitive skills, measured by proficiency tests of self-learning skills II (PTSII) and diagnostic test (DT), as well as the baseline non-cognitive skills, measured by Rosenberg self-esteem scale (RSES Index) and the children's perceived competence scale (CPCS Index).[14] Panel B shows the summary

[13]See Figure A4 in Data S1. From the fourth month until the end, there were some variations in the number of worksheets solved per student. We excluded these five months from our analysis for the sake of comparability.

[14]The DT is time-specific and requires students to answer 70 questions within a maximum of 10 minutes. The PTSII has two sections: The first section contains a total of 228 math questions within five categories that measure different dimensions of math problem-solving skills and we use the aggregate score as a measure of their cognitive ability. The second part of the PTSII-C comprises 27 questions that measure the aspects of non-cognitive abilities.

TABLE 1
Summary statistics

	Mean	*SD*	*25%-tile*	*Median*	*75%-tile*	*N*
Panel A: Individual-level Characteristics						
Fraction of girls	0.3821					335
Fraction of grade 4[a]	0.4060					335
Age	10.04	1.088	9	10	11	331
Initial sheet number[b]	638.3	162.0	481	681	681	335
Total days of attendance at Kumon sessions						
From August 2015 to April 2016	131.4	25.54	123	138	149	335
From August 2015 to October 2015	36.52	7.344	33	38	41	335
Baseline PTSII Score	35.07	10.53	28	34.5	42	326
Baseline DT Score	45.28	17.55	38	48	59	332
Baseline DT Time	9.497	1.318	10	10	10	332
Baseline DT Score per Minute	4.972	2.416	3.8	4.9	6.2	332
Baseline RSES	21.15	2.533	20	21	22.25	335
Baseline CPCS	27.89	2.976	26.23	28	30	335
Panel B: Daily-level characteristics						
Time for solving 10 worksheets	11.70	4.690	8	11	14	12,108
Total score of 10 sheets (full score = 1,000)[c]	985.3	48.89	995	1,000	1,000	12,230
Obtaining full score (full score = 1)						
in Sheet No. 1–3	0.8442	0.3627	1	1	1	12,230
in Sheet No. 4–7	0.7868	0.4096	1	1	1	12,230
in Sheet No. 8–10	0.7866	0.4097	1	1	1	12,230
Start level of the worksheet of the day[b]	93.34	56.76	41	91	141	12,234

Notes. Sample is selected by omitting observations with missing values in the variables on time, score, and level of the work sheets. PTSII-C stands for the proficiency tests of self-learning skills II, cognitive part, and DT stands for diagnostic test. These tests are used to measure student's cognitive ability. The second section of PTSII comprises 27 questions that measure the aspects of non-cognitive abilities. Among the 27 questions, eight are consistent with the Rosenberg self-esteem scale (RSES Index) (Rosenberg, 1965), and 10 are consistent with the children's perceived competence scale (CPCS Index) (Harter, 1979; Sakurai and Matsui, 1992). As non-cognitive ability measures, we created the RSES and CPCS Indices based on these questions. See Sawada *et al.* (2022) for more details.
[a] The sample contains third and fourth grade students.
[b] The worksheet levels are converted into numbers. See Table A1 in Data S1.
[c] The letter scores are converted into numbers. See Table A2 in Data S1.

statistics of the daily records. The average time is approximately 12 minutes, with a 5-minute SD; this is the amount of time needed to submit the 10 worksheets to the marking assistants. The total score of 10 worksheets is 1,000 and the average score obtained is 985, which seems high but the level of worksheet is adjusted to just the right level for each student. The likelihood of obtaining a full score is 78% and above, even on the last three worksheets when students tend to get more challenging questions, discussed in detail in Figure A3 in Data S1. The high likelihood of full scores is simply a result of the fact that the worksheets are designed for the students to learn the materials that are just right for them (i.e. learning at the right level). If they do not obtain full marks, some students spend additional time working on the problem within the 30-minute session.

