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Research Article

Determinants of Academic Achievement of Middle Schoolers in Turkey*

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Abstract

The purpose of this study is to discuss student and school factors, including cross level interaction, that cause inequalities in seven and eighth grade students' achievement in Turkish context by using national achievement test scores with a multi-level statistical approach. Our results are in line with most other studies with similar purpose. Our results show that approximately 17% of the variation in student test scores is explained by differences between schools, while the remainder of the variation is accounted for by within-school factors. Our results highlight that student-level variables alone explain nearly 73% of the between-school variance and approximately 19% of the within-school variance in student achievement scores. Our school-level variables explain a relatively small amount of the variation, approximately 5%. This has demonstrated that between- and within-school differences in student achievement are largely accounted for by the socio-demographic background of students. This is in line with the Coleman Study findings; the effect of school characteristics on student achievement was modest compared to the effect of students' socio demographic characteristics. Our results also show that average parent education and income, full-day schooling, attending an urban school and the percentage of female students in the classroom mediate the relationship between student-level variables and student test scores.

Keywords

Educational policy • Academic achievement • Students and school characteristics • Equality • Multi-level statistics

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While education provides individuals an opportunity for cognitive, social and emotional development, it maintains and creates social stratification (Montt, 2011). Socioeconomic factors, along with school- and community-related factors, cause inequalities in education. For instance, gender (being female) and wealth (being poor) are major obstacles to school enrollment and achievement (Filmer, 2005; Nguyen, 2006). In some countries, females still do not have the same opportunities as males. Females do not have equal access to education and have lower academic achievement than their male peers (Nguyen, 2006). The literature has pointed to socioeconomic-related educational inequalities in underdeveloped (Grimm, 2011) and developing countries (Martins & Veiga, 2010). Students who grow up in families of low socioeconomic status (SES), specifically, those whose parents have low levels of education, low incomes, or low-prestige occupations, generally show slower cognitive development than students whose parents have high SES (Gamboa & Waltenberg, 2012; Hertzman, 1994; Hertzman & Weins, 1996). This can be explained with Bourdieu's cultural capital reproduction theory (1986), which holds that "socioeconomic inequalities in education persist because highly educated parents give their children a better understanding of the dominant culture and an ability to act within it" (p. 1017, as cited in Martins & Vegia, 2010). Identifying the sources of inequalities in educational attainment and achievement and, reducing their effects are major concerns of educational researchers and policymakers worldwide.

School variables such as school culture, resources (e.g., books, teacher-student ratio), and the socioeconomic composition of a school can create learning situation that exacerbate imbalances in student achievement across schools (Baker, Goesling, & Letendre, 2002; Thrupp, Lauder, & Rabinson, 2002). The Equality of Educational Opportunity Study (Coleman et al., 1966), also known as the Coleman Study, surprised many researchers and policymakers, not only in the United States but throughout the world; it showed that, rather than the school itself, it was the socioeconomic and ethnic background of families that constituted the source of variation in achievement. Since then, much research has been conducted to verify whether these findings hold true in other countries as well. Some studies conclude that the impact of schools on student achievement is small in wealthy countries but relatively strong in poorer countries (Buchmann, 2002; Fuller & Clarke, 1994; Heyneman & Loxley, 1983). Other findings, however, are consistent with those of the Coleman Study (Baker et al., 2002).

Beyond the acknowledged effect of family factors on school participation, the influence of school- and community-related factors on student achievement remains essentially unexplored. Binder (1999) and numerous other researchers have drawn attention to this gap in the literature. Few studies have been conducted in Turkey to examine school and family effects on school outcomes such as achievement on national large-scale assessment and the Program for International Student Assessment

(PISA) (Alacacı & Erbaş, 2010; Dinçer & Uysal, 2010; Günçer & Köse, 1993; Tomul & Savaşçı, 2010). Existing Turkish studies have their own methodological limitations. For instance, they used data collected by the Program for International Student Assessment (PISA), which raises concerns about the validity of test results, sample coverage and representativeness (Ferreira & Gignoux, 2011). Pısa Sampling coverage rate is below 50% and no information about non-participant students is available (Carvalho, Gamboa, & Waltenberg, 2012).

The purpose of this study is to explore student and school factors that contribute to inequalities in seventh- and eighth-grade student achievement in the Turkish context by using national achievement test scores. We use multilevel modeling to assess the impact of family socio-demographic background and school characteristics on academic achievement.

Inequalities in School Attainment and Achievement in Turkey

Turkey is a country that has a challenging task to ensure 100% access to primary education for both females and males. Although there has been progress in reducing the number of out-of-school children since 1997 (Devlet Planlama Teşkilatı, 2006), enrollment figures for primary education has not reached the targeted level. Despite evidence of progress toward 100% access to primary education, statistics show that there are problems of gender equity as well as school enrolment (Eğitim Reformu Girişimi [ERG], 2015).

The United Nations Development Program (UNDP) reported a literacy rate of 87.4% (79.6% for females, 95.3% for males) for Turkish citizens over 15 years of age (UNDP, 2008). The Human Development Index for 2009 shows that, although the gap between female and male enrollment has decreased (81.3% for females, 96.2% for males), it still exists (UNDP, 2009). The 2012-13 Household Labor Force Survey showed that approximately 35% of Turkish youth between 15 and 19 years of age is out of education system and majority of this group have a primary school diploma (eight years schooling) at most (Gürsel, Uysal, & Kökkızıl, 2015).

Access to education in Turkey is monitored mainly through enrollment rates (ERG, 2015), but Lewin (2007) suggests that enrollment statistics should not be used as the sole indicator for school access. In fact, school access should be defined in terms of regular attendance, successful learning, age appropriate progression, completing school on time and other equal opportunities. Therefore, we need more statistics and studies to form an accurate picture of school access in Turkey.

