Social and Migration-related Inequality in Achievement in Primary and Secondary Education

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Social and Migration-related Inequality in Achievement in Primary and Secondary Education

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6.1 Introduction

This chapter will analyse the evolution of achievement gaps in Italy, as students move from primary to secondary schooling. Our chapter will thereby primarily address research question one, particularly the aspect of how social and migration-related gaps in educational achievement develop over time. Tackling these questions, we make use of population-level data from Italy capturing achievement of all students in Italian primary and secondary schools in a specific year by INVALSI – the Italian National Institute for the Evaluation of the School System. Combining such population-level data with a pseudo-panel design capturing end of primary schooling, lower and upper secondary schooling, our study can reveal with high precision how social and migration-related inequality in achievement evolves in the school career of students. Our study, however, was limited as to the second research question, since at the time of writing this chapter, population data could not be linked across years on the individual level.

Our chapter is structured as follows. First, by providing an overview of the education system in Italy, we locate our case in the overall framework of the report. Second, we describe the population data and discuss our analytical approach implementing a pseudo-panel design. Moreover, we discuss the construction of our central dependent and independent variables. Afterwards, we present our findings on social and migration-related achievement gaps. Our analysis will also inspect the intersection of gender and migration status in patterns of inequality of educational achievement. Finally, we draw a conclusion.

6.2 The education system in Italy

In Italy, children can go to pre-primary school (“Kindergarten”) which lasts for three years between the age of 3 and the age of 5. Although attendance is optional, a vast majority of children participate in it. For instance, in 2016 around 95% of Italian children (aged between 3 and 5) attended pre-primary school compared to an average attendance rate of 88% at EU–22 level (OECD 2018, Education at a Glance Figure B2.1a and 1b). Children enter school by September in the year a child turns to six. The first cycle, primary schooling, consists of 5 school years across

[1] The scientific output expressed does not imply a policy position of the European Commission. Neither the European Commission nor any person acting on behalf of the Commission is responsible for the use which might be made of this publication. The preparatory research work for this chapter was undertaken at the University of Milan-Bicocca while estimation of the empirical models and the final drafting of the text have been conducted when Stefano Verzillo took service at the European Commission, Joint Research Centre, Competence Centre on Microeconomic Evaluation (CC-ME).

the typical age range of 6 to 10. Primary schooling is followed by three years of lower secondary schooling from age 11 to 14. After that, students enter the upper secondary cycle lasts for the following five years between the age of 14 and 18, but students can leave school by the age of 16 (compulsory school age).

In general, Italy adopts a mixed tracking model in secondary schooling (Blossfeld et al. 2016). While primary and lower secondary in Italy is rather comprehensive, upper secondary education is formally differentiated by tracks (Contini & Triventi 2016). When entering upper secondary schooling students can decide to attend one of three separate tracks that provide quite distinct educational curricula and are embodied in different school types. The most prestigious and demanding track is the academic track (*Lyceum*). It aims at preparing students for educational maturity to enrol later at higher tertiary education. Hence, *Lycei* as the main route to university focus on teaching broader and rather generalist educational contents closely related to academic competencies. Within the academic track there is some differentiation across the Lyceum schools regarding specialisation (e.g., specialised in science or languages). Alternatively, students can enrol to a technical track (*instituti tecnici*) or vocational track (*instituti professionali*). Both of those tracks provide more practical education linked to non-academic, technical professions. However, the technical track prepares for upper-level jobs and the vocational track for lower level technical jobs. In contrast to other tracking systems like in Germany or the Netherlands, students are not formally allocated to tracks based on their prior educational achievement but instead are free to choose even though lower secondary teachers may issue track recommendations (Contini & Triventi 2016).

Having concluded a five-year upper secondary diploma, an Italian student may choose to attend a higher education bachelor's degree of 3 years followed by two years of master courses. On top, PhD programs represent the highest qualification achievable (with usually a length of 3 years).

Till today, the Italian educational system is characterised by comparably low educational attainment. Recent data from the OECD (2018) shows that in 2017, 39.1% of Italians aged 25–65 did not attain upper secondary education compared to the OECD average of 20.7%. Even though Italians meet with 42.2% upper secondary level attainment the OECD average versus (42.8%), they lag dramatically behind in attaining tertiary education (18.7% compared to OECD average of 36.9%). To be sure, educational attainment has risen across recent birth cohorts, but the pace of catching up is slow, especially for tertiary education. Therefore, Italy may reach the average of OECD countries only on the long-run.

Against this backdrop, it is important to realise that the Italian educational system is genuinely a public system. Only 5% of students attend private schools.[2] Among the OECD countries, Italy is still one of those countries with lower public (private) expenditure in the educational system in terms of GDP. Primary to post-secondary public (private) spending measured as percentage of GDP in fact was 2.78% (.16%) in 2016 while .54% (.33%) was spent on tertiary education. While expenditure for primary and secondary is close to the OECD average

[2] When parental education and SES are accounted for, the private sector reveals to be on average of lower-quality according to students' performances measured via standardised test scores. Possibly, this is mainly due to the presence of a relative majority of remedial schools within the private sector. In fact, recent research found that private schooling in Italy features a certain degree of heterogeneity (Checchi & Verzillo 2018). Concerning PISA results student achievement's levels of confessional private schools seems to be statistically indistinguishable from public ones while the ones of students attending remedial private schools are statistically worse than those of students attending public schools (Checchi & Verzillo 2018).

tertiary expenditure is dramatically lower.