Among them, eight are consistent with the Rosenberg self-esteem scale (RSES Index) (Rosenberg, 1965), and 10 are consistent with the children's perceived competence scale (CPCS Index) (Harter, 1979; Sakurai and Matsui, 1992). As non-cognitive ability measures, we created the RSES and CPCS Indices based on these questions. See Sawada *et al.* (2022) for more details.

Out of 335 total students in our sample, 268 students appeared to be the fastest at least once on a particular day during the intervention period (8 months). We provide the details of the fastest student characteristics in Table A3 in Data S1, whereby we do not see any significant difference with respect to gender, age, as well as other characteristics between the fastest students and the entire student sample reported in Table 1. Furthermore, as reported in Table A4 in Data S1, the fastest students appeared to change each day. These suggest that it was not easy for others to identify in advance who would be the fastest one on a day so that they could adopt their behaviour or respond accordingly.

IV. Empirical strategy

In our empirical analysis, we employ the following regression model:

$$y_{ids} = \alpha + \beta m_{ds} + \eta_{is} + \nu_d + \varepsilon_{ids}, \tag{1}$$

where y_{ids} is the outcome variable, either the time or score of student i on day d in school/classroom s. We use school and classroom interchangeably because of the one school-one classroom setting of the RCT study. When time is an outcome, we use the amount of time student i spent to solve and submit the 10 worksheets the first time. For the score, we use a dummy variable indicating a full score in the worksheets on day d. Specifically, we use a dummy that takes the value of one if a student obtains a full score in the last three worksheets, No. 8 to No. 10. This is because we expect that the students have witnessed the fastest ones finishing all the worksheets when they are solving the last set, given that they solve them in ascending manner.[15] The peer effects proxy variable, m_{ds}, takes either the fastest or median time of classmates for submitting 10 worksheets on day d in school/classroom s. Here, daily fastest/median submission time is determined within a specific classroom on a particular observation day, and changes every day across classroom. η_{is} is the fixed effects of student i in school s, and ε_{ids} is an error term.[16] We estimate the model using ordinary least squares, while clustering standard errors at the school level.

In this specification, there are two major identification challenges. The first is the direction of causality, and the second is Manski's reflection problem. First, in the Kumon sessions in our case, there is a clear direction of causality in terms of the time taken for problem-solving from students who finish earlier than those who finish later owing to the self-learning setting. The time taken by a peer to submit the worksheet is an exogenous shock for slower students, because the students do not know their peers' speed until they see someone submit their worksheets.[17] In other words, only at the submission point can a student know that a peer is faster.[18] During the 30-minute Kumon session in the

[15] We conduct a falsification test focusing on the first three set of worksheet. See Section V for the details.

[16] Note that these students' fixed effects also control for school fixed effects, given that each student is enrolled in only one school.

[17] Slower students mean slower than the fastest or median time of a day in a classroom. Relative to the fastest time or median time of a day within a classroom, slower students are everyone who submits 10 worksheets after the fastest submission time or median time, respectively.

[18] The same discussion applies to faster students: they get to know that they are faster than others only at the time of submission. We examined how frequently the fastest students changed over time and found that there were sufficient

classroom, students sit in an orderly fashion from front to back in three to four columns, with spaces on both sides, so that each student can focus on their own assignment and not look around or chat with friends.[19] Each student is looking down at the worksheet and therefore, the timing of when a classmate finishes their work early can come as a sudden shock (Figure A5 in Data S1). The behavior of the fastest student is highly noticeable to others because they stand up and proceed to the marking assistants in the front row of the classroom to submit their completed work. We exploit this property for our identification strategy.