Little research is available on educational inequalities in Turkey, compared to the amount of research available for other developing countries. Filmer (2005) used international household data sets to investigate whether a combination of gender and wealth generating inequalities in educational enrollment and attainment (completion of grade five) in 44 countries. He found significant gender inequality in Turkey, unlike for most other countries in the region. And although a gender gap exists across wealth groups, inequalities were more pronounced among poorer children. Similarly, Tansel (2002) examined determinants of school attainment in Turkey using the Household Income and Expenditure Survey. She found that school attainment was strongly related to household permanent income; higher income led to higher school attainment, and this effect was even stronger for females. Parent education on school attainment was similar to the effect of income. Students living in urban areas had higher school attainment than those in rural environments. Income also determines the school track that students choose. Those from low-income families tend to enroll in vocational high schools, while students from top income levels more often attend Anatolian high schools or science-oriented high schools (science high schools) (ERG, 2015).

Results from PISA 2006, 2009 and 2012 show that the average achievement of Turkish students in mathematics, science and reading is below OECD mean performance. Nineteen percent of the variability in Turkish student performance is explained by the students' socio-economic background. Students in urban schools perform better than students in non-urban schools, even after controlling for socio-economic background in PISA 2009 (OECD, 2010). In science and reading scores in PISA, there are 12 and 44 points difference, respectively, in favor of females. However, males tend to perform better (6 points) in mathematics than females (Eğitimi Araştırma Geliştirme Dairesi Başkanlığı, 2010; OECD, 2009). Among the countries participating in PISA in 2003, Turkey had the greatest variance in mathematics proficiency. A large portion of this variability can be attributed to significant disparities in the economic, social and cultural status (ESCS) index as well as the ESCS index of schools (OECD, 2004). The same is also valid for PISA 2012 results (Anıl, Özkan, & Demir, 2015).

Engin-Demir (2009) reported that parents' education, household size, wealth (home ownership and household possessions) combined explained 23% of the variation in academic achievement. When student characteristics were added to the model (e.g., gender, work status, participation in extracurricular activities), it explained 22% more variance. Only 5% more variability was explained with the addition of school quality indicators. The father's education, home ownership and the teacher-student ratio statistically significantly explained variance in achievement over other variables in her model.

The Turkish Education System in Short

Turkey adopted a top-down system in the early 1920s which mandated that school curricula, funding, teaching, employment, and other policies be set by the Ministry of National Education (MoNE). Educational goals and objectives and national testing decisions are made and implemented by the Ministry as well. In the early period, the school system was divided into four cycles of three years each. Later this was changed to a 5+3+3 system. The first five years were compulsory until 1997, when compulsory education was extended to eight years and secondary education school became four years. Students continuing to secondary education had to choose from among several tracks; general high schools, high schools with a science- and language-oriented curriculum, vocational/technical high schools, and religious (Islamic) vocational high schools. Unfortunately, the transition from primary education to secondary education did not reach the desired level during these years. In 2012, a new amendment brought three radical changes to the education system. It increased the compulsory education requirement to 12 years, which are divided into a 4+4+4 system, namely primary school (four years), middle school (four years), and high school (four years). The new regulations require children to start first grade at the age of five and a half and they are then required to choose their track after fourth grade. New reform makes it possible for students to attend Islamic schools as early as ten years of age and vocational school after grade eight. Since 1997, different systems have been used for the transition from eighth grade to ninth grade. Currently students' average grade in six subjects (science, math, history, Turkish, a foreign language, religion and ethics) and national exam score in these six subjects has been used for transition from eighth to ninth grade.

The data used in this study belongs the 2011-2012 academic year just before the current amendment was implemented. In this academic year, 10,997,301 students enrolled in 32,108 schools from first through eighth grade. Of those enrolled in compulsory education, 286,972 (2.61%) were attending private schools (MoNE, 2012).

Methodology

Data Analysis

Regression analysis is generally used to examine the relationship between student achievement and one or more predictor variables (e.g., gender, parent education, SES). One of the fundamental assumptions of these analyses is independence of observations, which means that observation/cases do not correlate with each other, i.e., one observation cannot be predicted from other observations (Glass & Hopkins, 1996, p. 295). Moreover, researchers assume that a relationship is constant across the entire sample (McCoach, 2010). Because of the nature of the population or the research design in educational research, however, these assumptions are usually violated. When students are nested within a classroom, classrooms are nested within a school, and schools are nested within a district, observation units such as students in the same classroom tend to resemble each other, compared to other students in other classrooms. It is plausible that the relationship among variables may vary by cluster. Ignoring the nested/clustered structure of the data may inflate the possibility of a Type I error (O'Connell & McCoach, 2008). Multilevel modeling techniques use a special regression analysis that takes into account the violation of the assumption (it adjusts error variance). Since this technique allows the relationship between criterion and predictor variables to vary across clusters, variability in regression lines can potentially be explained by using variables of a higher level (McCoach, 2010).

In building our multilevel hierarchical models, a step-by-step approach was adopted, as Hox (2010) suggested.[3] First, the null model was tested. Second, the random intercept, fixed slope model with only level-1 predictors and interactions of level-1 predictors was executed (model 1). Level-2 predictors were then added to the model to examine the intercepts (variability in school means) (model 2). Finally, the model with cross-level interactions was examined (model 3).

For our analysis we used the freely available lme4 package, (Bates, Maechler, & Bolker, 2012) which was developed for open source R software (R Core Team, 2012). The lme4 package does not report p-values by default. Because there is no consensus on how to calculate the degree of freedom for linear mixed models, there is no unique way to compute p-values in the mixed-models literature. Therefore, we used t-statistic to test for significance of an estimate. Given that we had a large number of students, it was reasonable to assume that our t-statistic closely followed a normal distribution. We therefore used critical values of 1.96 and 2.58 for the two-sided tests for 5% and 1% significance level, respectively.

