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Render unto Primary the Things which are Primary's. Inherited and Fresh Learning Divides in Italian Lower Secondary Education

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Abstract

We employ a pseudo-panel approach to link achievements of the same cohort of Italian students over two waves of the Trends in International Mathematics and Science Study (TIMSS). As we investigate the determinants of scores in math and science at the end of the lower secondary school (8th grade), we are able to circumvent cumulative effects of education by controlling for the estimated achievement at the 4th-grade. We find that the gender gap in math observed at the 8th grade should actually be ascribed to primary education, while responsibilities on the gap in science are shared by the two school levels. On the other hand, in both subject, the largest part of the learning divide due to family background originates at the lower secondary school. We also find that, although foreign-origin students are more prone than natives to be held back, they show a spectacular recovery at the lower secondary school, once the entry-level of competence is taken into account.

Key words: Pseudo-panel, TIMSS, learning divides, gender gap, socio-cultural gap, immigrant students, primary education, lower secondary education, cognitive achievement dynamics

JEL classification: C21, I24, Z13

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1 Introduction

Cross-country assessments reveal that Italy exhibits a relatively high intergenerational educational persistence that ultimately translates into very low intergenerational income mobility (Hertz et al. 2007, Chevalier et al. 2007). The responsibility of such an inequality across social groups is usually ascribed to the selection into tracks at the end of lower secondary education[1]. The students' level of achievement is extremely diversified across types of secondary schools with those in the academic track outperforming those in technical institutes which, in turn, outperform those in the vocational track (Montanaro 2008, Bratti et al. 2007). But the choice of the upper secondary track has been shown to be little meritocratic and extremely sensitive to the role played by family background and expectations (Checchi and Flabbi 2007, Checchi et al. 2008, Mocetti 2011). Due to cumulative effects of education, each track is associated with very different lifelong outcomes in terms of further human capital accumulation and labor-market performance, resulting in the final picture of a widespread immobility within the Italian society.

Mocetti (2011) suggests that the selection might start even earlier than the time of transition from lower to upper secondary school (age 14). He finds that family background significantly affects the probability to experience an irregular course of study in the compulsory education. Furthermore, a delay in the course of study impinges on the track choice and it is the single most powerful predictor of dropping out at a later stage of education. However, although it helps to single out a possible channel of family influence on achievements and choices, the delay in the course of study is a rather limited phenomenon in Italian compulsory education. The latest official statistics available about school failure (MIUR 2008) reveals that not more than 0.4% and 3.7% of pupils are held back in primary and lower-secondary education respectively, whereas irregular courses of study might sum up to 3.3% and 10% in the two stages; the reason for the difference in aggregate numbers is the existence of an exception to the age-grade rule for students of foreign origin[2]. But since more than one student out of two opts for either the technical or the vocational track once they transit to the upper secondary education, it is sensible to presume that much wider and pervasive learning divides across socio-demographic groups of individuals emerge during the compulsory education years than those revealed by simple statistics on irregular courses of study.

In this paper we provide new evidence on the learning divides in the final grade of Italian lower-secondary school. We investigate the determinants of cognitive achievement in math and science as measured by test scores at grade 8 of the 2007 edition of the Trends in International Mathematics and Science Study (TIMSS). In order

[1] Education in Italy is compulsory from 6 up to 16 years of age. Compulsory education covers the first cycle (8 years) and the first two years of the second cycle (upper secondary education). The first cycle includes *scuola primaria* (primary school, 5 years) and *scuola secondaria di primo grado* (lower secondary school, 3 years). The second cycle of education is made up of the *scuola secondaria di secondo grado* (upper secondary school, 5 years) falling under the responsibility of the State and offered by the *licei* (academic oriented course of study), the technical institutes and the vocational institutes, and of the vocational and training system falling under the responsibility of the Regions and offered by the recognized formative agencies operating nationwide.

[2] Newly arrived foreign students enter schools at lower grades whenever their competences are evaluated to be inadequate to fruitfully join peers in the regular path. On a representative sample of 44,490 Italian students aged 11 and 13, Berchialla et al. (2011) show that the probability of a delay in the course of study for a first generation immigrant student is 17.85 times higher at grade 6 and 19.32 times higher at grade 8 with respect to those of a native peer. Hence, looking at delayers means dealing with a group where students of foreign origin are overrepresented. Although it is likely that the family income, the socio-cultural status and the academic support received at home are not orthogonal to the origin of students, Mocetti (2011) fails to control for the immigrant status of parents of youngsters in his sample leaving such a source of hreterogeneity unaccounted for.

to circumvent cumulative effects of education, we employ a pseudo-panel approach to link achievements of the cohort of 8th-graders in 2007 with those of the same cohort of students in the 2003 edition of TIMSS, when they were enrolled in the grade 4. This allows us to distinguish the responsibilities of primary and lower-secondary education in generating the learning gaps observed just before the selection into upper-secondary school tracks.

Our results reveal that the gender gap in math observed at the grade 8 should actually be ascribed to primary education, while responsibilities on the gap in science are shared by the two school levels. On the other hand, in both subject, the largest part of the learning divide due to family background originates at the lower secondary school. We also find that, although foreign-origin students are more prone than their native peers to be held back, they show a spectacular recovery at the lower-secondary school, once the entry level of competence is taken into account.