Another identification challenge for investigating the peer effects of time on a student's performance of both time and score is the reflection problem discussed by Manski (1993). This is a common problem in peer effects and social interaction estimations. Identification becomes a challenge if faster students could monitor slower students' time to adjust their own time. If this is possible, the measurements of a peer's time would depend on one's own time, which leads to a classical reflection problem, and we would not be able to precisely estimate the peer effects. However, as discussed above, our measurement of peer effects is free from this problem. As the students were solving individualized worksheets, none could identify what others are solving at the same time.[20] This means that a student cannot predict other students' submission time beforehand. Instead, only student i, who is slower, is influenced by their peers' speeds when they observe faster students submit their worksheets, which comes as an exogenous shock. From these viewpoints, using the fastest or faster students' time largely addresses Manski's reflection problem.

However, we provide robustness analysis over potential concerns on contemporaneous correlation between the fastest student's and own speed, which might affect the former's time. Furthermore, another potential threat to the identification might arise as a reflection problem if the fastest student's speed today is affected by slower students' speed yesterday, that is, if there is any correlation between the median time yesterday and the fastest time today. We conduct robustness analyses to best cope with such concerns.

V. Results

Main results

The first three columns of Table 2 show the peer effects of classmates' speeds for solving 10 worksheets. We find that the fastest student's speed significantly improves students' overall problem-solving speed, which suggests that students compete with each other. We can interpret the result in Column (3) as follows: if the fastest student solves the worksheets a minute faster, the followers benefit by becoming 0.5358 minutes faster. This acceleration seems to happen in the last part of the session when students can observe their

variations among the fastest students, and it was not straightforward for others to learn about the fastest students' characteristics. For more details, see Table A4 in Data S1.

[19]BPS students sat in a circle for the regular curriculum and were able to see each other while answering questions from the teacher standing in front of the blackboard. The Kumon session's seating is unique to this intervention. In either case, there is no predetermined seating plan for a particular student.

[20]For the same reason, the individualized and self-learning nature of the programme prevents collusion on score among students. Therefore, we do not need to worry about cheating among students.

TABLE 2

Peer effects of the fastest students

	Time for solving 10 sheets			*Dummy of full score in All of sheets number 8–10 (Full score = 1)*		
Dependent variable:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Fastest student's time	0.8547	0.6503	0.5358	−0.0046	−0.0087	−0.0060
	(0.0898)	(0.0592)	(0.0593)	(0.0057)	(0.0034)	(0.0024)
[*P*-value]	[0.0000]	[0.0000]	[0.0000]	[0.4335]	[0.0217]	[0.0226]
Individual fixed effects		x	x		x	x
Day fixed effects			x			x
N	10,941	10,941	10,941	11,062	11,062	11,062

Notes: Estimated SEs clustered at individual level are in parentheses. Regression coefficients of the OLS are estimated based on the equation (1). Sample is selected by omitting observations with missing values in the variables on time, score and level of the work sheets.

peers finishing their worksheets.[21] Therefore, a reduction by a half minute solving the task (end stage) seems a large effect on slower students. We further examine how peers' speed affects the scores obtained by other students. In particular, we examine the existence of a trade-off between speed and learning; the dependent variable is an indicator variable that takes a value of one if a student obtains a full score in the last three worksheets, and zero otherwise. According to the score of the last three worksheets for which the fastest student's speed becomes apparent to the followers, shown in Columns (4) to (6) in Table 2, we find the negative significant coefficients, which suggests that, as the peer's time grows shorter (−), the likelihood of acquiring a full score becomes greater (+). Therefore, the positive peer effects on the score become evident. The coefficient of −0.0060 in Column (6) means that if the fastest student solves the worksheets a minute faster, the likelihood that the followers obtain a full score in the last three sheets increases by 0.6 percentage points. Given that students are supposed to obtain a full score and they indeed obtained it quite frequently, as illustrated in Table 1, this effect could be seen as large one. The findings are robust across specifications with different fixed effects. One might argue that the initial difficulty level of the worksheets might influence how a student is progressing over time. For this reason, we control for various worksheet levels in our analysis of peer effects, given that children are working on different assignments everyday (Appendix C.3 in Data S1). As shown in Tables C3 and C4 in Data S1, our peer effect results are robust to the different levels of worksheets that the students were assigned.[22]

The fastest peer's impact on other students might be heterogeneous, depending on how close a student's own speed is to the fastest peer's time in solving the worksheets. Therefore, we show the heterogeneous peer effects in Table 3. We control for individual fixed effects as well as day fixed effects in all specifications. In Panel A1, the measurement of peer effects uses the fastest student's time of each day within the classroom. The first

[21] However, we cannot test this directly because we do not have the data on time for each worksheet.