In addition to this, several studies have pointed out how Italy is one of the countries with low intergenerational mobility – with "*less intergenerational upward mobility between occupations and between education levels*" (Checchi et al. 1999). As a result, students' educational and employment careers are shaped by their parents' education to a considerable extent (Checchi 2003; Bratti, Checchi & Filippin 2007). For instance, compared to other educational systems with tracking such as Germany, social inequality (by parental education) in track allocation is remarkably substantial in Italy which has been explained by a less efficient sorting based on abilities in the Italian case (Checchi & Flabbi 2006). Finally, a relevant divide in educational attainment between students from the south and north is still a relevant issue in the Italian system (Bratti et al. 2007).[3]

6.3 Data and methods

Our chapter will analyse achievement gaps in Italy using population data collected by the Italian National Institute for the Evaluation of the School System (INVALSI)[4]. On an annual basis, INVALSI carries out standardised tests to assess students' proficiency levels at various grades. For our purposes, we exploited test data on literacy and math. Currently, the INVALSI database covers the years 2009 to 2016 with measurements taken in each year in four grade levels: Grade 2 (7-year-olds), Grade 5 (10-year-olds), Grade 8 (13-year-olds) and Grade 10 (15-year-olds). Unfortunately, at the present stage, it is still not possible[5] to link individual student data over time since student identifiers change at each measurement occasion. That circumstance precludes at this time a credible longitudinal data analysis based on the individual level. Instead, we treat the data as repeated cross-sectional data at different ages.

However, in the context of this report, a significant advantage of INVALSI data is the fact that achievement tests had been collected for the *whole population* of students in each grade since test participation is mandatory in Italy. Compared to other survey datasets used in this report (such as the NEPS analysed in Chapter 2 or the MCS data in Chapter 5), population data are not plagued by issues of sample selection or attrition. Hence, INVALSI data allows us to achieve a maximum of accuracy in studying the distribution of students' achievement at each grade in a particular year and social and migration-related gaps therein for the whole population of Italian students being in that grade in that year.

6.3.1 Pseudo-panel design

Despite the cross-sectional nature of the data we aimed at mimicking as much as possible a true longitudinal design similar to the other country analyses in this report. We did so by focussing on a specific cohort at grade j in a given year t and then shifting the observed window by k years. By that, we constructed a 'quasi-follow-up' of students belonging to the same cohort at time $t+k$ in grade $j+1$. Essentially, this strategy follows the same logic as the accelerated

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[3] Bratti and colleagues (2007) provide evidence of how the North-South divide in PISA scores seems to be mainly due to differences in the endowments of students, the efficiency of schools and the socio-economic environment.

[4] Source: INVALSI – estimate of the authors on INVALSI data – INVALSI Statistical Office

[5] A pilot program to build an individual panel dataset following students over different grades has been recently started at the INVALSI Institute; however, it is not yet completed at the moment of writing.

longitudinal design applied in Chapter 2 and 3 for the German and the Dutch case respectively, however with just one time point for a set of students. A natural limitation of our approach is that there is no way of accounting for school dropout or transfers which should be kept in mind when interpreting our results.

Table 1 illustrates our pseudo-panel approach for following up a cohort of five-graders in the school year 2010–2011. The first data point consists of the students being in Grade 5 in 2010–11. This cohort is measured again in Grade 8 using the cross-section from 2013–2014. Finally, the cohort is measured again in Grade 10 by the cross-section in 2015–2016. Hence, our design allows observing the development of achievement gaps as a cohort of more than 500,000 students who have been born in 2000 (the regular students) progress through primary and secondary schooling. Our study design is in line with an earlier ISOTIS report on achievement gaps utilising cross-national assessment data for a pseudo-panel approach (Rözer & Van De Werfhorst 2017) and similar previous research (Dämmrich & Triventi 2018).

We start with 526,462 students at Grade 5. Three years later at Grade 8 the sample size for the cohort slightly reduces to 520,917 students (–1.05%) while subsequently a significant reduction of around 26% is recorded at the second year of the upper secondary school (Grade 10). The substantial sample reduction at Grade 10 can be explained by student dropout which is likely to be selective by educational achievement and should be considered when interpreting the findings.

Table 1 Pseudo-panel design using available INVALSI data.

	Grade, Age and Stage		
	Grade 5 Age 10 *Primary (V)*	Grade 8 Age 13 *Lower secondary (III)*	Grade 10 Age 15 Upper secondary (II)
School year			
2010–2011	**X** N=526,462	–	–
2011–2012	–	–	–
2012–2013	–	–	–
2013–2014	–	**X** N=520,917	–
2014–2015	–	–	–
2015–2016	–	–	**X** N=383,255

Notes: **X** demarks cross-sectional data used for the analysis.