Our contribution to the literature is twofold. Firstly, we shed new light on the inequality of Italian education system by showing that family influence on students selection into tracks cannot be counterbalanced by intrinsic academic merit because lower-secondary education enormously amplifies disparities in learning opportunities across socio-economic groups. Secondly, we demonstrate that, lacking longitudinal data on students achievement, information collected on the same cohort of students by means of repeated cross sections can be linked with a pseudo-panel approach to effectively conduct system-level evaluation of the dynamics of cognitive achievement.

The paper is organized as follows: we describe the conceptual framework and our empirical strategy in Section 2; the data and the two steps of our pseudo-panel analysis are presented in Section 3; results obtained and the discussion of findings are in Section 4; finally, we draw some concluding remarks in Section 5.

2 The empirical strategy: a linear dynamic model of cognitive achievement

Learning is a cumulative process: current knowledge builds on past knowledge. As a consequence students achievement observed at a given step reflects past achievements along the schooling ladder. Longitudinal value added models[3] are usually employed to single out the contribution of a specific stage of the educational process. The individual net cognitive gain at the end of any given stage (*value added*) is computed as the difference between the observed *final level* of knowledge and competence and the *entry level*.

We adopt a similar framework to investigate how socio-demographic characteristics impact students' cognitive achievement at the end of lower secondary school. In order to disentangle the net contribution of lower secondary education as measured at the end of the first cycle of education (t), we need to control for the students' level of achievement at the end of primary school ($t - s$, where s is the lenght in years of lower-secondary

[3] See Meyer (1997) and Lissitz(2005, 2006) for a discussion of both general definitions and applications of value added models for the evaluation of school effectiveness. The implications of learing dynamics into the estimation of school inputs' effect on achievement are discussed in Meghir and Rivkin (2011). Todd and Wolpin (2003) review the methods for modelling the cumulative effects in the production function for cognitive achievement and discuss the identifying assumptions needed to justify alternative approaches.

education). So we can define an autoregressive model of cognitive achievement of the following type:

$$y_{i,t}^{c,s} = \alpha y_{i,t-s} + X_{i,t}^{'}\beta + Z_i^{'}\gamma + \delta^{c,s} + \phi^s + \varepsilon_{i,t}^{c,s}, \tag{1}$$

where $y_{i,t}^{c,s}$ denotes the achievement of student i in class c of school s at the grades t, $y_{i,t-s}$ is the entry level at lower secondary school, $X_{i,t}$ is a set of individual time-variant variables impacting learning at time t, Z_i is a vector of individual time-invariant determinants of cognitive achievement, $\delta^{c,s}$ is a class fixed effect capturing class-level determinants of learning (teaching quality, peer effects, etc.), ϕ^s is a school fixed effect capturing school level determinants of learning (management quality, organization, contextual factors, etc.) and $\varepsilon_{i,t}$ is a residual component.

To estimate such an equation one should rely on performance data collected for the same individuals over time which are not available for Italian students[4]. An alternative strategy is to follow Moffitt (1993) who shows that a consistent estimation of (1) can be obtained with data collected in repeated cross-sections (RCS) where sets of individuals are independently drawn from population at two or more points in time. In fact, even if in RCS data no lagged values for y_i are generally observed for single individuals, $y_{i,t-s}$ in (1) can replaced by an estimated value.

Where do we find the information necessary to estimate past achievements? For all individuals i in the cross-section t, we can take advantage from the fact that, by definition, we know the value at both points in time of variables in Z_i which are time-invariant. Of course, the same can be said for those time-varying observables in the vector $X_{i,t}$ that can be backcasted with reasonable accuracy. Moffitt (1993) suggests to compute the lagged variable in the autoregressive model as the predicted values of $\widehat{y}_{i,t-s}$ once we substitute the appropriate Z values for the individuals i in cross-section t in the projection:

$$\widehat{y}_{i,t-s} = Z_i^{'}\widehat{\gamma}_{t-s}, \tag{2}$$

where $\widehat{\gamma}_{t-s}$ is consistently estimated from data on the cross-section at time $t-s$ on different individuals than those drawn at time t, by means of the reduced form defined by the orthogonal projection:

$$E\left\{y_{i,t-s}|Z_i\right\} = Z_i^{'}\gamma_{t-s}. \tag{3}$$

Having done that, we can insert the predicted values into (1) to get:

$$y_{i,t}^{c,s} = \alpha \widehat{y}_{i,t-s} + X_{i,t}^{'}\beta + Z_i^{'}\gamma + \delta^{c,s} + \phi^s + u_{i,t}^{c,s}, \tag{4}$$

where

[4]The Italian National Institute for the Evaluation of the Education System (INVALSI) has introduced standardized test in reading and math at the 2nd-, 5th-, 6th- and 8th-grade since 2007. Unfortunately, individual scores are not linked over time. Furthermore, the investigation has taken a few years to stabilize with different sampling frames used across different grades. Hence INVALSI cross-sections lack a full comparability over time and cannot be effectively employed to provide an answer to our research question.

$$u_{i,t}^{c,s} = \varepsilon_{i,t}^{c,s} + \alpha \left(y_{i,t-s} - \widehat{y}_{i,t-s} \right), \tag{5}$$

with $(y_{i,t-s} - \widehat{y}_{i,t-s})$ being the measurement error on the achievement at time $t-s$ that will be (asymptotically) uncorrelated with the predicted value.

