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The impact of peer achievement and peer heterogeneity on own achievement growth: Evidence from school transitions

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Abstract

This paper estimates ability peer effects on achievement growth in reading and math. It exploits variation in peer characteristics generated at the transition from primary to secondary school in a sample of Berlin fifth-graders. As will be discussed in detail, this variation is exogenous in large parts. Results are similar for both achievement measures: pupils benefit from abler peers, but high-achievers do so to a smaller extent. The estimated impact of the variance in peer skills is negative, but insignificant. *JEL: I21, I28*

Keywords: ability peer effects in upper-secondary school, natural experiment.

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1 Introduction

Peer characteristics are important determinants of parental school choice decisions. Peer effects are also an issue in debates on school vouchers, desegregation, ability tracking or anti-poverty programs. This paper studies the impact of average peer achievement and peer heterogeneity on own achievement growth in reading and math. To do so, I estimate value-added models for Berlin fifth-graders at the transition from primary to secondary school. Although school choice is endogenous, assignment of students to classes within schools might be largely exogenous in the data analyzed here for two reasons. First, the schools under investigation, called G5 schools in the following, are highly selective as they enroll high-achieving elementary school pupils only. Parents who seek to enroll their child in such a school have to apply for a slot about six months in advance. Hence they cannot condition their class choice on peer quality. Second, G5 school principals know little about incoming students at the beginning of the fifth grade. For instance, course grades from primary school are noisy measures of achievement if students were taught by different teachers, who apply different grading standards.[1] As will be shown, the correlation between peer quality at the beginning of a school year and own predetermined characteristics is insignificant for reading and weak, though not insignificant, in math.

The results suggest that students benefit from abler peers but higher-achieving students do so to a smaller extent. More precisely, students who lie in the top percentiles of the class-achievement distribution (at the beginning of the fifth grade) do not benefit from abler peers. The strongest relationship between peer quality and own achievement growth is found for relatively low-achieving students. For a, compared to his/her classmates, median-achieving student, a one-standard-deviation increase in peer achievement raises own achievement by 0.07 standard deviations in reading and 0.10 standard deviations in math.[2] The results further indicate that students in heterogeneous classes are

[1] In the data, the number of elementary schools (classes) exceeds the number G5 schools (classes) by a factor of 13 (17). Teacher grading standards are investigated by, among others, Figlio and Lucas (2004) and Dardanoni et al. (2009).

[2] Ability peer effects of similar magnitude are found in many related studies. These are well summarized in Sacerdote (2011) and Epple and Romano (2011).

not worse off than students in more homogenous classes: the corresponding estimates are negative, but insignificant.

To date, it is still an open question whether high- or low-ability students benefit most from abler peers. Findings in Lavy et al. (2011) and Imberman et al. (2012) are similar to this study: in Lavy et al. (2011), low-achieving students suffer the most from an increase in the share of low-ability peers. Imberman et al. (2012) also find that good peers have the strongest (positive) impact on low-achievers. In contrast, Burke and Sass (2013) and Ding and Lehrer (2007) show that high-achievers benefit most from increases in peer quality. Duflo et al. (2011) report a U-shaped relationship between peer quality and own achievement growth: positive peer ability effects are found for both high- and low-achievers, but not for median-achieving students.

Empirical evidence is further inconclusive regarding the impact of heterogeneity in peer skills on own achievement growth. Vigdor and Nechyba (2004) report a positive relationship between peer heterogeneity and math achievement growth whereas a negative impact is found by Ding and Lehrer (2007) and Kang (2007). Similar to this study, related estimates in Hanushek et al. (2003) and Duflo et al. (2011) are insignificant.

This paper complements the existing literature in two ways. First, this study adds to the scarce (quasi-)experimental evidence on ability peer effects. Most of the related literature employs rich fixed effects frameworks to overcome endogeneity issues. Sund (2009) and Gibbons and Telhaj (2012) belong to the small group of peer effects papers that exploit variation in peer characteristics generated at school transitions.[3] Second, results from this study may only hold in the upper tracks of ability tracked systems.[4] Depending on the track, peer effects may operate in different ways which could be one reason for the mixed empirical evidence in the previous paragraphs. For instance, Lavy et al. (2011) show that disruptive students (who typically perform poorly in achievement tests) are an important reason for the observed positive relationship between peer achievement and

[3] Duflo et al. (2011) (Kenyan schools) and Boozer and Cacciola (2001) (project STAR) estimate peer effects using experimental data.