6.3.2 Main variables

6.3.2.1 Outcomes

Our outcome variables are student test scores measuring educational achievement in Literacy and Math. Even if good psychometric measures (IRT–Rasch scores) are directly provided by the INVALSI institute to ease the interpretation, in order to ensure comparability to the other countries (which adopt and collect data differently one from each other) we implement a two-step strategy to standardise original test scores. First, we derived the normalised ranked position of children (normalised ranks range from 0 to 100) in the achievement distribution separately for each wave. Second, we z-standardized the normalised ranks (z-scores). That is a suitable transformation of the original data since an individual z-score reflects the relative position of a student in the overall distribution but in a continuous metric, also providing correct standard errors, confidence intervals and ensuring the validity of inference of the obtained results. Notice that when outcome variables Y are normally distributed (as strongly supported by data in our case for both outcomes in each wave) this two steps strategy coincides *de facto* with the classic standardization process ($z_Y =(Y–\mu_Y)/\sigma_Y)$) of an outcome variable Y, since ranks are empirical quantiles of a normal cumulative distribution function (for details see theory on fitting distribution with qq-plots, see Shapiro and Wilk 1965).

6.3.2.2 Covariates

In addition to students' educational achievement, INVALSI collected background information from student and parent questionnaires. The main covariates we use is the highest *parental education* as a measure for socio-economic status of the student's family origin and *migration background*.

For *parental education*, we applied the dominance criteria by taking the highest educational level among a student's parents at the moment of the survey participants. We classified parental education into low (12 years of education or less), medium (13 to 15 years of education), and high (more than 15 years of education). Unfortunately, different to other educational surveys (such as PISA[6]), the INVALSI survey does not provide other relevant information related to the socio-economic dimension such as parental income, home ownership, familial educational resources or similar indicators.

For capturing *migration background* of Italian students, we used a threefold classification: Native (no migration background); first-generation migrant (child born abroad); and second-generation migrant (child born in Italy, but at least one parent born abroad). Unfortunately, the scientific use file of the INVALSI data does not allow distinguishing between specific groups of migrant children regarding ethnicity or country of origin.

6.3.3 Data description

Table 2 presents descriptive statistics on the distribution of covariates and outcome variables. Parental education is missing for around 17% and 20% of students of Grade 5 and 8 respectively while only 10% for students in Grade 10. The distribution of parental education is reasonably constant between Grade 5 and 8 (14% high, 35% medium and 30% low) while it changes

6 The OECD Programme of International Student Assessment (PISA) provides a composite index of economic, social and cultural status based on parents' education, family wealth, cultural possession at home, ICT resources, home possession and home educational resources. See Vol II of the PISA Results for more details.

considerably at Grade 10 with a lower proportion of students from disadvantaged families (from 30% to 22%) and larger fractions of students from medium (from 35% to 42%) and high (14% to 24%) parental education status. The reduction of students from disadvantaged socio-economic backgrounds in Grade 10 in favour of medium and high SES when compared with earlier grades clearly indicates the existence of significant differences in drop-out probabilities by SES in Italy (O'Higgins et al. 2007, Checchi 2010).

Students' migration background shows a stable distribution of natives and first- and second-generation migrant students among the different grades. A vast majority of natives (around 87%) cohabits in the school system with around 5% of both first- and second-generation students in the primary school as well as in lower and upper secondary levels. Significantly different between the primary and secondary school grades is the percentage of student non-reporting information on their ethnicity. The 5% of missing data in Grade 5 to 1% reduces to .8% in Grade 8 and 2.4% in Grade 10.

Finally, Table 2 reports simple descriptive statistics regarding the standardised achievement scores in Literacy and Math. As expected, z-score measures for math and literacy were highly correlated with the corresponding original test scores (corr > .97 for Math, corr > .96 for Literacy in all the considered grades).

Table 2 Distribution of parental education, migration background and z-scores by grade.

	Grade 5	Grade 8	Grade 10
Parental education (column %)			
Missing	17.6	20.6	10.2
Low	31.5	30.0	22.8
Medium	36.2	35.0	42.2
High	14.7	14.4	24.8
Total	100.0	100.0	100.0
Migration background (column %)			
Missing	5.2	0.8	2.4
Native	86.0	89.3	87.6
1st generation migrant	4.4	5.2	4.8
2nd generation migrant	4.4	4.7	5.3
Total	100.0	100.0	100.0
Total number of students	526,462	520,917	383,255
Educational achievement (z-scores)			
Literacy			
Mean	0	0	0
Standard deviation	1	1	1
Min / Max	–3.18 / 2.77	–4.21 / 3.89	–2.67 / 3.34
Valid cases	515,104	520,917	371,882
Math			
Mean	0	0	0
Standard deviation	1	1	1
Min / Max	–3.27 / 3.18	–4.72 / 4.32	–2.57 / 3.57
Valid cases	508,615	520,917	383,255

6.4 Results

6.4.1 Achievement gaps by parental education

We start by inspecting overall patterns of inequality in math and literacy achievement by parental education. Least-square means for groups were calculated after accounting for age. Figure 1 shows how average z-score levels develop across Grade levels for children from different social backgrounds concerning parental education. Additionally, Figure 2 plots for each outcome variable and each grade the gaps in math and literacy achievement using high parental education as the reference category. All point estimates for these and following results are available in the Appendix of this report (Appendix Section 6).