When we are able to observe the same cohort of individuals - although not the same individuals - over time, equation (4) can be consistently estimated by OLS as, by construction, there are no cohort effects in the unobservables:

$$E\left\{\varepsilon_{i,t} | Z_i\right\} = 0. \tag{6}$$

A second condition for consistency of OLS is that $X_{i,t}$ should be uncorrelated with $u_{i,t}$. Verbeek and Vella (2005) point out this is a rather demanding restriction as, even if $X_{i,t}$ is exogenous with respect to $y_{i,t}^{c,s}$ and thus uncorrelated with $\varepsilon_{i,t}^{c,s}$, it can still be correlated with the measurement error $(y_{i,t-s} - \widehat{y}_{i,t-s})$. Typically, this is what happens when the observables in $X_{i,t}$ are serially correlated. In this case, consistency can be achieved through the exclusion from $X_{i,t}$ of all variables with an autoregressive process. Alternatively, an IV strategy is needed. In the latter case, variables in Z_i become the natural candidates as instruments for $X_{i,t}$ because they satisfy a condition like (6) by construction[5].

3 The data and the pseudo-panel approach

Italy has taken part to Trends in International Mathematics and Science Study (TIMSS) in 1995, 1999, 2003 and 2007. TIMSS measures trends in mathematics and science achievement at the fourth and eighth grades. Given the timing of waves, TIMSS provides information about relative progress across grades: the cohort of students assessed at the fourth grade in one cycle moves to the eighth grade four years later (i.e., the fourth grade students of 2003 became the eighth grade students of 2007). In Italy, the 8th-grade corresponds to the final year of lower secondary education, while 4/5 of the primary education have gone when students are observed in their 4th-grade. The cognitive progress between the 4th- and the 8th-grade can be considered a reasonable approximation of the specific contribution of lower secondary education.

Since different waves of the study are conducted over different sets of individuals independently drawn from population, we cannot link individual scores in this case either. But we can exploit the properties of RCS highlighted by Moffit (1993) and described above to estimate past achievements of 8th-graders.

Two reasons force us to work solely on the latest two waves of the study (TIMSS 2003 and TIMSS 2007): a) the poor quality of 1995 Italian data that have not been accepted in the official international database; b) the unavailability of an assessment for 4th-graders in TIMSS 1999[6].

TIMSS provides information about a set of time-invariant variables (Z_i) that can be employed to predict

[5] For a discussion of identification conditions underlying these estimators in RCS see Verbeek and Vella (2005).
[6] See IEA (2004, 2008a, 2008b) for details on TIMSS 2003, TIMSS 2007 and a cross-country comparison of system-level results.

backward the performance as 4th-graders in 2003 of 8th-graders in 2007. In particular, we are able to use: gender, place of birth (Italian born, foreign born), parents' place of birth (Italian born, foreign born), area of residence and socio-cultural background.

For the sake of comparability of the two samples independently drawn from the same cohort in 2003 and 2007, we need to get rid of all individuals of foreign origin arrived in Italy after 2003. Thus, we drop 1.95% of 8th-graders in our 2007 sample as they report an age of 10 or above at their arrival in Italy.

Although TIMSS collects information on studens' month and year of birth, we cannot employ such variables in our estimates. In fact, as discussed above, the year of birth can be considered as a proxy of regularity in the course of study. Unfortunately, those reporting a delay as 4th-graders in 2003 are not necessarily comparable to those reporting a delay as 8th-graders in 2007 as grade repetition may have occurred at different stages (and more than once) as a result of peculiar cognitive difficulties. Consequently, profiling students according to their year of birth would not ensure comparability over time and we have to desist from using such a time-invariant individual covariate. Furthermore, delays are not orthogonal to socio-demographic factors and including such an indicator in our cognitive production function would confound our results on the variables of interest[7].

We include in the vector Z_i some variables that, although time-variant, are likely not to have changed over time: the area of residence (5 macro-regions) and an indicator of familiar socio-cultural background.

The area of residence is expected not to be affected by relevant group switching as Italy is no longer experiencing massive migration from South to North as in the 1950s and 1960s. Furthermore, Mocetti and Porello (2010) show that, over the 2005-2007 time span, the within-Italy mobility of families with young children was the lowest compared to that of both single movers and married couples without children.

The indicator of socio-cultural background is at the center of our investigation on the influence of family on achievement (and choices). The education attainment of parents is often taken as a proxy of the amount and quality of family (material and immaterial) inputs. Unfortunately, in TIMSS, such kind of information is collected for 8th-graders only. So we have to rely on another proxy that is usually collected in surveys on young students to avoid misreporting on parents' education attainment: the number of books at home[8]. The cross-tabulation of book possession and the parents' education attainment for 8th-graders in 2007 reveals a clear association among the two covariates (Figure 1), so we believe that this variable is able to discriminate among students according to family background and it can be used to estimate past performances. Of course, the number of books at home may vary over time and we need to rely on the assumption that this variable is serially correlated, which is not implausible.

[Figure 1 here]

We report descriptive statistics of variables included in our pseudo-panel in the Table 1.