[22] We look into peer effects of classmates' speed on the score by changing the later worksheets. In the main analysis, we use worksheets 8–10 as later worksheets. Here, we change this and define later worksheets as either 10, or 9 and 10. As shown in Appendix C in Data S1, the results are mostly consistent with our main findings.

TABLE 3
Heterogeneous peer effects

	Faster students than median (1)	*Slower students than median (2)*
Panel A: Effects on time for solving 10 sheets		
Panel A1: Effects of the fastest student's time		
Fastest student's time	0.5283	0.4448
	(0.0386)	(0.0672)
[*P*-value]	[0.0000]	[0.0000]
Individual and day fixed effects	x	x
N	5,777	5,164
Panel A2: Effects of the median finishing time		
Median finishing time		1.0934
		(0.0495)
[*P*-value]		[0.0000]
Individual and day fixed effects		x
N		5,164
Panel B: Effects on score in sheet no. 8–10		
Panel B1: Effects of the fastest student's time		
Fastest student's time	−0.0077	−0.0037
	(0.0037)	(0.0041)
[*P*-value]	[0.0548]	[0.3806]
Individual and day fixed effects	x	x
N	5,776	5,286
Panel B2: Effects of the median finishing time		
Median finishing time		−0.0089
		(0.0037)
[*P*-value]		[0.0308]
Individual and day fixed effects		x
N		5,286

Notes: Estimated SEs clustered at individual level are in parentheses. Regression coefficients of the OLS are estimated based on equation (1). Sample is selected by omitting observations with missing values in the variables on time, score, and level of the work sheets. The results without fixed effects are shown in Table C11 in Data S1.

column shows the results for students who solved the problems faster than the median time of the class on that day. The second column shows the results of students who solved the problems slower than the median time of the class of the day. In Panel A2, for the slower-than-median-speed students, the median time of the class of the day is also used as a proxy to investigate peer effects.[23] We find positive and significant effects of the fastest or faster peers' time on individual students' time, regardless of student type, that is, faster or slower in problem-solving than the median time of the class. Each coefficient of peers' time can be interpreted as follows: among the faster-than-median students, when the fastest peer's time is shorter by one minute, an individual student's time will reduce from 0.5283 to 1.0934 minutes on average.

[23]We do not report the effects of the median time of the day on the faster student (faster than median) because they do not observe slower students submitting worksheets, which include the median time, and this makes any interpretation difficult. Rather, slower students, including the median, could be affected by the faster students' submission timing. Therefore, the peer effects of median time on faster student outcomes will be endogenous.

We further examine how peers' speed heterogeneously affects the scores obtained by other students. Panel B of Table 3 shows the heterogeneous peer effects of classmates' speeds on the scores of the last three worksheets.[24] Again, the dependent variable is the indicator variable for whether a full score is obtained. As was the case in Panel A, Panels B1, and B2 use different measurements of a peer's time: the fastest peer's time and the median time in the class, respectively. As a result, we find negative and significant coefficients of the fastest peer's time on the individual students' scores among the faster students. Again, this indicates that, as the peer's time grows shorter (−), the likelihood of having a full score becomes greater (+). However, the corresponding coefficients in Panel B1 among the slower students are insignificant. Instead, for the slower students, we observe negative and significant coefficients of the median time in Panel B2. These results suggest that the speed competition seems to work positively for both faster and slower students. However, given that in the final three worksheets, the math problems are more challenging and require more attention and effort, these speed competition effects are visible only among the students who are closer to each other in speed: the fastest student's speed improves the faster students' scores and the median speed improves slower students' scores, while no effects are observed between the fastest and the slower.