Results for both domains, math and literacy, indicate strong associations of achievement and socio-economic background of children. Figure 2 suggests that social inequality in achievement, particularly in terms of the gaps between children from low and high educated parents, are most pronounced for the literacy domain. Moreover, those SES gaps in achievement appear to be quite stable over subsequent grades. All gaps between students from low, medium and high educated parents are statistically significant. Although our observation could not capture earlier developments in gaps, it is likely that those gaps resemble gaps in cognitive achievement that arise very early in children's educational careers (Fernald et al. 2013; Lee & Burkam 2002; Magnuson et al. 2004).

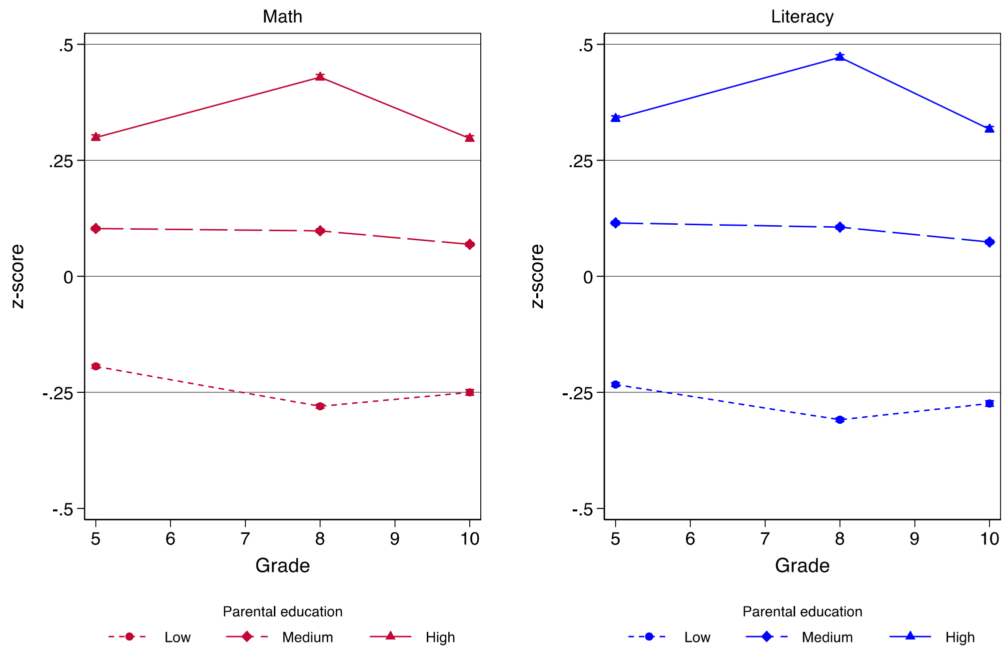

Figure 1 Average educational performance in math and literacy by parental education (adjusted for age).

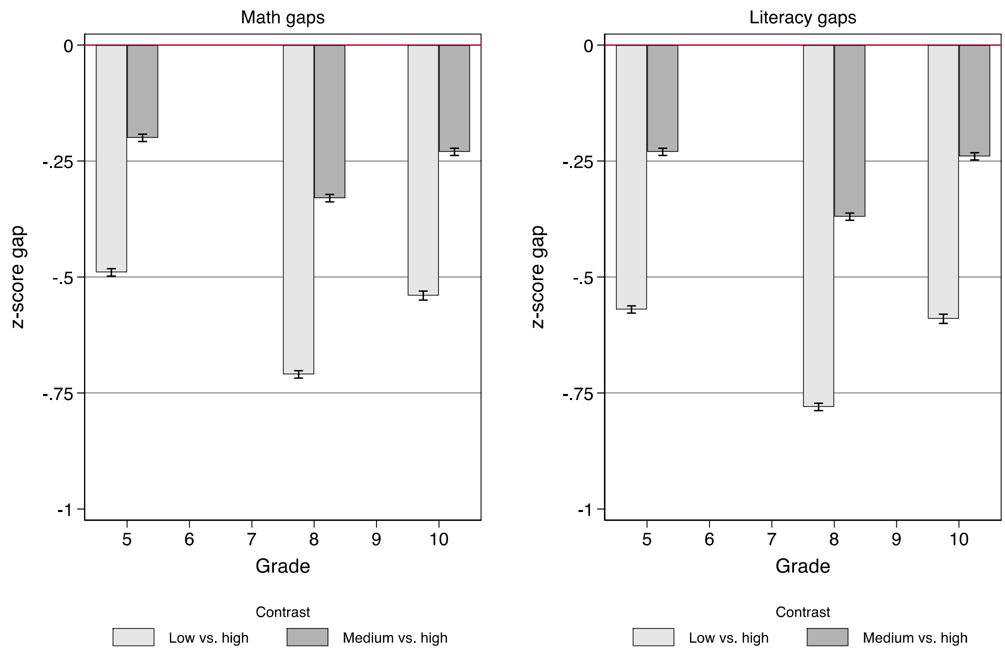

Figure 2 Achievement gaps by parental education (adjusted for age, ‘high’ as reference).