[7] We report in Appendix A (Table A1) the results obtained by estimating a probit model where socio-cultural characteristics of 8th-graders students in our sample are employed as predictors of the probability to be delayers. As expected, the (female) gender and the education of parents act as protection factors against an irregular course of study, while being a 1^{st} generation immigrant students implies an increase in the probability to show an irregular course of study by 54 percentage points with respect to a native peer with Italian parents. As discussed in the introductive section, this is mainly the consequence of the application of an exception to the age-grade rule.

[8] In TIMSS, the question explicitly excludes magazines, newspapers and school books.

Table 1: Descriptive statistics

		Grade 4					Grade 8				
Variables		*Obs*	*Mean*	*Std.Dev.*	*Min.*	*Max.*	*Obs*	*Mean*	*Std.Dev.*	*Min.*	*Max.*
Math score		4282	501.3	78.8	221.6	722.8	4322	480.9	72.9	226.8	740.6
Science score		4282	514.2	80.8	235.6	771.2	4322	495.4	73	258.9	757.9
Female		4282	0.482	0.5	0	1	4322	0.480	0.5	0	1
		Freq	%				*Freq*	%			
Books at home											
	Up to a shelf	2181	50.9				1438	33.3			
	One bookcase	1141	26.7				1198	27.7			
	Two or more bookcases	960	22.4				1686	39.0			
Parents' education											
	Up to lower sec ed	-	-				1128	28.8			
	High-school degree	-	-				1620	41.3			
	Post-sec ed, College degree	-	-				1176	29.9			
Own and parents' place of birth											
	Native	3574	87.6				3909	90.4			
	Born to mixed parents	315	7.72				261	6.0			
	Native, non-Italian parents	115	2.82				54	1.25			
	Non-native, non-Italian parents	75	1.84				98	2.27			
Homework											
	No time	218	5.2				176	4.1			
	$<$ 1 hour	1410	33.9				652	15.1			
	$>$1 but $<$ 2 hours	1551	37.3				1628	37.7			
	$>$ 2 but $<$ 4 hours	546	13.1				1285	29.7			
	$>$ 4 hours	438	10.5				581	13.4			
Perception of being safe in school											
	Low	1082	25.9				229	5.3			
	Medium	1762	42.2				1367	31.6			
	High	1327	31.8				2726	63.1			
Area of residence											
	North-West	938	21.9				925	21.4			
	North-East	653	15.3				381	15.8			
	Center	716	16.7				809	18.7			
	South	1208	28.2				1157	26.8			
	South-Islands	767	17.9				750	17.3			

3.1 First step: a backward prediction of achievements at the 4th-grade

Our aim is to approximate the net impact of lower secondary education on the level of literacy in math and science for students in the cohort enrolled at grade 8 in 2007. So we need to estimate an entry level for each of them. In our case the entry level can be proxied by the student performance four years before, when he/she was enrolled at grade 4.

For each subject j (j = math, science), we estimate first the impact of time-invariant variables, Z_i^{4th}, on the performances of $4th$-graders in 2003, $y_{i,2003}^{4th}$:

$$y_{i,2003}^{4th} = Z_i^{4th'}\gamma^{4th} + \varepsilon_{i,2003}^{4th}, \tag{7}$$

where γ^{4th} denotes the vector of coefficients attached to the time-invariant individual characteristics, $\varepsilon_{i,2003}^{4th}$ is a residual term and we suppressed the j subscript for the sake of simplicity.

We cannot include neither class- nor school-level variable as, proceeding from primary to lower-secondary school, Italian students often face a change of school. As a consequence they experience a significant change in class composition and they are always assigned to a fully new teacher body[9]. Such an important source of variation in data cannot be exploited to consistently predict backward scores at grade 4.

The weighted OLS estimation results of equation (7) for math and science are reported in Table 2 (column 1 and 3 respectively). All variables have a statistically significant impact on test scores and coefficients report the expected sign. Girls lag behind boys in both math and science although the gap is not statistically significant in the latter subject. Learning divides across socio-economic groups of students are already in place at the 4th grade, although we do not observe a linear pattern. Analogously, foreign-origin students show lower test scores with respect to natives, apparently with little difference, at this stage, among first (non-native with non-Italian parents) and second generation (native with non-Italian parents) immigrant students.

Since equation (7) does not take into account neither time-variant individual specific variables nor school-level indicators its explicative power is rather limited. This suggests that demographic and socio-cultural characteristics are not yet one of the main determinants of learning divides at this stage[10]. However, a large amount of unobserved heterogeneity is left uncaptured and this can translate into biased coefficients. As a robustness check, we estimated a specification of equation (7) including school fixed effects as well (Table 2, column 2 and 4). The fit of the model increases significantly for both Math and Science but parameters are not substantially affected[11]. We conclude that the possible bias in results obtained estimating equation (7) is

[9] Over recent years, the Ministry of Education has been promoting the diffusion of *istituti comprensivi* (vertically integrated school) that tend to bring together primary and lower secondary schools operating in the same district (small towns, city area, etc). The main objective is to save on management and administrative costs, although this process of integration could incidentally favor a smoother transition of students from primary to lower secondary education. Our dataset does not allow for a distinction of vertically integrated schools from independent schools. However, primary and secondary schools remain *de facto* independent form each other in vertically integrated schools, as well: teacher bodies, *curricula*, pedagogical approach remain practically unaffected and thus the students still face a significant discontinuity when they transit from primary to secondary school.