As a potential mechanism, we can think that these effects may be driven by rivalry formation, which creates a motivational boost among students for higher performance while trying to outperform peers. First, as suggested by (Kilduff *et al.*, 2010), similarity, repeated competition, and competitiveness are the three conditions for rivalry formation. The finding that peer effects are visible among students who are closer in speed is consistent with this assertion. Second, when people are in a competition, they tend to take risks (To *et al.*, 2018). In our case, if students increase their speed of solving math questions, there could be more mistakes as they are spending less time on each question. Therefore, we can interpret that they take more risk when engage in competition. Third, we utilize information obtained from the baseline survey to show that competition orientation or a sense of rivalry can affect performance.[25] In particular, by conducting a sub-sample analysis for students who have shown higher competition orientation, we find that the coefficients in absolute values of peer effects are larger compared to the full sample (see Figure B1 in Data S1). This indicates that peer effects are stronger among students with a higher competition orientation than average students. Furthermore, in Appendix B in Data S1, we examine gender heterogeneity. Our results suggest that female students tend not to engage in speed competition, as indicated by the very small, statistically insignificant but negative coefficient of the interaction term between the fastest student's speed and the female dummy (Columns (1) to (3)). The lack of statistical significance in the gender differences might be attributed to the characteristics of our subjects; unlike the existing experimental subjects who are college-age or grown-ups, our sample comprises children of elementary school age. The direction of the estimated coefficient of our female interaction

[24]In the main analysis, we use linear probability. We also examine the result based on the Logit and Probit models, but the result remains robust to alternative specifications.

[25]The survey question asks about how far a student agrees with the statement: 'There is someone who I do not want to lose against'. The choices are 1. Strongly agree, 2. Somewhat agree, 3. Somewhat disagree, and 4. Strongly disagree. Here, we focus on the students who answered 1.

term, is however consistent with a few other studies (e.g. (Gneezy *et al.*, 2003; Niederle and Vesterlund, 2007; Niederle and Vesterlund, 2011)). Indeed, Gneezy *et al.* (2009) find that competition orientation changes with the social environment. Intriguingly, female students seem more sensitive to test scores than male students, despite the estimated coefficients are statistically insignificant (Columns (4) to (6)). This latter finding may be in line with (Gneezy *et al.*, 2003), which suggests that in an incentivized setting, women's performance is comparable to that of men.

Thus, the main finding suggests that there are overall positive peer effects on students' learning outcomes — math problem-solving speed and their scores. We do not observe a trade-off between the speed and score. Rather, we find similar ability students gain more from a 'competition', without negatively affecting others.

Robustness analysis

We conducted several robustness checks to with respect to our main findings.[26] First, we show the results of regressions, as a falsification test, whereby we replace the outcome variables with a dummy variable that takes a value of one if a student obtains a full score in all of the sheets no. 1–3, and zero otherwise. In the main analysis, we use that for sheets no. 8–10, assuming that students who are solving the last set of worksheets have already witnessed the fastest students' finishing all the worksheets. We, therefore, expect some peer effects on the test score and indeed, find so. In the falsification test, instead, we assume that students have not observed the fastest students' completing the worksheet when they are solving the first set. We can assume this because students are supposed to solve all the 10 sheets in the ascending order. If this is the case, we do not expect any effect. Tables C1 and C2 in Data S1 show the results. Although the magnitude of coefficients are similar to that in the main results, they cannot be distinguished from zero, thereby supporting our main hypothesis and the findings.[27][28]

Second, we examine whether the result changes or not depending on the definition of first and last sets of worksheets. In the main analysis and the falsification test, we pick the first and the last three sheets to construct the dummy variables. However, some might argue that the number three is arbitrary, so we reconduct the same analysis varying the range of the set of worksheets. The result are shown in Figures C1 and C2 in Data S1, and they confirm the results are consistent regardless of the definition of the outcome variables.