6.4.2 Achievement gaps by migration status

Next, we assessed achievement gaps by migration status of students. Figure 3 and Figure 4 illustrate results on migrant-native gaps and their trajectory over grades (like for parental education all analyses adjusted for age). Compared to native students, a substantial disadvantage is visible for students with migration background across all grades although gaps slightly reduce for the Grade 10 population. Furthermore, migrant-native gaps are larger for literacy than for math; for example, while the math gap in Grade 8 is about a third of a SD (–.33) to the disadvantage of migrant students, the literacy gap amounts to almost a half of a SD (–.49).

In additional models that modelled a linear trend in z-scores, we found for Math a statistically significant increasing trend over time for immigrants (linear trend coefficient $\beta_t = .052$; $p < .001$) while no significant trend rises for natives. Moreover, despite the fact that Italian data are non-longitudinal in their own nature, we try to assess if and how these three achievement gaps change over time – adopting an empirical strategy *à la difference in difference* – by considering grade/wave as a continuous variable and including in the econometric model the interaction term between wave and migrant status (*wave*$\times$*migrant*), whose coefficient (beta) is the one of primary interest. In this model, we found a statistically significant reduction of the skill gap between the two groups over time (p-value=.0012). As regards literacy we found no statistically significant reduction of the gap between the two groups over time (p-value=.221) and only a non-significant increase of z- scores over grades for migrants.

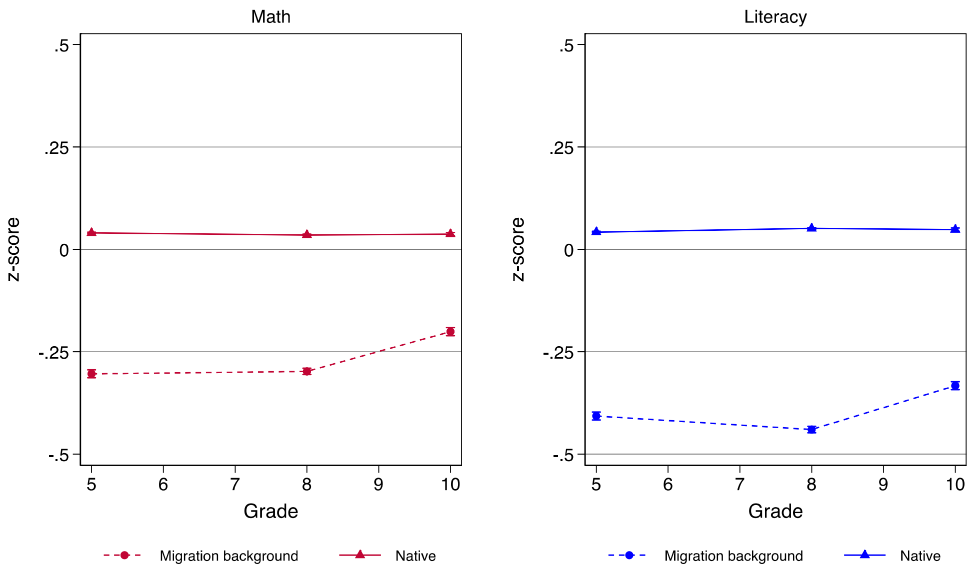

Figure 3 Average performance by migration status (adjusted for age).