Data Source

The data set of the study was drawn from e-School, an education management information system created by the Turkish MoNE. The e-School is used nationwide in both public and private primary and secondary schools in Turkey. Schools are required to enter student- and school-related data, such as grades, family demographic background, and the number of teachers in the school.

The original sample was drawn from 10% of the total population of approximately 10 million students across the country, systematically selected. For systematic sampling first, all students in the population were sorted by province, county/town,

3 For a comparison of different approaches see West et al. (2007).

village/school, grade level, classroom, and gender and then we assigned a consecutive number from 1 to N. The sampling started by selecting one student from the first 10 students. After that every tenth student in the list was included in the sample. The final sample included 1,032,000 students from public schools from the first grade to the eighth grade.

Since grades on report cards assigned by classroom teachers are not comparable across teachers or schools, we used the results of a nationally-administered test (Seviye Belirleme Sinavi [SBS]) as an achievement indicator. This national test had been administered to sixth-, seventh- and eighth graders at the end of each academic year from 2008 to 2013 to measure students' whole-year performance. However, we had to drop the sixth graders because the majority of them had no test score.

In the data set, only 93,569 seventh graders and 91,918 eighth graders provided usable data for a multilevel analysis (where we had 128,370 and 123,688 observations for seventh and eighth grades, respectively). Most of the students in the sample were in schools located in urban areas (80%). The average age of the seventh graders was 12.18 years, with a standard deviation of 0.64. These numbers are 13.16 and 0.64 for eighth graders. The percentage of females was 48.1 for seventh grade and 47.5 for eighth grade.

Measures and Variables

Based on previous studies and the availability of data in the e-School system, variables at the student and school level were selected (see Table 1). Student-level variables were obtained directly from the e-School system, while some school-level variables were calculated using student-level variables, e.g., average of peer's family income, female ratio, average of peer's parent education, average of peer's family income. In addition to these variables urban variable was obtained directly from s-School. The rest of the variables shown in Table 1 were used as predictor variables in either level 1 or level 2. Test score was the score on the large-scale achievement test score that seventh and eighth graders took at the end of academic year.

Table 1
Variables (7th- and 8th-grade students only)

Variable Name	Coding	Percent	Mean	(SD)	Min.	Max.
Test score			311.38	(80.76)	0	500
Gender (Female)	0= No 1=Yes	47.81				
Age			12.66	(.81)	10	17
Father's education	Years of education level attained		7.15	(3.55)	0	22
Mother's education	Years of education level attained		5.56	(3.49)	0	22
Age-grade equivalent	0= age in grade congruence 1= age in grade incongruence (younger or older than grade level)	75.89				
Absenteeism	Number of days that student does not attend school		11.47	(18.29)	0	183
Income	1= low, 2, 3 = average, 4, 5 = high		2.93	(.87)	1	5
Working	0 = no 1 = yes	1.91				
# of siblings	Number of siblings		3.42	(2.07)	1	30
Teacher/Student	The # of teachers serving in the classroom divided by the # of students in the classroom		.33	(.11)	0	6
Full-day schooling	1 = yes; 0 = no	50.36				
Urban	1 = yes; 0 = no	80.53				

Findings

Tables 3a and 3b show our estimates for fixed and random coefficients of the three hierarchical linear models for seventh and eighth graders separately. We will discuss our results separately for each of the three models below, but first we need to execute the unconditional (null) model, where none of the predictors at either level 1 or level 2 are included in the model to determine whether or not multilevel analysis is needed.

Level 1: $\textit{Test score} = \beta_{0j} + r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + u_{0j}$

i refers to the student and j refers to the school in the above notation. There are significant differences in mean test score among schools. The intra-class correlation coefficient (ICC), which is defined as the ratio of school-level variance, Var(u_{0j}), to the total variance, sum of Var(u_{0j}) and Var(r_{ij}).

Tables 2a and Table 2b show our estimates for these variances. For seventh grades, Var(u_{0j}) and Var(r_{ij}) are respectively given by 1120 and 4943; while for eighth grades we have 1164 and 5742. As a result, the ICC is found to be 0.1848 for seventh graders and 0.1686 for eighth graders. This means that only 18.48% and 16.86% of the variability in scores is accounted for by differences between schools for seventh and eighth grade students respectively and within-school factors account for the rest. Given the amount of ICC, it would be wrong to assume that these data were independent. Further, we computed Likelihood Ratio (LR) tests to determine whether these school effects were significant. To do this, we compared the null multilevel model above with a null standard linear model without random effects i.e.,

$$Test\ score = \beta_0 + r_i$$

The LR statistic is calculated as twice the difference in the log likelihoods. We got 7,740 and 6,765 for seventh and eighth graders, respectively. For 5% significance level the critical value for chi-square distribution is 3.84 with 1 df. Hence, we concluded that school effect is significant.