Third, as briefly mentioned above, we examine whether the result could change when we take the levels of worksheet into account. Although other students' worksheet levels are not observable to a student thanks to the individualized programme and therefore this should not affect their learning outcomes, some might say that a student might not compete if there is a potentially large difference in students' levels. To deal with this potential

[26] All robustness check results are shown in Appendix C in Data S1.

[27] This similarity in magnitude may be interpreted as potential peer effects for the very slow students who might have observed the fastest student's completion of 10 sheets while still working on their initial sheets no. 1–3.

[28] As shown in Column (5) of Panel B of Table C2 in Data S1, when controlling for only individual fixed effects, as the median time becomes faster (−), the likelihood of getting a full score is higher (+). This makes sense if classmates start to submit worksheets when the slower students are solving the earlier sets of worksheets.

issue, we control for the fastest students' and/or their own level in the regressions; we also trim the subset of students who solve similar levels of worksheets. Tables C3 and C4 in Data S1 show that the results do not change and support the plausibility of the individualized learning setting.

Fourth, we deal with a concern that the day-to-day learning environment, particularly weather, might affect students' learning (Park *et al.*, 2020; Park, 2022) and hence peer competitions. Therefore, we control for the precipitation and surface temperature of the classroom of the day. Although we do not have the exact records for the classrooms, we collect the data from the weather stations nearest to each school/classroom based on the stations' and schools' latitude and longitude. The data on precipitation is from JAXA Global Rainfall Watch, while that on surface temperature is from the Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer Surface Kinetic Temperature.[29] Based on the result shown in Table C5 in Data S1, we confirm that our main result is robust to differences in the learning environment (weather condition). One might argue that other environmental issues not captured by precipitation or surface temperature might affect students' competition. Although we cannot control for day-classroom fixed effects because the main variation in the fastest students' time is at day-classroom level, we further control for day-branch fixed effects, in addition to individual- and day fixed effects that are already controlled in the main analysis. Given that the maximum distance among schools in the same branch is just 7.249 km, these further fixed effects will control for unobserved circumstances that students in the same branch are likely to share. Although this potentially sacrifices the statistical power, Table C6 in Data S1 shows that we still find statistically significant peer effects with estimates quantitatively consistent to the main findings.

Fifth, as mentioned in the empirical strategy section, a potential threat to the identification might arise if the fastest student's speed today is affected by slower students' speed yesterday, that is, if there is a serial correlation in peer effects. Indeed, there is a correlation between the fastest time today (t) and the median time the day before ($t-1$); however, the magnitude is minuscule (Columns (1) and (2) of Table C7 in Data S1). The coefficient of 0.2124 in Column (2) means that when the median student finished a minute earlier yesterday, the fastest student finished 12 seconds faster the following day. Considering that the majority of changes in median time are less than 2.5 minutes, as shown in Figure C3 in Data S1, the fastest student's time shortens by at most about 30 seconds. In practical situations, such a change is difficult to be noticed by other students, given the median time for solving 10 worksheets is 11.70 minutes (Table 1).[30] Nevertheless, we conduct a robustness analysis to alleviate this concern. Specifically, we report the estimates using only the observations of Saturdays' sessions. We focus on Saturday because students return to class after a weekly off, Friday. We can expect that Saturdays' observations are not affected by the same way as described above for any other

[29] See https://sharaku.eorc.jaxa.jp/GSMaP/index.htm (Last access: 13 September 2022) for the rainfall data and https://lpdaac.usgs.gov/products/ast_08v003/ (Last access: 13 September 2022) for the surface temperature data.