[4] The large body of the tracking literature is reviewed by Betts (2011).

own achievement growth. The sample analyzed here, however, comprises students who are concentrated in the right tail of the achievement distribution, thus disruptive behavior might be less relevant. Instead, better peers may exert a positive impact on own learning effort.

The remainder of the paper proceeds as follows. The next section briefly reviews the institutional background and describes the data. Section 3 outlines the empirical strategy and discusses possible endogeneity problems. Results are presented and discussed in section 4. Section 5 concludes.

2 Institutional background and data

2.1 Institutional background

In Germany, elementary school generally lasts until the fourth grade when children are 10 years old. Thereafter, students are segregated by ability into three types of secondary schools (called tracks): lower-secondary (Hauptschule), middle-secondary (Realschule), and upper-secondary school (Gymnasium). Upper-secondary school is the most academic track and prepares students for university study. The Berlin educational system is somewhat different since primary education lasts six years. However, some Berlin upper-secondary schools allow transition to secondary education already after four years of elementary school. These upper-secondary schools are referred to as G5 schools. In the school year 2002/03, around 24,200 fourth-graders where enrolled in one of 402 Berlin elementary schools. 7% of these pupils attended one of 31 G5 schools in the following school year. Transition to lower- or middle-secondary schools is not possible after the fourth grade.

Admission to G5 schools is regulated by the education act of the federal state Berlin.[5] If the number of applicants exceeds the number of available slots, selection basically

[5] "Schulgesetz für das Land Berlin" from 2004, §56, It can be found at http://gesetze.berlin.de/ (accessed November 27, 2012).

depends on three criteria. These are (ranked in descending order): (i) The student's track recommendation which is issued by his/her primary school teacher. (ii) The G5 school's relative proximity to the student's home (a student is preferred if the second nearest G5 school is far away). (iii) If the number of applicants still exceeds the G5 school's capacities, selection is made by lot (i.e. randomly). In addition, the first year in G5 schools is a probationary period. Students who do not succeed have to switch to a lower-level track in the following school year.

2.2 Data

The data set analyzed here (ELEMENT) is a longitudinal survey on reading comprehension and math achievement of Berlin elementary and G5 pupils.[6] It includes the universe of fifth-graders who attended a G5 school in the school year 2003/04 (31 schools, 59 classes, 1700 pupils) and a random sample of 71 Berlin primary schools. To account for endogenous school choice (by adding school fixed effects), schools that run only a single class at the fifth grade are excluded. This reduces the sample to 22 schools, 50 classes and 1467 pupils. Participation in standardized tests at the beginning and end of the fifth grade was compulsory. Thus attrition in the data is solely caused by class repetitions, absence at the time of the test, or school switching. Test scores are comparable across grades and were not made available to teachers or school principals. Additional pupil information is collected from questionnaires completed by students and parents on a voluntary basis.

Columns 1 and 2 in Table 1 contain summary statistics for the analyzed sample of G5 students. For each variable, the number (share) of missing values is reported in the third (fourth) column. For comparisons, additional summary statistics for primary school fifth-graders are reported in columns 5 and 6. Test scores in math and reading are

[6] "Erhebung zum Lese- und Mathematikverständnis: Entwicklungen in den Jahrgangsstufen 4 bis 6 in Berlin", English translation: "Survey on reading comprehension and math achievement in Berlin schools, grades 4 through 6". Detailed data descriptions and a codebook (both in German) are available on the homepages of the Berlin senate department for education, science, and research (Berliner Senatsverwaltung für Bildung, Wissenschaft und Forschung).

normalized with mean 0 and standard deviation 1 in G5 schools, i.e. for any student i in a G5 or elementary school,

$$T_{i,t} \equiv \frac{\tilde{T}_{i,t} - \tilde{\mu}_t^{\mathrm{G5}}}{\tilde{\sigma}_t^{\mathrm{G5}}}.$$

$\tilde{T}$ is the original math or reading test score in the data. $t = 0$ $(t = 1)$ if $\tilde{T}$ has been measured at the beginning (end) of the fifth grade. $\tilde{\mu}_t^{\mathrm{G5}}$ is the mean value of $\tilde{T}_t$ in the sub-sample of G5 students, and $\tilde{\sigma}_t^{\mathrm{G5}}$ is the corresponding standard deviation in $\tilde{T}_t$.