[10] We replicated the same estimation on INVALSI data. The time-invariant individual characteristics considered here are able to account for up to 11% of the variation in 5th-graders' performance on math test (% of correct answer) in the 2010 wave. Thus, the predictive power of such variables remains limited at the primary school also when the dependent variable comes from a test tailored on the Italian schooling system. See Table A2, Appendix A for details.

[11] The only coefficients that shows some variation are those related to the achievement gaps of students with mixed parents and

rather limited.

Table 2: Weighted OLS estimation of time-invariant observables' impact on test scores at grade 4

	Math		Science	
VARIABLES	(1)	(2)	(3)	(4)
Female	-9.008***	-9.096***	-3.711	-3.586
	[2.791]	[2.205]	[2.906]	[2.385]
Origin (Ref. Native with Italian parents)				
Born to mixed parents	-17.59***	-14.52***	-14.98***	-9.273*
	[4.827]	[4.113]	[5.682]	[5.156]
Native with non-Italian parents	-41.01***	-28.35***	-43.83***	-32.21***
	[7.131]	[6.300]	[8.399]	[6.439]
Non-native with non-Italian parents	-42.79***	-41.97***	-44.69***	-40.27***
	[9.303]	[8.884]	[9.478]	[8.940]
Books at home (ref. Up to one shelf)				
One bookcase	18.46***	16.80***	16.63***	14.76***
	[3.262]	[2.589]	[3.539]	[2.731]
Two or more bookcases	11.43***	11.89***	16.27***	15.24***
	[4.036]	[2.823]	[4.023]	[3.165]
Constant	518.3***	539.4***	528.5***	546.0***
	[4.785]	[1.992]	[4.903]	[2.054]
Area of residence fixed effects	Yes	Yes	Yes	Yes
School fixed effects	No	Yes	No	Yes
Observations	4,079	4,079	4,079	4,079
R-squared	0.049	0.392	0.046	0.385

Note: Robust standard errors clustered by school in brackets. Estimation has been performed using sample weights provided by IEA. *** p<0.01, ** p<0.05, * p<0.1

We are now able to predict the test scores as 4th-graders for the 8th-graders in 2007. We simply substitute the appropriate Z_i values for 8th-graders and we employ the vector of coefficient estimated by means of equation (7), $\widehat{\gamma}^{4th}$, as parameters for the following projection:

$$\widehat{y}_{i,2003}^{4th} = Z_i^{8th'} \widehat{\gamma}^{4th}. \tag{8}$$

We report descriptive statistics of the *estimated entry levels* ($\widehat{y}_{i,2003}^{4th}$) in Table 3. The limited variability is not surprising given the small impact of socio-demographic factors (Z_i) on performances at grade 4. The estimated entry levels will be our starting point for the next step in the analysis of learning divides in math and science generated within compulsory education.

Table 3: Estimated entry levels in Math and Science

Descriptive Statistics

$\widehat{y}_{i,2003}^{4th}$	Obs	Mean	Std.Dev.	Min	Max
Math	4322	507.6	15.9	443.8	436.8
Science	4322	521.4	16.1	454.8	545.1

2^{nd} generation students. However, this may be due to the small size of these two groups in our sample that could affect the precision of estimates.

3.2 Second step: Determinants of the achievements at the 8th grade

Next we turn to the estimation of linear dynamic model in the fashion of equation (4). Suppressing the time subscript for the sake of simplicity, we define the test score of a student i in class c of school s at grade 8 as:

$$y_{i,c,s}^{8th} = \alpha \widehat{y}_i^{4th} + X_i^{8th'} \beta + Z_i^{8th'} \gamma + \overline{y}_{c,s}^{8th} + \phi_s + u_{i,c,s}^{8th}, \tag{9}$$

where X_i^{8th} is a set of individual-level time-variant variables impacting learning at the 8th-grade, $\overline{y}_{c,s}^{8th}$ is the class-average test score capturing class-level factors that affect individual performance, ϕ_s is a school-level fixed effect, and

$$u_{i,c,s}^{8th} = \varepsilon_{i,c,s}^{8th} + \alpha \left(y_i^{4th} - \widehat{y}_i^{4th} \right).$$

As discussed above, since we observe the same cohort of individuals - although not the same individuals - over two points in time (4th grade and 8th grade), possible cohort effects in the unobservables are not an issue.

The other condition to estimate equation (9) consistently with OLS is that X_i^{8th} should be uncorrelated with $u_{i,c,s}^{8th}$. We make sure this is the case by including in the equation two observables that are likely not to show an autoregressive process: a) the time spent doing homework; b) the students' perception of being safe in school. The former present a different distribution over the two grades because of a structural differences between primary and lower secondary school in Italy: full-time attendance decreases as the level of schooling and students age increases, with students of higher grades beign assigned much more work to be done at home in the afternoon. The latter shows no correlation over time because proceeding from primary to lower secondary education implies a change of school which in turn implies a significant change in class composition[12]. Possible disruptive behavior of schoolmates at grade 8 needs not to be related to attitudes of former schoolmates at the grade 4.

It is worth noticing that, in our model, class-level performance ($\overline{y}_{c,s}^{8th}$) will not capture the influence of peers ability on individual students. In fact, since we control for each student entry level of knowledge, the class-average score will reflect just the impact of factors that jointly affect the performance of all individuals in class c (i.e., quality of teaching, class climate, etc)[13].

