QUADERNI IEIL
ISTITUTO DI ECONOMIA DELL'IMPRESA E DEL LAVORO

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n. 65 – gennaio 2012

UNIVERSITÀ
CATTOLICA
del Sacro Cuore

QUADERNI DELL'ISTITUTO DI
ECONOMIA DELL'IMPRESA E DEL LAVORO

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* La Redazione ottempera agli obblighi previsti dalla Legge n. 106 del 15.04.2006, Decreto del Presidente della Repubblica del 03.05.2006 n. 252 pubblicato nella G.U. del 18.08.2006 n. 191.

Social interactions between native and non-native students: mechanisms and evidence

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This version: December 31, 2011

Abstract

This paper focuses on mechanisms of 'social interactions' between native and non-native students. We present a theoretical framework based on Lazear (2001) education production function and test the theoretical predictions exploiting an extremely rich and totally new dataset of Italian junior high schools. Our results show that non-native school share has small and negative impacts on Language test scores of natives' peers, while it does not significantly affect Math test scores. The 'disruptive mechanism of native/non-natives peer interactions' is partly rejected by the empirical analysis, which rather support the 'integration model'. In fact, as long as non-native school share is sufficiently low, non-native students presence is not able to generate negative spillovers on natives' outcomes suggesting that an 'integration mechanism' is at work. In particular, for sufficiently low values of non-native school share (below 10%), non-native students do not significantly affect natives' attainment. Interestingly, all the results show that Language skills are the most influenced by peer interactions between natives and non-natives.

JEL Classification: J15, I21, I28

Keywords: peer effects, native and non-native students, social interactions mechanisms

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1. Introduction and motivation

In the last two decades, a lot of Western countries have experienced massive immigration waves. Despite the growing relevance of this phenomenon in Europe, and the well-established desegregation literature in the U.S., studies investigating peer interactions between native and non-native students in European schools are just a few. Although it is widely accepted that non-native students typically face more problems at school and have lower scores in standardized tests, causes, consequences and possible policy implications of such interactions are still unclear (OECD, 2010). Moreover, while there is a vast literature on the effects of immigration on natives' labour market outcomes, economic literature on the effects of non-native students on native peers' attainment levels is quite limited, and the specific question of whether non-native peers affect natives' educational outcomes has received relatively little attention and presents mixed evidence (Brunello and Rocco, 2011; Gould *et al.*, 2009[2]).

The first study mentioning the contribution that the school ethnic composition has on the individual achievement is the 'Coleman Report' (Coleman, 1966)[3]. Starting from Coleman (1966), scholars in the sociology of education have long argued that, apart from students' ability and background, peers influence and class ethnic composition are important determinants of students' achievement (Kramarz *et al.*, 2008). However, there is not clear evidence on possible consequences of social interactions between natives and non-natives in educational settings, and it might happen that such interactions (if they exist) could tend either to increase or decrease the existing attainment gaps. For instance, Jensen and Rasmussen (2011) find a negative effect of school ethnic concentration on cognitive outcomes for Danish native students[4]. Brunello and Rocco (2011) provide cross-country evidence of a negative but small effect of the share of immigrants on natives' educational attainment exploiting PISA data for a sample of 27 countries (mainly from Europe and the Anglo-Saxon world). On

[2] "*[...] the effect of immigration on the local labour market has received considerable attention in the literature, but little is known about the impact of immigration on the school system",* Gould *et al.* (2009).

[3] "*[...] those inputs characteristics of schools that are most alike for Negroes and whites have least effect on their achievement. The magnitudes of differences between schools attended by Negroes and those attended by whites were as follows: least, facilities and curriculum; next, teacher quality; and greatest, educational backgrounds of fellow students. The order of importance of these inputs on the achievement of Negro students is precisely the same: facilities and curriculum least, teacher quality next, and backgrounds of fellow students, most*", Coleman (1966).