As indicated by the first four rows in Table 1, G5 students have much better math and reading skills than primary school pupils. Elementary school pupils are also more likely to have a migration background and are 3 months older on average.[7] Most G5 students have a favorable socioeconomic background: in 75% of cases, at least one parent finished upper-secondary school and average HISEI values are high compared to elementary school.[8]

The last rows in Table 1 compare peer characteristics in G5 and elementary schools. For any student i, peer achievement at the beginning of the fifth grade, denoted by $E_{-i,0}$, is simply the mean test score of i's classmates:

$$E_{-i,0} \equiv \frac{1}{n_c - 1} \sum_{j \in \mathcal{I}_c \setminus \{i\}} T_{j,0}.$$

$T_{j,0}$ is the test score of classmate j at the beginning of the school year, as indicated by the zero subscript. c identifies i's class which is composed of n_c students whose IDs are collected in the set $\mathcal{I}_c$. Similarly, peer variance is defined as

$$V_{-i,0} \equiv \frac{1}{n_c - 1} \sum_{j \in \mathcal{I}_c \setminus \{i\}} \left(T_{j,0} - \mu_0^c\right)^2.$$

μ_0^c is the class test score mean, which is constant for any student $i \in \mathcal{I}_c$.

Similar to own test scores, peer characteristics in Table 1 are normalized with mean 0

[7] Here, a student has a migration background if either he/she was born abroad or one of his/her parents was not born in Germany.

[8] ISEI is the international socio-economic index of (parental) occupational status, see Ganzeboom et al. (1992). The higher the occupational status, the higher the value of the ISEI. HISEI is the highest ISEI value among the student's parents. Here, the HISEI is normalized to lie between 0 and 1.

and standard deviation 1 in G5 classes. The last column suggests that the between-class variation in peer achievement E_0 is larger in elementary school (the standard deviations are $1.89 > 1$ in reading and $1.39 > 1$ in math).[9] The summary statistics for peer variance V_0 further indicate that within-class variation in reading skills (math skills) is smaller (larger) in G5 schools as the corresponding mean values are $0.93 > 0$ ($-0.65 < 0$). Hence, G5 classes are on average less (more) heterogeneous in reading (math) than elementary school classes.

3 Empirical strategy

3.1 Baseline model

The impact of peer characteristics on achievement growth is estimated with the following value-added model:

$$T_{i,1} = \beta_0 + \beta_1 E_{-i,0} + \beta_2 V_{-i,0} + \gamma_1 T_{i,0} + \gamma_2 R_{i,0} + \gamma_3' X_i + \lambda_s + \varepsilon_i.$$

$T_{i,1}$ is pupil i's math or reading test score at time 1, the end of a school year. All explanatory variables are measured at time 0, the beginning of the school year. This framework rules out reverse causation because realizations of the dependent variable are measured about 10 months after realizations of the explanatory variables. The variables of interest are peer achievement E_0 and peer variance V_0, both measured at the class level at time 0. As discussed in the previous section, $E_{-i,0}$ is the average test score of i's classmates and $V_{-i,0}$ is the dispersion in i's peers' skills. Computation of both variables excludes i's own test score at time 0, which is emphasized by the subscript $-i$.

$T_{i,0}$, the math test score at the beginning of the fifth grade, is assumed to capture i's

[9] One should not get confused by the large negative mean values of E_0 in primary school. In Table 1, test scores and peer characteristics are standardized using the mean and standard deviation in G5 schools (thus peer characteristics have mean 0 and standard deviation 1 in G5 schools). Compared to own test scores, there is much less variation in peer achievement. Thus standardization inflates the magnitude of E_0 in primary school.

past educational inputs. $R_{i,0} \in [0, 1]$ is pupil i's class percentile rank in reading or math test scores. Within classes, the highest-achieving pupil has rank one, the median-achiever has rank 0.5, and the lowest-achiever in the class has rank zero.[10] X_i is a column-vector of additional control variables (age, a girl dummy, and indicator variables for migration and socioeconomic background). Missing values in X are replaced with imputed values.[11] λ_s is a school fixed effect, and estimated standard errors are clustered at the class level.