4 Results

In Table 4, we report the results obtained by estimating equation (9) for achievements in math and science. We distinguish the models that control (columns A and C) from those which do not control (columns B and

[12] The index of "Students' perception of being safe in school" is developed from IEA on the basis of the answers to the students' reports on things happening in their school during the month prior to the test. The items are the following: Something of mine was stolen, I was hit or hurt by other student(s) (for example, shoving, hitting, kicking), I was made to do things I didn't want to do by other students, I was made fun of or called names, I was left out of activities by other students. Answers are re-coded in a variable that takes the following values about safeness: Low, Medium, High.

[13] Since TIMMSS 2007 sampled 524 classes in 341 Italian schools, with an average of 1.5 classes in each school, we cannot employ a strategy where both class- and school-level factors are controlled by means of fixed effects (dummies). In fact, in about half of the cases a class fixed effects would coincide with a school fixed effect.

D) for the estimated entry level at lower secondary school of 8th-graders ($\widehat{y}_i^{4th}$). By doing this, we are able to highlight the net impact of lower secondary education on learning divides across demographic and socio-cultural individual characteristics. Contrasting the two types of models we can detect three groups of learning disparities:

- *inherited from primary school*, i.e. those for which the significance of coefficients on the relevant indicators does not survive the inclusion among the explanatory variables of the estimated entry level;
- *newly generated within lower secondary school*, i.e. those for which the significance and the scope of coefficients on the relevant indicators survive the inclusion of the estimated entry level;
- *already in place but made worse by lower secondary school*, i.e. those for which the coefficients on the relevant indicators remain significant after the inclusion of the estimated entry level, but that simultaneously show a reduction in size.

We are able to estimate the models on fewer observations with respect to the full sample (9% drop) because of missing values on the parents' education variable[14]. All specifications include a full set of dummies for the area of residence and school fixed effects.

4.1 The gender gap

The occurrence of a gender gap in math and science test scores has been documented for a number of countries over time and Italy makes no exception. Italian girls lag behind boys at all grades[15]. But, to our knowledge, so far nobody has taken into account the possible cumulative nature of the gap for Italian female students. If we focus on column A of Table 4 we can see that, other things equal, girls score on average 10 points less than boys in math test. But as soon as we control for the entry level (column B), the gap shrinks and becomes insignificant. This means that the gap we observe at the 8th grade has been actually generated during the primary school years and the lower secondary school does not make it worse. When we look at performances in science we face a very different picture: 60% of the gap observed at the grade 8 has been actually generated within the 4 years going from the 4th to the 8th grade (column D). Why would the gap grow later in science than in math? One reason could be related to fact that science becomes one of the major subjects only at the lower secondary school. During the first years of schooling much more weight is given to the attainment of the basic literacy in Italian language and math. So had the gap been already in place at the 4th grade, we would not be able to observe it properly as long as primary school students are asked to perform very easy tasks in science.

[14] We also performed an estimation on the full sample by replacing the missing observations on parents' education with a common value. It delivered very similar results (available from authors upon request).

[15] See INVALSI (2010) for national test scores in math of Italian pupils at grades 2, 5, 6 and 8. For a cross-country comparison of test scores see IEA (2008a, 2008b) for students in grade 4 and 8, and OECD-PISA (2004, 2007) for test scores in math and science of 15 years old students. Niederle and Vesterlund (2010) argue that gender gap is exacerbated by the poor response of women to competitive test-taking environments.

We do not have enough information to investigate the determinants of the observed gender gap, and it is beyond the scope of this paper to contribute to the heated "nature vs nurture" debate on this topic[16]. We just report that, in accordance with Fryer and Levitt (2010) that document the emergence of a gender gap in math in the early years of schooling, we found no meaningful variation of the gender gap across socio-cultural strata in the sample[17]. However, as Guiso et al. (2008) show, several other factors might be at work within the family and in the society at large, undermining girls in math and science[18].

4.2 Achievements of immigrant vs native students

A comparison of results obtained for grade 4 (Table 1, column 1 and 3) with those reported in Table 4 (columns A and C) for grade 8 reveals that foreign-origin students' gap is being narrowed over the lower secondary schooling years, with the notable exception of first generation immigrant students. In fact, for all groups but the latter, the negative sign persists over time but the coefficients become insignificant. The process of catching up becomes evident when we control for the entry level (Table 4, column B and D): students in all groups show a spectacular recovery as compared to natives, although we find a limited catching up for first generation immigrant students in both subject (not significant in math). This is not surprising as the improvement is a function of the degree of similarity with respect to native students. As they arrive in a new country, first generation immigrant students need to learn a new language and to adapt to the host country schooling system. The higher is their age at arrival the larger is the initial negative shock. So their recovery cannot be as quick as that of their native peers with parents born abroad[19]. It is worth to be noticed that the quicker catching up observed in science seems to suggest that the improvement of language skills is central in the recovery. In fact, over the first cycle of schooling, science teaching is much more theory-based than hands-on, and language skills play a crucial role in the achievement of good results. The relative smaller improvement of first generation students can be also ascribed to the higher probability of being held back at their arrival in the country and their higher exposure to grade repetitions. A growing number of contributions show that grade repetition does not favor the catching up of weaker students in the short-run (Jacob and Lefgren 2009, Manacorda 2010, OECD 2011) and it also has negative long-run implications for education attainment and labor market performance (Checchi 2010)[20].