Table 2a
Null Model (7th grades)

	Fixed effects			Random effects		
	Estimate	Std. Error	t value	Name	Variance	Std.Dev.
(Intercept)	312.12	0.38	812.10	(Intercept)	1120.30	33.47
				Residual	4943.30	70.31
				N obs: 93569, N s.id: 15928		

Table 2b
Null Model for (8th grades)

	Fixed effects			Random effects		
	Estimate	Std. Error	t value	Name	Variance	Std.Dev.
(Intercept)	312.12	0.38	812.10	(Intercept)	1164.30	34.12
				Residual	5741.60	75.77
				N obs: 90918, N s.id: 15835		

Model 1: Random Intercept, Fixed Slopes, only Level 1 Predictors

In model 1, test scores were regressed on level-1 variables to determine which level-1 predictors were important in explaining the variation in test scores. While we assumed that the intercept of the relationship between predictors and outcomes differs between schools, the nature or strength of the relationship (the slope) is the same. This model included not only main effects but also interactions between gender and other variables: working, siblings, father's level of education, mother's level of education. The inclusion of interactions between first-level predictors may be important, as indicated by Bauer and Cai (2009). They show that failure to take into account nonlinear effects at a lower level (e.g., student level) might lead to spurious random slopes and cross-level interactions. Upon investigation, an interaction term between the gender dummy and the following variables were proven to have more explanatory power: working dummy, number of siblings, father's level of education and mother's level of education.

Level-1 $\quad Test\ score = \beta_{0j} + \beta_1(female)_{ij} + \beta_2(Age\text{-}grade\ equivalent)_{ij} + \beta_3(Absenteeism)_{ij} + \beta_4(Income)_{ij} + \beta_5(Teacher/student)_{ij} + \beta_6(Working)_{ij} + \beta_7(Siblings)_{ij} + \beta_8(Father\ education)_{ij} + \beta_9(Mother\ education)_{ij} + \beta_{10}(Female{*}Working)_{ij} + \beta_{11}(Female{*}Siblings)_{ij} + \beta_{12}(Female{*}Father\ education)_{ij} + \beta_{13}(Female{*}Mother\ education)_{ij} + r_{ij}$

Level-2 $\quad \beta_{0j} = \gamma_{00} + u_{0j}$

Tables 3a and 3b summarize our results. Our first model (model 1) presents student-level predictors and their interactions. After student-level predictor variables were added, approximately 79% of the between-school variance and 19.8% of the within-school (between-student) variance in student achievement scores for seventh grade are explained.[4] For eighth grade, these numbers are 79.07% and 19.83%. These relatively high numbers are rather surprising. Adding exclusively student-level predictors explains more than 79% of the between-school variance for seventh grade. Thus, student-level variables have relatively more predictive power for explaining between-school variance, implying that there are important compositional differences between schools, i.e., student characteristics such as family income, number of siblings, gender, teacher-student ratio, and parent education vary greatly across schools. Given the high degree of stratification in Turkey's schools, one would expect that gender composition, average level of parental education, and socioeconomic factors differ from one school to another. In fact, this is corroborated by the statistics given above.

This paragraph interprets our findings for both grades. All main predictors for both grades and three- and two-interaction predictors for seventh and eighth grade are statistically significant. Absenteeism and having a job have a negative effect on test scores, as expected. However, the effect of working is less important for females in seventh grade. The level of education of both the father and mother are significant and correlate positively with test scores. The father's level of education has a greater impact on test scores for males, while there seems to be no difference between males and females regarding the level of the mother's education. In an age-grade equivalent classroom, family income and the teacher-student ratio both have a positive and

4 The explained between-school variance, for seventh grades, is computed as the proportional change in Var(u_{0j}) comparing m1 in Table 3a to the null model in Table 2a. Mathematically this is

$$\frac{Var^1(u_{0j}) - Var^0(u_{0j})}{Var^0(u_{0j})}$$

where $Var^1(u_{0j})$ is $Var(u_{0j})$ of m1 and $Var^0(u_{0j})$ is $Var(u_{0j})$ of the null model. For seventh grades this is (1120-234.5)/1120=0.7907. Again for seventh grades, the explained within-school variance is computed as the proportional change in $Var(r_{ij})$ comparing m1 to the null model. Mathematically this is

$$\frac{Var^1(r_{ij}) - Var^0(r_{ij})}{Var^0(r_{ij})}$$

where superscripts 1 and 0 are defined similarly. For seventh grades this is (4943-3963)/4943=0.1983.

significant impact on test scores. The number of siblings affects males and females in the opposite direction: for males, the number of siblings is correlated positively with test scores, while for females the effect is the opposite. We will discuss this surprising and important point later in the text.

Table 3a
Model Estimations (7th grades)

	m1			m2			m3		
Fixed Effects	Estimate	Std. Err.	*t*-value	Estimate	Std. Err.	*t*-value	Estimate	Std. Error	*t*-value
(Intercept)	219.24	2.05	107.07	195.75	4.06	48.19	207.26	5.04	41.16
Absenteeism	-2.15	0.03	-62.91	-2.13	0.03	-62.56	-1.90	0.11	-17.87
Age-grade eq.	4.34	0.73	5.94	3.62	0.73	4.97	3.75	0.73	5.15
Income	7.32	0.35	20.91	6.26	0.36	17.29	3.09	0.82	3.77
Tch/student	29.78	2.85	10.47	10.77	2.94	3.66	10.85	2.94	3.69
Gender	25.72	2.04	12.64	25.93	2.03	12.78	17.39	4.97	3.50
Work	-14.64	2.96	-4.95	-14.45	2.95	-4.90	-14.21	2.96	-4.79
Siblings	0.59	0.25	2.34	1.46	0.26	5.73	1.49	0.26	5.69
Father educ	5.61	0.13	41.95	5.13	0.14	37.99	5.01	0.14	36.23
Mother educ	3.64	0.15	24.88	2.91	0.15	19.48	2.79	0.15	18.05
P.Female				-5.04	4.42	-1.14	-18.18	6.09	-2.99
Urban				-2.11	0.86	-2.44	-9.44	2.91	-3.25
C.educ				3.94	0.27	14.57	4.11	0.32	12.66
C.inc				4.56	1.37	3.32	4.92	1.38	3.56
Full-day				4.06	0.66	6.11	5.49	0.87	6.31
Female*Work	11.91	4.46	2.67	11.75	4.45	2.64	11.70	4.44	2.64
Female*Siblings	-1.36	0.35	-3.89	-1.38	0.35	-3.97	-1.59	0.36	-4.42
Female*F.educ	-0.83	0.19	-4.43	-0.82	0.19	-4.39	-0.63	0.19	-3.24
Female*M.educ	0.17	0.21	0.82	0.17	0.21	0.83	0.39	0.22	1.77
Female*P.Female							27.18	8.35	3.26
Female*C.educ							-0.68	0.36	-1.92
Female*Urban							-2.69	1.54	-1.75
Absent*Full-day							-0.22	0.08	-2.89
Absent*Urban							-0.31	0.10	-3.08
Income*Urban							3.87	0.89	4.37
Random effects		Variance	Std.Dev.		Variance	Std.Dev.		Variance	Std.Dev.
(Intercept)		234.51	15.31		188.28	13.72		376.13	19.39
Absent								0.40	0.64
Female								60.64	7.79
Income								24.79	4.98
Residual		3963.19	62.95		3956.46	62.90		3901.29	62.46
	N: 56298, Ng: 13406			N: 56278, Ng: 13400			N: 56278, Ng: 13400		