3.2 Are peer characteristics exogenous in new G5 classes?

Estimates of β_1 and β_2 are biased if some determinants of the class formation process that also affect achievement growth are unobserved. In this context, choices made by parents and school principals are considered as the most relevant sources of endogeneity. School choice made by parents is accounted for by the inclusion of school fixed effects λ_s. Class choice made by parents is assumed to be exogenous because parents have to apply for a slot in a G5 school about 6 months in advance. Thus parents cannot condition their class choice on peer characteristics.

The class formation process itself, however, may lead to biased estimates. For instance, school principals could assign "good" teachers to "good" students. There are two reasons why this should not be a great cause of concern: first, G5 schools are attended by students with above-average skills in math and reading thus ability grouping should play a minor role in G5 schools. Second, G5 schools know little about incoming students: the most relevant information about their skills is summarized in their school reports from elementary school. These reports contain course grades and written teacher assessments on the student's educational progress. Compared to achievement tests, course grades are subjective to some extent as they are assigned by teachers.[12] As already mentioned,

[10] R_0 and T_0 are conceptually different: two pupils who attend different G5 classes may have similar ranks but large differences in T_0 at the same time.

[11] Imputed values were computed by the data provider. Results in Section 4 are insensitive to their in- or exclusion (estimates available on request).

[12] For example, Dardanoni et al. (2009) find for 14 of 16 OECD countries that schools with high shares of underperforming students tend to set lower grading standards.

however, the number of elementary schools is 13 times larger than the number of G5 schools. As class size is smaller in elementary school, the number of elementary school classes exceeds the number of G5 classes by a factor of 17. Therefore it is reasonable to assume that most fifth-graders in G5 schools were taught by different elementary school teachers. Students might therefore be heterogeneous in skills even if their course grades from elementary school are similar.

Estimates of β_1 and β_2 may still be contaminated if large shares of pupils in newly created G5 classes previously attended the same elementary school class. To illustrate this potential source of bias, let ψ_i^p denote a permanent shock on i's achievement growth that has been determined in primary school p. ψ_i^p may include learning techniques or problem-solving skills that have been acquired through i's elementary school teacher(s) and former peers. Let j be a classmate of i in a newly formed G5 class. $\psi_i^p = \psi_j^p$ if i and j were already classmates in primary school. To some extent, j's test score at the beginning of the school year in G5 school, $T_{j,0}$, is determined by his/her learning techniques ψ_j^p from elementary school. Thus ignoring ψ_j^p leads to a violation of the (strict) exogeneity assumption $\mathbb{E}(\varepsilon_i \mid E_{-i,0}, V_{-i,0})$, because ε_i contains the omitted variable $\psi_i^p = \psi_j^p$, and $T_{j,0}$ is used to compute $E_{-i,0}$ and $V_{-i,0}$. The larger the share of former classmates in newly built G5 classes, the more relevant this source of bias. The ELEMENT data contain no information on the previously attended elementary school of G5 students which precludes the inclusion of primary school class fixed effects. As already mentioned, however, the number of elementary school classes is 17 times larger than the number of G5 classes. This suggests that $\psi_i^p \neq \psi_j^p$ for most classmates i and j in G5 classes.

To summarize, there are good reasons supporting the claim that $\hat{\beta}_1$ and $\hat{\beta}_2$ are not severely biased in newly formed G5 classes. Following the procedure in Carrell et al. (2009), one way to test the exogeneity assumption is by regressing $E_{-i,0}$ and $V_{-i,0}$ on $T_{i,0}$ and other student characteristics (measured at time 0). Intuitively, random mixing of pupils into classes implies that individual pretreatment characteristics cannot predict $E_{-i,0}$ and $V_{-i,0}$.

Estimates are reported in Table 2. In panel A, own reading achievement (columns 1 and 2) or math achievement (columns 3 and 4) is the only explanatory variable along with school fixed effects. Throughout, individual and aggregated measures of test scores have mean 0 and standard deviation 1. Panel A, column 1 shows a negative, but insignificant relationship between own reading skills and peer reading skills at the beginning of the fifth grade. Similarly, there is no linear relationship between own reading skills and the dispersion in peer reading skills once school fixed effects are accounted for (column 2). Column 3 suggests that students with good math skills have somewhat worse peers on average: an increase in own math achievement by one standard deviation is associated with a decrease in peer math achievement by 0.029 standard deviations. This association is of very small magnitude but significant at the 5% level. The relationship between own math achievement and peer math variance is also small, though significant.