It is worth to be stressed that, by taking into accounting the dynamics of the learning process, our results shed new light on the relative position of foreign-origin students as compared to natives. An analogous conceptual framework has been recently developed by Meunier et al. (2011) that investigate in a pure longitudinal dataset

[16] Recent contributions on the issue include, among the others, Pope and Sydnor (2010) that deals with geographic variation of gender gap over U.S. regions, and Ellison and Swanson (2010) that discuss the disparity in backgrounds of males and females at high achievements levels in math.

[17] Such results are obtained in a separate estimation where we introduce an interaction term grouping male and female students on the basis of their family background. Estimates' output is available from authors upon request.

[18] On a study conducted over 34 countries, Nosek et al. (2009) show that stereotypes associating science with males more than with females predict nation-level sex differences in 8th-grade science and mathematics achievement.

[19] See Schnepf (2007) and Schneeweis (2011) for recent cross-country studies showing how the educational disadvantage with respect to natives, as measured by test scores, varies between first and second generations of immigrants. Chiswick and DebBurman (2004) had previously shown that similar patterns emerged in the overall educational attainment in the population.

[20] In our sample of 8th-graders, for each grade repeated, a delayer scores more than 30 points less with respect to a regular student in math and about 24 points in science.

the impact of migrant status on cognitive progression between age 5 and age 10 for UK second generation students. The effectiveness of our pseudo-panel approach is confirmed by the similarity of our results with respect to theirs.

Table 4: Weighted OLS estimates of test scores' determinants at grade 8

	Math		Science	
VARIABLES	(A)	(B)	(C)	(D)
Estimated test score at grade 4		0.967***		1.445***
		[0.138]		[0.138]
Female	-10.37***	-1.900	-12.48***	-7.507***
	[2.240]	[2.539]	[1.969]	[1.998]
Origin(Ref. Native with Italian parents)				
Born to mixed parents	-2.362	14.08***	-0.0916	20.38***
	[4.227]	[4.540]	[4.447]	[4.542]
Native with non-Italian parents	-15.67	26.45*	-10.46	57.32***
	[13.42]	[13.81]	[11.03]	[12.00]
Non-native with non-Italian parents	-28.78***	14.51	-43.47***	25.64***
	[7.432]	[9.785]	[7.473]	[9.216]
Parents' education(Ref.Up to lower sec. ed.)				
Secondary education	27.33***	24.58***	24.04***	18.99***
	[2.670]	[2.633]	[2.603]	[2.605]
Post-secondary ed., college ed. or above	30.80***	27.19***	31.87***	23.72***
	[3.229]	[3.287]	[3.192]	[3.293]
Daily time spent doing homework (Ref. No time)				
Less than 1 hour	25.35***	25.35***	28.38***	28.22***
	[5.896]	[5.953]	[5.759]	[5.744]
1-2 hours	32.42***	31.89***	35.64***	34.79***
	[5.636]	[5.737]	[5.325]	[5.340]
More than 2 but less than 4 hours	38.31***	37.03***	38.88***	36.59***
	[5.778]	[5.915]	[5.359]	[5.366]
4 or more hours	33.46***	31.52***	43.16***	39.88***
	[6.326]	[6.475]	[5.793]	[5.846]
Perception of being "safe at school"(Ref. Low)				
Medium	10.82**	11.02**	5.781	6.541
	[5.374]	[5.350]	[5.387]	[5.222]
High	18.27***	18.60***	10.06*	10.84**
	[5.353]	[5.330]	[5.392]	[5.224]
Class-average test score	0.868***	0.853***	0.870***	0.839***
	[0.0230]	[0.0253]	[0.0255]	[0.0294]
Constant	22.51*	-496.9***	26.33*	-744.1***
	[12.98]	[73.21]	[13.79]	[73.50]
Area of residence fixed effects	Yes	Yes	Yes	Yes
School fixed effects	Yes	Yes	Yes	Yes
Observations	3,924	3,924	3,924	3,924
R-squared	0.425	0.433	0.454	0.472

Note: See Table 2.

4.3 Family background and achievement in compulsory education

Italian lower secondary education does not seem to be able to ensure equal learning opportunities to all students regardless of their family background. In particular, students with a disadvantaged background (i.e., parents with at most lower secondary education completed) score over 20 points less than those with better educated parents (see Table 4, columns A and B) both in math and science. Therefore, other things equal, one out of four students in our sample lags behind her/his peers just because of her/his socio-cultural background. Once we contrast results in columns A and C with those reported in columns B and D that include the entry level, our estimates reveal that up to 90% of the learning divide across socio-economic groups in Math is generated at the lower-secondary school (79% in Science).

This represents a major failure for the Italian education system. In fact, the present model of lower secondary education was introduced in 1962 precisely to fight the huge social disparities in terms of education opportunities and to improve social mobility. About half a century later we find that extending the common path from five to eight years by postponing the first formal tracking from age 10 to age 14 was not enough to tackle that issue. Lower secondary education does not succeed where the primary school does.