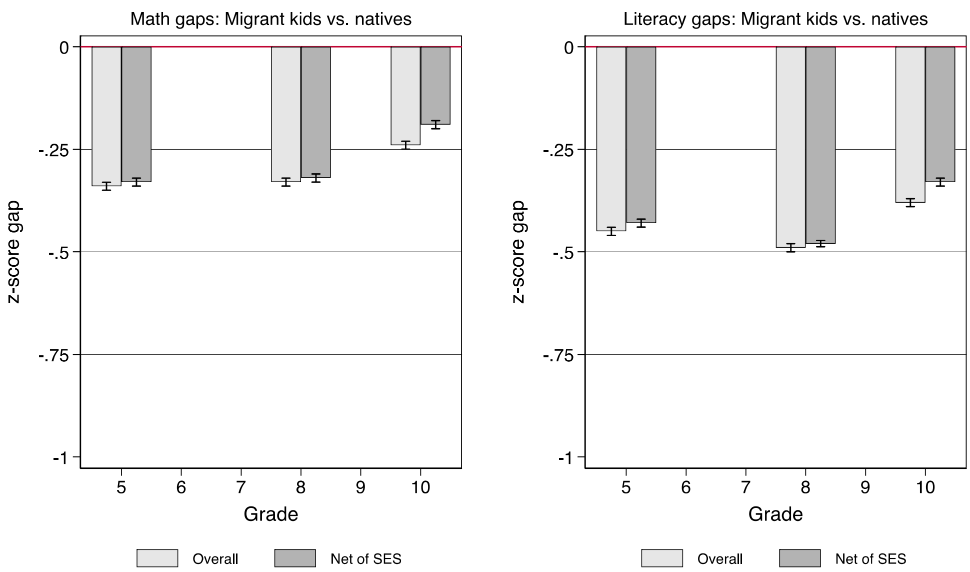

Figure 4 Migrant versus native gaps in achievement overall and after controlling for parental education (adjusted for age, 'native' as reference).

Moreover, we how much of the migrant-native gaps remain after accounting for the effects of parental education. Figure 4 shows that gaps only slightly reduce after additionally accounting for parental education (see 'Net of SES' bars). We observe a significant reduction of the achievement gap between migrants and natives especially from Grade 5 to Grade 10 (a reduction of .14 SD for math and .10 SD for literacy), even though this is due essentially to the decreasing achievement trajectories for the native students only over the considered grades. To this end, we compare the first-to-last grade differences for the two grade populations: the migrant-native gap from Grade 5 to 10 shows a statistically significant reduction of .14 SD in math ($p < .0001$). At the same time, for literacy, we find a less pronounced but also statistically significant reduction of the achievement gap by .1 SD ($p < .0001$). Finally, we found a statistically significant trend of increasing Math scores (conditional on parental education) for immigrants with respect to natives (coeff. = .02 and $p < .001$). For literacy, however, the trend for migrant children was not statistically significant despite the decreasing migrant-native gap.

6.4.3 First- and second-generation migrants

We further distinguished among migrants between first- and second-generation migrants. As Figure 5 indicates the first-generation migrant versus native gap is significantly larger than the second-generation migrant versus native gap for both domains of math and literacy (all analyses adjusted for parental education and age). Furthermore, we see an apparent reduction of the second-generation migrant versus native gap from Grade 5 to 10. The first-generation migrant versus native gaps increase for Grade 8 but shrink again in Grade 10. In Figure 6, we plotted first- and second-generation migrant versus native gaps that are additionally adjusted for parental education which, however, does not change any conclusion.

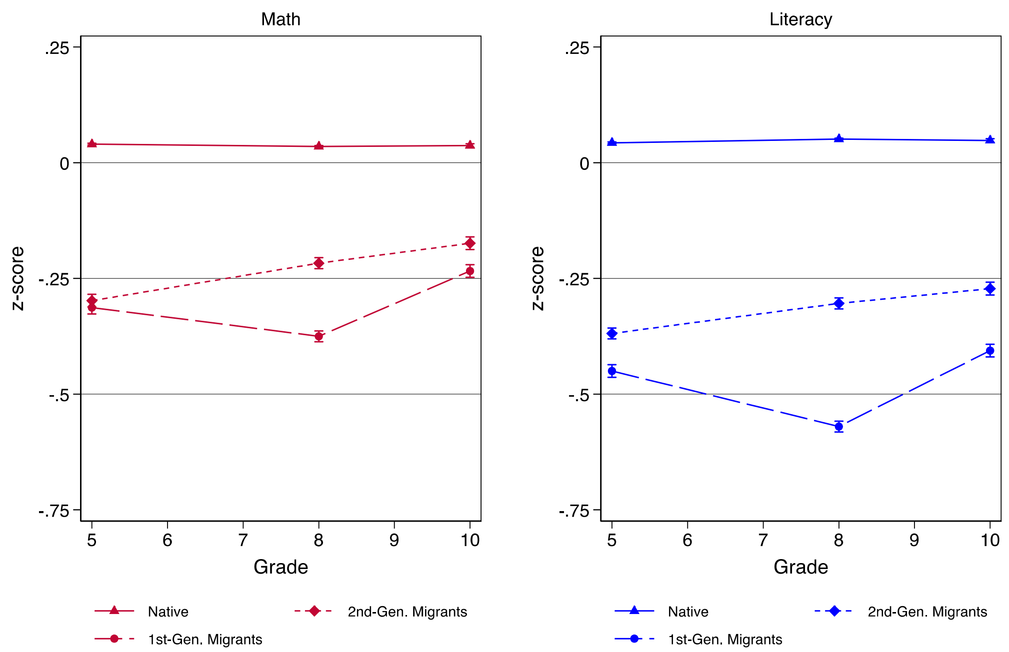

Figure 5 Average performance by migration status differentiated by first- and second-generation migrants (adjusted for age).

6.4.4 Migrant-native by parental education

Do migrant-native gaps vary by levels of parental education? Figure 7 plots average z-scores for migrant and native students by the most extreme groups of parental education (high and low) for both domains under study. This strategy has the advantage to assess more specifically the gaps in each group of interest, instead of using parental education as a control variable in the model as before.