Additional controls are accounted for in panel B. Again, observable student characteristics cannot predict the mean and dispersion in peer reading skills. Regarding math, a weak, but significant relationship remains. The first F test statistic (at the bottom of the Table) is computed for the null hypothesis that, once school fixed effects are controlled for, own achievement and additional controls are not correlated with the dependent variables. The second F test is computed with respect to the additional controls only. To summarize, the institutional setup and Table 2 suggest that the variation in peer characteristics is exogenous in large parts, at least for reading skills. Endogeneity cannot be ruled out completely for math, but is likely to play a minor role.

4 Results

Table 3a (Table 3b) reports estimates of the impact of peer characteristics on reading (math) achievement growth in G5 schools. Additional controls are omitted in columns 1 and 2 and included in columns 3 and 4. To allow for different slopes of the peer effect, peer characteristics are interacted with the student's rank in columns 2 and 4.

For both achievement measures, own achievement at the beginning and end of the fifth grade are strongly correlated. Regardless of their skill level, highly ranked pupils learn more than otherwise comparable students with lower ranks. This result is consistent with Cullen et al. (2006), who show that a student's relative position among his/her peers is a determinant of his/her school success.

Columns 2 and 4 reveal that the relationship between achievement growth and average peer achievement depends on a student's relative position among his/her classmates: once peer achievement is interacted with a student's rank, point estimates for peer achievement become highly significant.[13] For both achievement measures, highly ranked pupils benefit less from an increase in peer achievement. Using estimates from column 4 in Table 3b, the total differential of the estimated conditional expectation function $\hat{\mathbb{E}}(T_1 \,|\, .)$ is

$$\mathrm{d}\hat{\mathbb{E}}(T_1 \,|\, .)\Big|_{\mathrm{d}R_0 \neq 0, \mathrm{d}E_0 \neq 0} = (0.612 - 0.206E_0)\mathrm{d}R_0 + (0.206 - 0.206R_0)\mathrm{d}E_0$$

(leaving the other variables unchanged).[14] The first term indicates that students benefit from a rank increase, however, the effect is smaller in classes with high peer achievement. Regarding the second term, all pupils benefit from an increase in peer achievement as $R_{i,0} \in [0, 1]$, but highly ranked pupils do so to a smaller extent. Compared to highly ranked pupils, students with low ranks may benefit more from abler peers because they can ask more classmates for help. One can further infer from this result that assigning an average pupil to a weak (in terms of test scores) class is not necessarily harmful: on the one hand, that pupil's educational progress is lowered by his/her peers, on the other, that pupil benefits from an increase in his/her percentile rank.

Pupils might further respond differently to changes in peer variance which is also

[13] Burke and Sass (2013) also find small, but significant peer effects in linear-in-means models. The magnitude of the peer effects becomes economically significant once they allow for nonlinearities in their regression models.

[14] If the same computation is made for column 4 in Table 3a, the second term may become negative. $\hat{\mathbb{E}}(T_1 \,|\, .) = \hat{\mathbb{E}}(T_1 \,|\, E_0, V_0, R_0, T_0, X, \lambda)$.

investigated in columns 2 and 4. For reading, peer variance seems to have no impact on achievement growth. Although insignificant, estimates in Table 3b indicate that heterogeneity in peer math skills may harm students with low ranks. All reported patterns (magnitude of point estimates, significance levels) are virtually the same if observations with missing values in the additional control variables are excluded.[15]

5 Concluding remarks

This paper estimates the impact of average peer achievement and peer heterogeneity at the class level on achievement growth in reading and math. Making use of a natural experiment in a sample of Berlin fifth-graders at the transition from primary to upper-secondary school, the results indicate that students benefit from abler peers, but pupils with high class percentile ranks do so to a smaller extent. Holding other things constant, a one-standard-deviation increase in peer achievement raises achievement growth of a median-ranked student by 0.07 standard deviations in reading and 0.10 standard deviations in math. Peer heterogeneity seems not to harm achievement growth. Even though estimated achievement gains from better peers are of relatively small magnitude, Chetty et al. (2011) show that peer quality at early stages matters for long-run outcomes like earnings or college attendance rates.