Table 3b
Model estimations (8th grades)

	m1			m2			m3		
	Est.	Std. Err.	*t*-value	Est.	Std. Err.	*t*-value	Est.	Std. Err.	*t*-value
(Intercept)	208.23	2.22	93.98	180.95	4.43	40.87	188.85	5.48	34.47
Absenteeism	-2.19	0.03	-67.84	-2.17	0.03	-67.41	-1.99	0.11	-18.77
Age-grade eq.	5.66	0.77	7.31	4.80	0.77	6.22	4.94	0.77	6.41
Income	6.80	0.37	18.14	5.74	0.39	14.78	2.74	0.87	3.15
Tch/student	26.06	3.05	8.54	9.41	3.12	3.02	8.87	3.12	2.84
Gender	36.32	2.20	16.52	36.59	2.19	16.69	36.07	5.33	6.77
Work	-10.78	2.95	-3.66	-9.98	2.94	-3.40	-10.03	2.95	-3.40
Siblings	1.41	0.27	5.23	2.42	0.27	8.87	2.49	0.28	8.95
Father educ	6.09	0.14	43.07	5.59	0.14	39.07	5.44	0.15	37.02
Mother educ	3.67	0.16	23.60	2.94	0.16	18.53	2.79	0.16	17.06
P.Female				-7.30	4.76	-1.53	-15.36	6.61	-2.32
Urban				-2.25	0.94	-2.40	-9.29	3.11	-2.98
C.educ				4.23	0.29	14.60	4.43	0.35	12.71
C.inc				5.34	1.48	3.60	5.75	1.50	3.85
Full-day				3.51	0.72	4.85	5.79	0.97	5.95
Female*Work	4.23	4.77	0.89	2.98	4.75	0.63	2.84	4.73	0.60
Female*Siblings	-1.87	0.38	-4.96	-1.86	0.38	-4.95	-2.09	0.39	-5.42
Female*F.educ	-1.09	0.20	-5.50	-1.10	0.20	-5.56	-0.86	0.21	-4.15
Female*M.educ	0.31	0.22	1.37	0.29	0.22	1.32	0.58	0.23	2.46
Female*P.Female							14.15	8.92	1.59
Female*C.educ							-0.84	0.38	-2.19
Female*Urban							-4.02	1.66	-2.43
Absent*Full-day							-0.27	0.07	-3.85
Absent*Urban							-0.13	0.10	-1.32
Income*Urban							3.68	0.94	3.91
Random effects		Variance	Std.Dev.		Variance	Std.Dev.		Variance	Std.Dev.
(Intercept)		307.04	17.52		246.55	15.70		400.84	20.02
Absent								0.41	0.64
Female								122.75	11.08
Income								19.92	4.46
Residual		4526.41	67.28		4522.57	67.25		4449.52	66.70
	N: 56278, Ng: 13415			N: 56255, Ng: 13407			N: 56255, Ng: 13407		

Model 2: Random Intercept, Fixed Slopes, Both Level Predictors

In this model, we assessed the extent to which interschool variability of test scores can be explained by level 2 variables: the proportion of female students (female ratio), full-day schooling, urban, peer parents' average education, and peer family average income.

Level-1 $\quad$ *Test score* $= \beta_{0j} + \beta_1(Female)_{ij} + \beta_2(Age\text{-}grade\ equivalent)_{ij} + \beta_3(Absenteeism)_{ij} + \beta_4(Income)_{ij} + \beta_5(Teacher/student)_{ij} + \beta_6(Working)_{ij} + \beta_7(Siblings)_{ij} + \beta_8(Father\ education)_{ij} + \beta_9(Mother\ education)_{ij} + \beta_{10}(Female{*}Working)_{ij} + \beta_{11}(Female{*}Siblings)_{ij} + \beta_{12}(Female{*}Father\ education)_{ij} + \beta_{13}(Female{*}Mother\ education)_{ij} + r_{ij}$

Level-2 $\quad \beta_{0j} = \gamma_{00} + \gamma_{01}\ (Female\ ratio)_j + \gamma_{02}\ (Urban)_j + \gamma_{03}\ (Average\ of\ peer's\ parent\ education)_j + \gamma_{04}(Average\ of\ peer's\ family\ income)j + \gamma_{05}\ (Full\text{-}day\ schooling)_j + u_{0j}$

Adding both level variables to the null model helps explain more than 78.82% of the between-school variance and explains 21.23% of the within-school variance in student achievement scores for eighth graders. For seventh grade, these percentages are 83.1 and 19.9. (see explanations in footnote 2 for the way we compute changes in between- and within-school variation). As expected, the addition of school-level variables increases the explained variance at the school level. Compared to model 1, the within-school explained variance does not change significantly (0.07% in the case of eighth graders and 0.14% for seventh graders), while the between-school variance is explained much better (5.20% for eighth grade and 4.13% for seventh grade).