Interestingly, among students from low education backgrounds, we found an impressive reduction of the migrant-native math gap of almost .18 SD ($p < .0001$) between Grade 5 and 10. In stark contrast, the migrant-native gap in math remains stable among children from high education backgrounds. Similarly, for literacy, we found a significant reduction of the migrant-native gap from Grade 5 to 10 (–.12 SD, $p < .0001$) for students from a low educational background, while stable gaps for students from high education backgrounds.

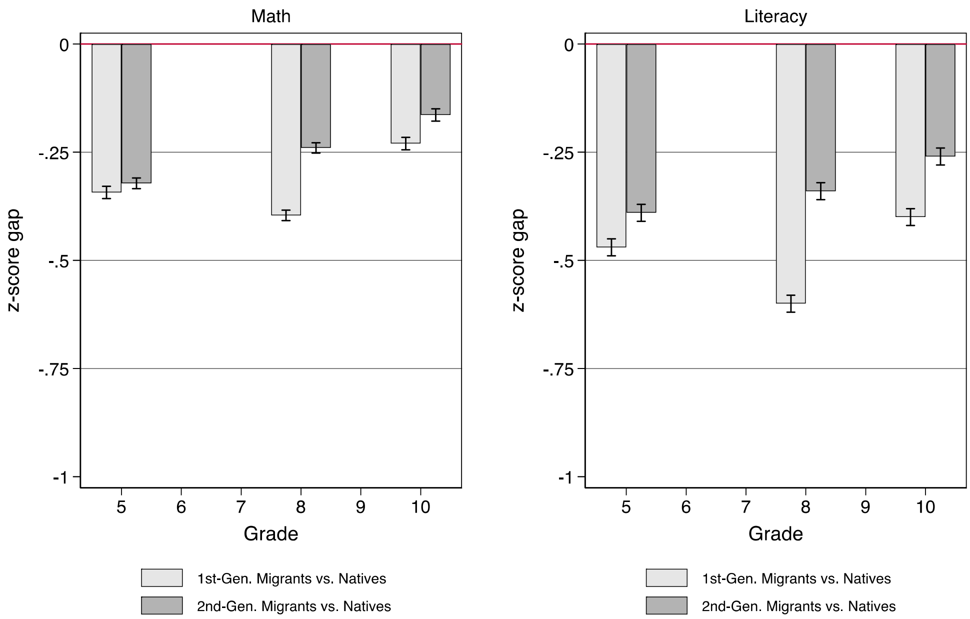

Figure 6 Gaps for first- and second-generation migrants versus native students (adjusted for parental education and age, 'native' as reference).

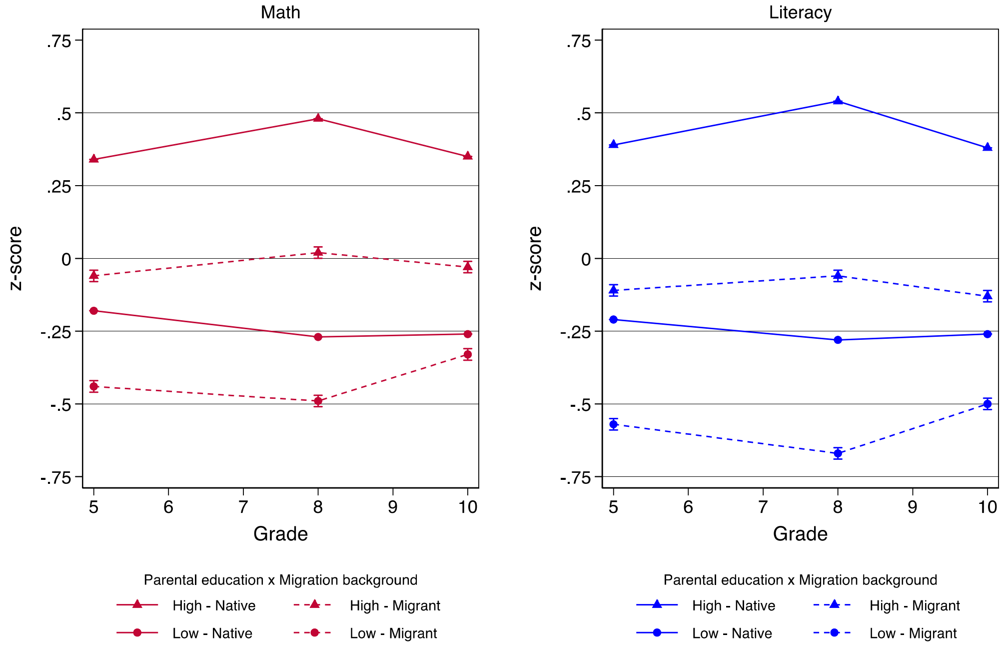

Figure 7 Migrants versus native gaps by parental education (adjusted for age).