The peer effects literature acknowledges that peer achievement or peer heterogeneity are proxies for unobserved factors that ultimately affect achievement growth. If peer effects operate through many, mutually dependent channels, reduced-from estimates of peer effects are of limited use to inform policy about optimal grouping of students.[16] As noted by Hanushek et al. (2003), “The role of peers can be complex. Influences may come from friends or role models, or peer group composition may alter the nature of instruction in the classroom… The most common perspective is that peers, like families, are sources

[15] Estimates are available on request. Table 1 reports shares of missing values.

[16] Carrell et al. (2011) show that Pareto-improving grouping of students based on reduced form estimates may lead to unintended outcomes.

of motivation, aspiration, and direct interactions in learning." To arrive at reliable policy recommendations, further research needs to uncover the most relevant mechanisms that cause the relationship between peer quality and own achievement growth.

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Tables

Table 1: Summary statistics for G5 fifth-graders

School type:	G5				primary	
	mean	s.d.	missings		mean	s.d.
			(#)	(%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Own characteristics						
Reading achievement (beg.) T_0^{read}	0.00	1.00	46	3.1	-1.40	1.36
Reading achievement (end) T_1^{read}	0.00	1.00	47	3.2	-1.59	1.41
Math achievement (beginning) T_0^{math}	0.00	1.00	46	3.1	-1.27	1.01
Math achievement (end) T_1^{math}	0.00	1.00	50	3.4	-1.42	1.10
Girl	0.51		3	0.2	0.48	
Migration background	0.28		222	15	0.41	
Age (year)	11.32	0.43	7	0.5	11.57	0.58
Parental education						
Lower-secondary	0.03		202	13.8	0.18	
Middle-secondary	0.22		202	13.8	0.44	
Upper-secondary	0.75		202	13.8	0.38	
HISEI $\in [0, 1]$	0.64	0.21	225	15.3	0.44	0.23
Peer characteristics						
Peer reading ach. (beginning) E_0^{read}	0.00	1.00	46	3.1	-3.74	1.89
Peer reading variance (end) V_0^{read}	0.00	1.00	46	3.1	0.93	1.50
Peer math achievement (beg.) E_0^{math}	0.00	1.00	46	3.1	-3.50	1.39
Peer math variance (end) V_0^{math}	0.00	1.00	46	3.1	-0.65	1.10
N(pupils)	1467				3169	
N(classes)	50				140	
N(schools)	22				71	

Standard deviations not reported for dummy variables. Columns (#) and (%) contain the number and share of missing values, respectively. “beginning/end” refers to the beginning/end of the fifth grade (indicated by the subscript 0/1). Peer achievement E_0 and peer variance V_0 are the mean and variance of a pupil’s classmates’ skills (both measured at the beginning of the fifth grade as indicated by the 0 subscript). “Parental education” is the highest secondary school degree of the parents. ISEI is the international socio-economic index of (parental) occupational status, see Ganzeboom et al. (1992). The higher the occupational status, the higher the value of the ISEI. HISEI is the highest ISEI value among the student’s parents.

Table 2: Relationship between peer and own pretreatment characteristics

Dependent variable:	E_0^{read} (1)	V_0^{read} (2)	E_0^{math} (3)	V_0^{math} (4)
A: No additional controls				
Own reading/math achievement	-0.015	0.033	-0.029**	-0.056***
(beginning of the school year)	(0.01)	(0.02)	(0.01)	(0.02)
School fixed effects	yes	yes	yes	yes
R^2_{adj}	0,7436	0,5611	0,7684	0,4275
B: With additional controls				
Own reading/math achievement	-0.014	0.029	-0.021	-0.060***
(beginning of the school year)	(0.01)	(0.02)	(0.01)	(0.02)
Girl	0.018	0.021	0.065**	-0.057
	(0.03)	(0.04)	(0.03)	(0.04)
Migration background	-0.015	-0.002	0.011	0.051
	(0.03)	(0.05)	(0.03)	(0.05)
Age	0.013	0.055	-0.044	-0.045
	(0.03)	(0.04)	(0.03)	(0.05)
Parental education: middle-secondary	-0.027	0.211	0.038	-0.143
(Ref. category: lower-secondary)	(0.10)	(0.14)	(0.08)	(0.14)
Parental education: upper-secondary	-0.081	0.169	0.066	-0.092
	(0.10)	(0.14)	(0.08)	(0.14)
HISEI $\in [0, 1]$	0.019	0.041	-0.079	-0.057
	(0.07)	(0.10)	(0.07)	(0.12)
School fixed effects	yes	yes	yes	yes
R^2_{adj}	0,7432	0,5611	0,7691	0,4276
F-test: own ach. + add. controls (p-val.)	0,6765	0,4801	0,0363	0,0912
F-test: additional controls only (p-value)	0,6842	0,6253	0,1273	0,4648
N(pupils)	1421	1421	1421	1421