A combination of structural factors and endogenous families strategies can be put forward to find the rationale behind such an explosion of social disparities between grade 4 and 8. As regards structural factors, the international literature shows that equality and effectiveness are not independent from the design of the education system. In systems where the first cycle of education is split up in a primary school and a lower secondary school, students are required to cope with a demanding transition in a early stage of life and, as a result, the weakest among them might fall or start lagging behind their peers (Alspaugh 1998, Bedard and Do 2005, Crockett et al. 1989, Rockoff and Lockwood 2010). A second structural factor, specific to the Italian schooling system, is the drop of full-time attendance after the transition to lower secondary school. Mocetti (2011) demonstrates that full-time attendance reduces family background influence on students' attainment in the short-run and is 'protective' with respect to the prospective drop out of weakest students at a later stage. Of course, families can respond to the implications of such institutional factors and endogenously adopt strategies able to offset the possible negative impact of transition. For example, parents with a high educational attainment (and income) can increase their effort to support their kids with the homework and/or they can pay for after-school tutoring. Furthermore, Ferrer-Esteban (2011) finds that in Italian lower secondary education there is a significant within-school social segregation at the class level, implying that, under certain circumstances, families can systematically interfere with class-formation policy. When this is the case, peer effects can push further up the achievement of students with highly educated parents (self-selected in specific classes) and depress further the achievement of socially disantvantaged students.

4.4 Effort at home, safeness at school and class-level factors

As expected, the individual effort of students (time spent doing homework) and their perception about being safe at school correlate positively with test scores. The introduction of predicted past scores (level of entry) does not affect the coefficients on these variables: our presumption of them being related to grade-specific characteristics and not showing an autoregressive process seems to be correct. So we conclude that there are no endogeneity issues emerging from the correlation of the indicators in the X_i^{8th} vector with the measurement error component of $u_{i,c,s}^{8th}$ in equation (9).

Interestingly, test scores increase as the effort increases, but for math we observe a concavity. Gains from homework tend to decrease beyond a certain amount of time devoted to study (4 hours), implying that, as far as competence in math is concerned, individual talent and effort are not "perfect substitutes". A safer learning environment is clearly associated with better achievement of students, especially in math. This result replicates what has been shown by several contributions in the literature where the negative short- and long-run effects of bullyism and victimization on school attainment/achievement and earnings in adulthood have been clearly documented[21].

Finally, we find class-level factors to be in operation: a 1 point increase in class-average score is associated with an almost equivalent (0.8 points) increase in individual performance both in math and science.

5 Conclusion

We have focused on learning divides across social-groups in the first cycle of the Italian education system (primary and lower secondary school) to show that intergenerational educational persistence and social immobility originates in the early stages of the schooling process. Students with a disadvantaged familiar background face significant learning gaps in math and science at grade 8 already, and this translates into a social tracking along the upper secondary's tracks (academic, technical, vocational). We provide evidence that lower secondary education has to be charged for the major responsibility of such an inequality of opportunities while primary school is able to limit the influence of family background on achievement. On the other hand, Italian middle schools do not deteriorate further girls' gap in math and allow for a noteworthy recovery of students' of foreign origin.

In order to disentangle the specific pros and cons of the primary and lower secondary education we define a linear dynamic model of cognitive achievement that is taken to the data by means of a pseudo-panel technique. In fact, we are able to link achievements in math and science of the same cohort of Italian students at grades 4 and 8 as sampled in two following waves of TIMSS (2003, 2007).

To our knowledge, this is the first attempt to exploit dynamically the information on students' achievement collected for the same cohort of students over two repeated cross-sections. Results suggest that, under certain circumstances, this approach can be a suitable substitute for system-level dynamic analysis when longitudinal data are unavailable.

[21] See Brown and Taylor (2008) for a study on a panel of British students. Juvonen et al (2011) focus on middle school grades and find a clear association between bullying experiences and compromised academic performance, which could be explained by the multi-dimensional negative implications of being bullied (or being considered a victime) in a crucial stage of life such ad early adolescence.

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APPENDIX A

Table A1: Probit model of socio-demographic determinants of grade repetition
8th-graders students (marginal effects)

	Repetition (1/0)
VARIABLES	
Female	-0.036***
	[0.0067]
Origin (Ref. Native with Italian parents)	
Born to mixed parents	0.022
	[0.0173]
Native with non-Italian parents	0.013
	[0.0349]
Non-native with non-Italian parents	0.541***
	[0.0565]
Parents' education (Ref.Up to lower sec. ed.)	
Upper Secondary Education	-0.039***
	[0.0068]
Post-secondary ed., College ed. or above	-0.046***
	[0.0061]
Area of residence fixed effects	Yes
School fixed effects	No
Observations	3,924
Pseudo R-squared	0.15

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets.

Table A2: Weighted OLS estimation of time-invariant observables' impact on math test scores at Grade 5

	Math - INVALSI test
VARIABLES	
Female	-0.027***
	(0.0021)
Origin (Ref. Native with Italian parents)	
Native with non-Italian parents	-0.070***
	(0.0055)
Non-native with non-Italian parents	-0.088
	(0.0045)
Parents education (Ref.Up to lower secondary ed.)	
Upper secondary education	0.056***
	(0.0023)
Post-secondary ed., college ed. or above	0.116***
	(0.033)
Constant	0.524***
	(0.0030)
Area of residence fixed effects	Yes
Observations	38999
R-squared	0.11

Note: Robust standard errors in brackets. Estimation is done using sample weights provided by INVALSI. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Number of books at home by parents' attainment in education