6.4.5 Migrant-native gaps by gender

Finally, we inspected the moderating role of gender for migrant-native gaps. Figure 8 shows migrant-native gaps by gender, all adjusted for age and parental education. Overall, we observe a reduction of the migrant-native gap in math over the three grades for both boys and girls (left panel in Figure 7). For boys, the migrant-native gap reduced from Grade 5 to Grade 10 by .12 SD ($p < .0001$). In comparison, for girls, the reduction was more pronounced by .16 SD ($p < .0001$). However, within the populations of native students as well as students with migration background the gender gap in math scores was increasing over grades (to the advantage of boys).

The right panel in Figure 7 shows the same analysis for literacy scores. Although migrant-native gaps were reducing too, the reduction was more pronounced among boys (–.12 SD, $p < .0001$) than for girls (–.07 SD, $p < .0001$). Reversed to math, we see a female advantage for literacy which is growing for both populations of native and migrant students.

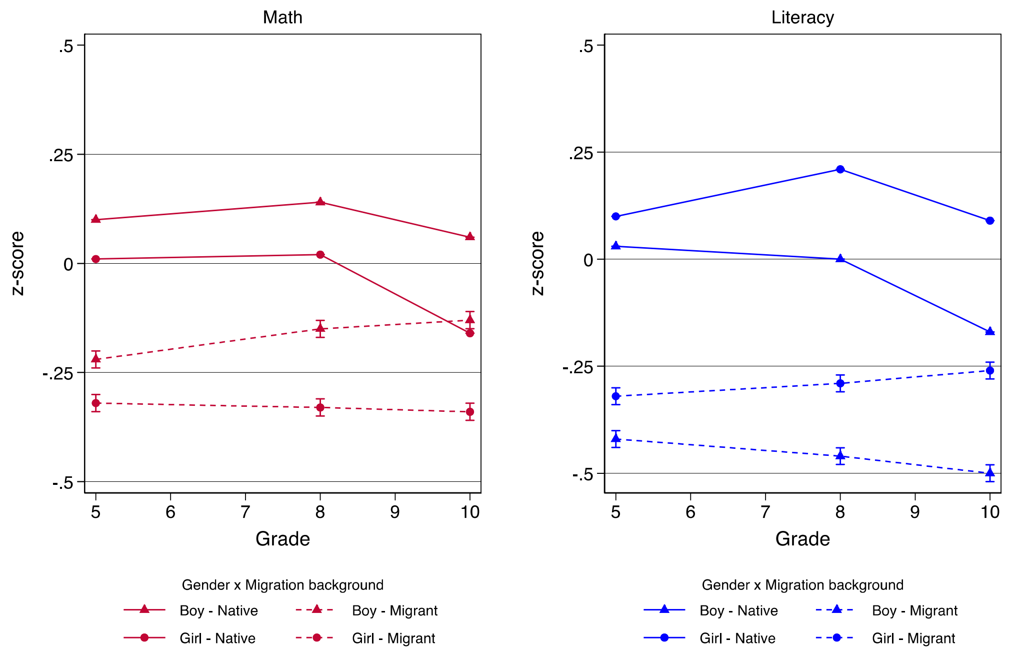

Figure 8 Migrants versus native gaps by gender (adjusted for parental education and age).

6.5 Conclusions

This chapter aimed to study the evolution of social and migration-related achievement gaps in Italian primary and secondary education. Our empirical analyses exploited census data on Italian students' educational achievement in math and literacy, two foundational domains of educational achievement. Using this population data, we constructed a pseudo-panel design that started with a cohort of students who were observed in Grade 5 in 2010–11 (last year of primary schooling) and subsequently followed that cohort up over Grade 8 (third year of lower secondary schooling) and Grade 10 (second year of upper secondary schooling).

Family SES, in our case measured by parental education, plays a substantial role in shaping the educational achievement of students in Italy. In Grade 5, when students were about 10 years old, students from lowly educated parents scored roughly 50% of a SD lower than students from highly educated parents. This gap rose up to roughly 75% of SD in Grade 8 (age about 13) and, albeit a bit smaller, remained substantial in Grade 10 (age about 15).

In contrast to that, we observed migration-related gaps to shrink over time. Moreover, we found that first-generation migrants are most disadvantaged in educational achievement and that educational disadvantage of migrants, in general, is larger for literacy than for math. More refined analyses inspecting the intersection of parental education and migration status revealed that migrant-native gaps in education are smaller for students from lower rather than higher educated parents. Also, we found that convergence of achievement levels among migrant and non-migrant students seem to be driven by the lower SES groups. In contrast, in the higher SES groups, migrant-native gaps remain astoundingly stable.

Finally, gender played a role in achievement. Female students are better in literacy and male students better in math, and the gender gap grows over time for both domains. However, we found an interesting gender interaction with respect to the development of migrants' educational disadvantage. From Grade 5 to Grade 10, male and not female migrant students gained considerable grounds in math while female and not male migrant students gained ground in literacy. Thus, within both genders, migrant-native gaps were shrinking over the observed time window.

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