Adding the school variable does not significantly change our findings from model 1. The interesting finding in model 2 is the asymmetric effect of siblings for males and females. Having siblings is positively correlated with test scores for males, while for females this is almost zero. Similar to model 1, this model shows that urban residence negatively affects test scores, while the effect of full-day schooling, average of peer's parent education and average of peer's family income is positive. Both seventh and eighth graders attending school in urban areas are expected to score more than 2 points lower than students living in non-urban areas. Similarly, both seventh and eighth graders attending a school for a full day were expected to score approximately 4 points higher than students attending a half-day school. A one-year increase in the average parent level of education in the school raises test scores approximately 4 points for both grades, as opposed to a one-point increase in average of peer's family income results in an increase of almost 5-points for both grades.

Since model 2 and model 1 are nested models (one can derive model 1 from model 2 by removing school-level variables) we use the deviance (or likelihood) parameter to compare them, where each model is estimated using "full maximum likelihood" (FML). The deviance parameter which measures model misfit indicates that model 2 fits better than model 1, according to a chi-square test.

Model 3: Random Intercept-Random Slope Model with Cross-Level Interactions

In model 3, we assess not only whether level 2 predictors influence average test scores in a school, but also whether they interact with any level 1 predictors. Before running model 3, we determined which slopes needed to vary across schools by running model 2 with a slope variance component, as suggested by Hox (2010). Based on these results, we decided to let slopes for female, absenteeism, income, sibling and age-grade equivalent vary across schools.

Level-1 $\quad$ $Test\ score = \beta_{0j} + \beta_{1j}(Female)_{ij} + \beta_{2j}(Age\text{-}grade\ equivalent)_{ij} + \beta_{3j}(Absenteeism)ij + \beta_{4j}(Income)_{ij} + \beta_{5}(Teacher/\ student)_{ij} + \beta_{6}(Working)_{ij} + \beta_{7}(Siblings)_{ij} + \beta_{8}(Father\ education)_{ij} + \beta_{9}(Mother\ education)_{ij} + \beta_{10}(Female^{*}Working)_{ij} + \beta_{11}(Female^{*}Siblings)_{ij} + \beta_{12}(Female^{*}Father\ education)_{ij} + \beta_{13}(Female^{*}Mother\ education)_{ij} + r_{ij}$

Level-2 $\quad$ $\beta_{0j} = \gamma_{00} + \gamma_{01}\ (Female\ ratio)_{j} + \gamma_{02}\ (Urban)_{j} + \gamma_{03}\ (Average\ of\ peer's\ parent\ education)_{j} + \gamma_{04}\ (Average\ of\ peer's\ family\ income)_{j} + \gamma_{05}\ (Full\text{-}day\ schooling)_{j} + u_{0j}$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}\ (Female\ ratio)_{j} + \gamma_{12}\ (Urban)_{j} + \gamma_{13}\ (Average\ of\ peer's\ parent\ education)_{j} + u_{1j}$$

$$\beta_{2j} = \gamma_{80} + u_{8j}$$

$$\beta_{3j} = \gamma_{50} + \gamma_{51}\ (Full\text{-}day\ schooling)_{j} + \gamma_{52}\ (Urban)_{j} + u_{5j}$$

$$\beta_{4j} = \gamma_{60} + \gamma_{61}\ (Urban)_{j} + u_{6j}$$

Model 3 provides a more complex picture of the effects of predictors in the model. The results of this model show that level-1 predictors not only significantly affect the average test score in a school (intercept effect), but that there are also significant cross-level interactions. Significant interaction terms show that level-2 variables in the model moderate the relationship between test scores and level-1 variables.

The fixed part of model 3 yields quantitative findings similar to those as the one in model 2. One minor change appears in the coefficient of sibling variable. Its effect is positive for males and negative for females, suggesting that females are penalized when the number of siblings is higher, whereas males are favored.

Looking at cross-level interactions, if we consider a 5% significance level, we see that the interaction between absenteeism and full-day schooling is significant and negative for both seventh and eighth grades. The cross-level interaction between urban and family income is found to be significant and positive for both grades. In terms of the interactions between the female and the urban dummy, female and average parent education are significant and negative in the case of seventh graders. For eighth graders, the interaction between the female dummy and the percentage of female students in the school is significant and positive, while the interaction between absenteeism and the urban dummy is negative and significant. Taking into account direct effects along with these interactions, our results suggest that

i. the effect of family income on test scores is relatively more important in urban areas than non-urban areas.

ii. the negative effect of absenteeism on test scores is more pronounced both at schools with full-day education than half-day education and at school in urban areas than non-urban areas. This result indicates that attending a full-day school in an urban area boosts the negative effect of absenteeism on test scores.

iii. female students are more likely to be successful when the percentage of females in the school is higher.

iv. female student achievement is less pronounced in urban schools and in schools where average parent education is higher.

v. the education level of both the father and the mother has a positive effect on test scores. However, the parents' education level differs in magnitude with respect to gender. The mother's has a larger effect for females while the father's has a larger effect on the test scores of males.

Relative to models 1 and 2, model 3 fits better. We used FML estimations to compare model 3 with models 1 and 2 in terms of deviance (also AIC and BIC). A chi-square test shows improvement in model fit. Details of the model comparison statistics are provided in Tables 4a and 4b in the Appendix.