Significance levels: * 10%, ** 5%, *** 1%. Standard errors (heteroskedasticity-robust, not clustered at the class or school level) in parentheses. Used data: ELMENT fifth-graders in G5 schools. Peer achievement E_0, peer variance V_0 and own achievement have mean 0 and standard deviation 1, and are measured at the beginning of the fifth grade. The number of observations is lowered by missing values in test scores. Missing values in additional control variables (see Table 1 for details) are imputed. The first F test is computed for the null hypothesis that, once school fixed effects are controlled for, own achievement and additional controls are not correlated with the dependent variables. The second F test is computed for the null hypothesis that, once school fixed effects and own achievement are controlled for, the additional controls are not correlated with the dependent variables.

Table 3a: Impact of peer characteristics on reading achievement growth

Dependent variable:	Reading achievement (end of the fifth grade)			
	(1)	(2)	(3)	(4)
Own reading achievement (beg.)	0.351***	0.345***	0.340***	0.329***
	(0.08)	(0.07)	(0.07)	(0.07)
Rank (1=best, 0=worst)	0.518**	0.535**	0.505**	0.538**
	(0.23)	(0.22)	(0.23)	(0.22)
Peer reading achievement	0.054	0.246***	0.061	0.257***
	(0.06)	(0.07)	(0.06)	(0.07)
Peer reading variance	-0.011	-0.006	-0.012	-0.017
	(0.05)	(0.06)	(0.05)	(0.07)
Rank*peer reading achievement		-0.370***		-0.377***
		(0.08)		(0.08)
Rank*peer reading variance		-0.031		-0.009
		(0.06)		(0.06)
Additional controls	no	no	yes	yes
School fixed effects	yes	yes	yes	yes
$R^2_{adj.}$	0,2953	0,3063	0,3053	0,3167
N(pupils)	1376	1376	1376	1376

Table 3b: Impact of peer characteristics on math achievement growth

Dependent variable:	Math achievement (end of the fifth grade)			
	(1)	(2)	(3)	(4)
Own math achievement (beginning)	0.460***	0.406***	0.455***	0.403***
	(0.10)	(0.09)	(0.09)	(0.09)
Rank (1=best, 0=worst)	0.450	0.643**	0.424	0.612**
	(0.29)	(0.29)	(0.29)	(0.28)
Peer math achievement	0.092	0.214***	0.088	0.206***
	(0.07)	(0.07)	(0.07)	(0.07)
Peer math variance	0.004	-0.066	0.002	-0.068
	(0.02)	(0.05)	(0.02)	(0.05)
Rank*peer math achievement		-0.212***		-0.206***
		(0.07)		(0.07)
Rank*peer math variance		0.143		0.141
		(0.09)		(0.09)
Additional controls	no	no	yes	yes
School fixed effects	yes	yes	yes	yes
$R^2_{adj.}$	0,3869	0,3919	0,3914	0,3961
N(pupils)	1373	1373	1373	1373

Significance levels: * 10%, ** 5%, *** 1%. Standard errors (in parentheses) are clustered at the class level. Used data: ELEMENT fifth-graders in G5 schools. All explanatory variables are measured at the beginning of the fifth grade. The rank $R_0 \in [0, 1]$ is a pupil's class percentile rank in reading or math. By definition, the rank lies between zero and one. Additional controls are: dummy variables for sex and migration background, age, indicator variables for parental education, and HISEI. The number of observations is lowered by missing values in test scores. Missing values in additional control variables (see Table 1 for details) are imputed.