[30] Figure C3 in Data S1 shows the distribution of the first difference of the median time in the unit of a minute. This shows that most of the changes in the median time are less than three minutes (about 85% are equal to 2.5 minutes or less). Therefore, most of the changes in the fastest student's time is at most 30 seconds faster, which is about 4.3% of the median time for solving 10 worksheets (Table 1).

day. Not surprisingly, we find a much weaker correlation using the Saturdays-only sample, as shown in columns (3) and (4) of Table C7 in Data S1. Using this sub-sample, we find a consistent pattern of peer effects in Table C8 in Data S1, supporting our main conclusion. Furthermore, we also conduct the same analysis using only the observations in the very first session. This allows us to abstract our analysis from possible serial correlation, at the cost of losing some statistical power. The result reported in Table C9 in Data S1 suggests that our main findings on time and score competition effects are robust with relatively large SEs as predicted. Besides, we also consider the model with the AR (1) process of the fastest students' time – we exploit the residual of the AR (1) process of the fastest time and use it as an exogenous shock. According to Table C10 in Data S1, we obtain qualitatively the same result as that of the main analysis.

Finally, we check if the effects change with respect to another specification with different sets of fixed effects. According to Tables C11 in Data S1, the results do not change across specifications with different sets of fixed effects. They are comparable to the main analysis, suggesting no discouraging effects.

Thus, all the robustness checks support the main findings that there are overall positive peer effects on students' learning outcomes, there is no trade-off between the speed and score, and students with similar ability gain more from a competition, without negatively affecting others.

VI. Conclusion

We investigate the peer effects of problem-solving speed on learning outcomes along two dimensions: the speed of math problem-solving time and the score. In particular, we examine whether there are potential trade-offs or complementarities between the speed and the quality of learning. Our results show positive peer effects on problem-solving time for everyone in a classroom, irrespective of their speed. Further, we find positive peer effects of speed competition on the scores of students who have similar speeds of solving problems.

Our results show efficiency gains from non-market competition in the context of education and learning. In our setting of individualized self-learning sessions, students are not in direct competition in a zero-sum game. However, obtaining a full score in each worksheet is a precondition to move to the next level, leading to an incentive to perform in a timely manner. Hence, students would want to perform beyond the ordinary competitive spirit (win and reward). This might also be driven by rivalry formation, which creates a motivational boost among students for higher performance while outperforming peers. This is consistent with the psychological theories of work motivation (Vroom, 1964; Van Eerde and Thierry, 1996; Kilduff, 2014), which suggest that motivation and rivalry are positively correlated, allowing competitors to succeed. Our setting also conforms to the three conditions for rivalry formation: similarity, repeated competition and competitiveness (Kilduff *et al.*, 2010). Furthermore, our finding that competition improves performance is consistent with non-real-time competition in education studied by Tran and Zeckhauser (2012), who shows that students who were told the ranking of their practice exam performed better in official standardized international final test in Vietnam.

Based on Hanushek and Woessmann (2016), which found that differences in average mathematics and science test scores account for strong East Asian and weak Latin American growth, focusing on programmes that develop basic skills is critical for inclusive development across the world. From this perspective, the improvement of learning outcomes in South Asia is an unresolved policy question (Asim *et al.*, 2017), and our findings are important for policies and interventions focusing on improving learning outcomes and basic skills. As argued by Pritchett and Beatty (2015), the potential for learning is much higher when instructional levels and student skills are synchronized in a way that minimizes the gap between curricular learning and the actual pace of learning. For example, teaching at the right level (TaRL) programmes (Banerjee *et al.*, 2007; Duflo *et al.*, 2011; Banerjee *et al.*, 2016), as well as self-led learning have shown great promise in solving the learning crisis (Muralidharan, Singh, and Ganimian, 2019; Rodriguez-Segura, 2021; Sawada *et al.*, 2022). Moreover, according to our results, an educational setting that motivates students to perform in a 'competitive manner' can be very effective in developing basic mathematical skills.

Regarding the external validity of our findings, one might argue that this is rather limited due to the unique setting of Kumon session, wherein students solving individualized worksheets, as opposed to the conventional classroom problem solving or exam situation. However, such self-learning programmes are becoming popular in online education programmes, which could incorporate the aspect of peer competition via tournaments. Yet, given our sample is not representative and constitute a disadvantageous group of students, external validity of the findings could be examined with further experiments.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Supporting information