Discussion

Educational achievement and attainment are important educational and political concerns in Turkey. Although school enrollment, especially that of females, has risen considerably since 2000, disparity in academic achievement between various subgroups in term of social demographics and geographical area is still a concern. Alacacı and Erbaş (2010) showed that students, according to PISA results, are nested in schools based on their SES and claimed that not only school factors but also family and student socioeconomic factors have a significant impact on student achievement in Turkey. This finding parallels our results.

The data set drawn from e-School has 184,487 seventh and eighth graders from public schools. We show that approximately 17% of the variability in student achievement in large-scale testing is accounted for by differences between schools, and the rest of the variability is accounted for by within-school factors. Thus, it is worth examining sources of variability between schools as well as within school variability. Our student-level predictors explain more than 73% of the between-school variance and explain approximately 20% of the within-school variance for both grades. These relatively high numbers are rather surprising. A significant amount of explained variance between schools with exclusively student-level predictors indicates stratifications of schools in terms of student-level variables. Thus, student-level variables have relatively more predictive power for explaining between-school variance. This implies that there are important compositional differences between schools, i.e., student characteristics such as family income, number of siblings, gender, teacher-student ratio, and the level of parent education vary greatly across schools. This is not surprising, given the high degree of stratification in schools in Turkey.

Parent Education and Family Income

Our results related the effect of family income and parent education validate previous studies which analyze the relationship between family SES and educational achievement (Blanden & Gregg, 2004; Chevalier, Harmon, O'Sullivan, & Walker, 2005; Chevalier & Lanot, 2002; Davis-Kean, 2005; Ferreira & Gignoux, 2010; Fuchs & Wößmann, 2004; Hanushek & Luque, 2003; Kalender & Berberoglu, 2009; Schiller, Khmelkov, & Wang, 2002; Tansel, 1998, 2002; Tomul & Savaşçı, 2010).

Engin-Demir (2009) and Dinçer and Uysal (2010) report that the effect of the father's education level on achievement is significant, whereas the mother's is not. Tomul and Savaşçı (2010), on the other hand, report significant effects of both the mother's and father's education level on student scores on national large-scale assessment tools. Another study in the Turkish context (Günçer & Köse, 1993) also reported that the father's level of education is a far more significant predictor of academic achievement than school-related factors. Our study also shows that the father's education level has higher predictive power than the mother's. The mother's education level has a greater effect for females, while the father's education has a greater effect for males.

Similar to parental education level, the higher the family income is, the higher the scores is. School location also moderates this relationship. The positive effect of family income on achievement is relatively more significant in urban areas. This finding is particularly important because our study also shows that the average test score of students in urban area schools is lower than the average test score of schools in non-urban areas. This means that students from low-income families living in urban areas are at a disadvantage in education.

Average parent education and average family income as school-level variables show that the higher the average of peer's parent education or the higher the average of peer's family income, the more likely it is that students at both grade levels will score higher on the test. This result is consistent with Dinçer and Uysal's (2010) findings. Moreover, our analysis reveals that male students' achievement is more pronounced in schools where average of peer's parent education is higher for eighth grade but not for seventh grade. Again this is in line with Zhao et al.'s findings (Zhao, Valcke, Desoete, & Verhaeghe, 2012): Students from disadvantaged families show higher achievement in a school with a higher family SES compared to students in a school with a lower family SES.

Gender

The question of gender differences in academic achievement in general and mathematics and science achievement in particular is a specific concern of researchers. Some report that gender disparity in educational outcomes has decreased over time (Else-Quest, Hyde, & Kinn, 2010; Hyde, Lindberg, Linn, Ellis, & Williams, 2008). Others, however, still report gender disparity in educational outcomes, especially in poor countries (Grimm, 2011). Males scored better in the 2009 PISA math than females in 54 of 65 countries (Doris, O'Neil, & Sweetman, 2013).

Our results show that females' average test scores are higher than those of males. While Dincer and Uysal (2010) reported no gender difference for PISA science literacy scores, Engin-Demir (2009) reported findings similar to ours, showing that female students had higher achievement even after controlling for family backgrounds, and surprisingly, she added that gender is the most important predictor among student characteristics (those characteristics are whether or not student attends school and work at the same time, grade level, student's participation in an extracurricular activity, level of homework completion, time spent on leisure activities, and student's perception of their parents' follow up)

Female seventh graders are more likely to be successful when the percentage of female students in their school is greater. Unlike our analysis, however, Dinçer and Uysal's (2010) examination of the share of females as student level data yielded no correlation between PISA scores and proportion of females in a school. This study also shows that the achievement gap between genders increases in favor of female students in urban schools and in schools where the average of parent's education level is higher for eighth graders.

Absenteeism

Absenteeism has been found to be detrimental to academic achievement and may result in school drop-out rates. It may also exacerbate academic and sociological risk factors in later years (Finn, 1993; Lamdin, 1996). In our analysis, absenteeism is shown to negatively affect student achievement, as expected. This result is in line with national studies and is confirmed by international studies (Engin-Demir, 2009; Gottfried, 2009; Lamdin, 1996). Absenteeism is a serious problem and is likely to grow in Turkey as a result of the extension of compulsory education from 8 years to 12, because there will be more unmotivated students. Students with high absenteeism are likely to be working at jobs outside school time and therefore prefer to go to half-day schools because it allows them to work the rest of the day (Strulik, 2008).

Although our analysis shows that attending a full-day school improves test scores, the interaction between absenteeism and school-level variables shows that school-related variables moderate the relationship between test scores and absenteeism. The negative effect of absenteeism on achievement is stronger in full-day schools and in urban schools. This means that, all other things being equal, students with high absenteeism have lower test scores in full-day schools compared to those students in half-day schools. Similarly, the negative effect of absenteeism on achievement is greater in urban schools.

Number of Siblings

There is no consensus regarding the effect of siblings on educational outcomes in the literature. Obviously, research contexts rule the direction of this effect. While some papers analyzing Western culture report negative sibling effects, other studies analyzing Eastern cultures report positive sibling effects or no direction (Downey, 2001; Smith & Gündüz-Hoşgör, 2006). However, it is recognized that family resources are distributed among family members and, as the number of children in the family increases, the amount of resources such as money and parental time per child declines (Downey, 1995, 2001). Lindskog (2013) reported negative effects of younger siblings' school attendance on girls' schooling, and positive effects of younger sisters' literacy on boys schooling.

Normally, given that schooling costs increases with number of siblings, one would expect that having siblings would be negatively associated with test scores. But, in our case, having more siblings affects males and females in an asymmetric way: while for males, the number of siblings is correlated positively with test scores, for females it is the opposite. This asymmetric effect may be interpreted in more than one way. First, this may be seen as "learning externalities" among siblings through spillover effects and knowledge sharing. Second, this may reflect a sexist labor division in the family. If the second thesis is true, one may think that female students have to help with domestic chores while male students are able study in part of this additional time. This may be true in the case of Turkey, where family culture is generally paternalistic. Smith and Güngör-Hoşgör (2006) show that having a brother decreases the chance of female students getting an education because cultural norms give priority males in the family. This finding supports our asymmetric finding regarding sibling effect.

Working

We find that working negatively affects test scores. In contrast, Engin-Demir (2009) reported no significant effect of working in the study conducted in a poor urban Turkish area. However, the vast majority of research reports negative effects from child labor. For instance, Gunnarsson, Orazem, and Sánchez (2006) find that child labor negatively affects academic achievement, especially in elementary school in nine Latin American countries. According to Heady (2003), child labor in Ghana has a substantial effect on learning, particularly in the key areas of reading and mathematics if a child works outside the home. Moreover, students who work outside the home do worse in school than those who work only in the home (Bezerra, Kassouf, & Arends-Kuenning, 2009).

Teacher-Student Ratio

The results show that, as the teacher-student ratio increases, the more likely students are to get a higher score. Engin-Demir (2009) also found that the teacher-student ratio is the most substantial indicator among school-quality indicators. International research concludes either no effect or a positive effect of smaller class size (Chingos, 2012; Rivkin, Hanushek, & Kain, 2005; Wößmann & West, 2006).

Conclusion

Using data from the MoNE's e-School education management information system, we explored the causes of inequalities in academic achievement of students in Turkey by using multilevel hierarchical models (school and student level). Our results are in line with most other studies exploring the determinants of academic achievement inequalities. Our results show that approximately 17% of the variation in student test scores is explained by differences between schools, while the remainder of the variation is accounted for by within-school factors. More importantly, our results highlight that student-level variables alone explain nearly 73% of the between-school variance and approximately 19% of the within-school variance in student achievement scores. Our school-level variables explain a relatively small amount of the variation, approximately 5%.

This has demonstrated that between- and within-school differences in student achievement are largely accounted for by the socio-demographic background of students. This seems plausible, given the relatively high social stratification of students in the Turkish education system. This is in line with the Coleman Study findings; the effect of school characteristics on student achievement was modest compared to the effect of students' socio demographic characteristics. This is not to suggest that schools make no difference, however.

After controlling for student-level variables, our school-level variables can explain a small amount (approximately 5%) of the variation in test scores. Unfortunately, e-School did not provide us variables that might have been able to show the quality of our schools, e.g., educational materials, teacher quality or school climate. However, given the limited number of school-level variables, 5% is not a negligible amount. Our results show that average parent education and income, full-day schooling, attending an urban school and the percentage of female students mediate the relationship between student-level variables and student test scores.

Based on our results, schools would have to take on more responsibility for educating parent about the importance of school attendance and, they may organize free remedial teaching or after school session for children who are academically behind their peers and especially for girls coming from low SES families with many children. The ministry should eliminate policies that magnify a detrimental effect of socio economic status on students' achievement. The ministry should take measures to improve students' attendance by considering the reasons of student truancy and focused on protective factors associated with truancy.

For future studies, researchers may design studies to explain the mechanisms that underlies a relationship between achievement and variables studied in this study by adding new variables. These variables could have a moderator, mediator, confounder and suppressor role in this mechanism. Such studies is crucial in order to developed preventive interventions and strategies in our schools to eliminate inequalities in students' achievement.

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Appendix

Model Comparisons

Table 4a
Model Comparisons (7th grades)

	Df	AIC	BIC	logLik	Chisq	Chi Df	Pr(>Chisq)	
Model 0	3	1073106	1073135	-536550				
Model 1	16	628984	629127	-314476	444148	13	2.20E-16	*
Model 1	16	628984	629127	-314476				
Model 2	21	628193	628380	-314075	801.7	5	2.20E-16	*
Model 2	21	628193	628380	-314075				
Model 3	36	628077	628398	-314002	145.94	15	2.20E-16	*

* $p < .001$.

Table 4b
Model Comparisons (8th grades)

	Df	AIC	BIC	logLik	Chisq	Chi Df	Pr(>Chisq)	
Model 0	3	1055589	1055617	-527791				
Model 1	16	636577	636720	-318272	419038	13	2.20E-16	*
Model 1	16	636577	636720	-318272				
Model 2	21	635744	635932	-317851	842.28	5	2.20E-16	*
Model 2	21	635744	635932	-317851				
Model 3	36	635618	635940	-317773	155.98	15	2.20E-16	*

* $p < .001$.