[4] Evidence on school composition and immigrant lower test scores for Denmark and Switzerland is also provided by Schindler (2007) and Meunier (2010), respectively.

top of that, even less is known on the possible underlying mechanisms that such peer interactions may follow (De Giorgi and Pellizzari, 2011).

The study of peer interactions between native and non-native students has also important policy implications ranging from the implementation of re-allocation programs (e.g. the 'Boston Moving To Opportunity Program', Angrist and Lang 2004, and many others implemented in the US under a wide variety of desegregation programs), to non-native students allocation rules across classes or schools, or even 'share-cap' rules that fix a maximum level to non-native students concentration in each school. Nevertheless, economic literature has not yet find a clear answer to the basic question of whether non-native students significantly affects natives' attainment and the effectiveness of desegregation programs is still a controversial issue (see, among others, Hanusheck and Rivkin 2009, Fryer 2011).

The Italian context offers a particularly interesting case-study. Contrary to many other European countries, immigration flows to Italy and the consequent presence of immigrant children in the Italian school system have a relatively recent history. Italy experienced only limited immigration before 1970, and until the early Nineties there was a substantial internal migration (from the South to the North) and still relevant external migration. Massive immigration to Italy from North Africa first, and Eastern countries then, only started in the Nineties, but sharply increased over the last decade (Mencarini *et al.*, 2009). The foreign resident population has risen rapidly: in 1999 it only accounted for 1.9% of the total resident population in Italy, in 2008 the share of foreign residents has grown up until 7.3% (Billari and Dalla Zuanna, 2008)[5]. As a consequence, 'non-native students' are nowadays a relevant part of the total school population: in 1996-97, only 0.7% of students in the Italian school system had a non-Italian citizenship, while in 2008-09 the average percentage has grown up to 7.0%, with peaks of more than 8% in primary and junior high schools (Figure 1). In this setting, massive migration waves generate a wide range of occasions of peer interactions between students of different ethnic origins giving rise to a quantitatively large, but relatively unknown, phenomenon.

[5] Data from Billari and Dalla Zuanna (2008) are more realistic than the official Istat statistics as the foreign resident population in Italy includes both documented and estimated undocumented non-Italian citizens. In the school context, it is worthy to consider both documented and undocumented immigrants, given that all immigrant children, independently from their legal or illegal residential status have the right and the duty to go to school (DPR 394/99, art. 45).

The aim of the paper is twofold. On the one hand, we propose a theoretical framework to stylize the possible mechanisms of peer interactions between native and non-native students based on 'disruption' vs. 'integration' models of education production. On the other hand, we test the theoretical predictions identifying the causal link between non-natives' school concentration and native students' educational outcomes[6]. The main research questions we want to answer are the following: is the 'disruption mechanism' sufficient to explain peer effects between native and non-native students? Does non-native school share induce negative peer effects on natives' attainment? Do different levels of non-native school share have different impacts on natives' attainments? We use as outcome measure attainment levels contained in an extremely rich and totally new dataset combining *INVALSI First Cycle Exams* (test scores of all 8th grade students enrolled in Italian junior high schools[7]) with census and administrative records on schools characteristics and socio-economic environment.

In particular, the theoretical models are based on Lazear (2001) model of education production. We assume that non-native and native students are characterized by different levels of propensity to 'disrupt'[8] so that it is possible to identify two types of students. Thus, in mixed schools, the presence of non-native students (i.e. the disruptive type) generate negative spill-overs (i.e. peer effects) on natives' attainment levels and this effect is marginally decreasing with respect to non-native share. This framework stems from an underlying 'bad apple principle' which is incorporated in the education production function à la Lazear proposed: one 'disruptive student' is enough to generate bad spill-overs on all the class, and the greater is the concentration of more 'disruptive types', the lower will be the increase of the negative effects. This mechanism is partially rejected by the empirical analysis proposed, which rather shows that, as long as non-native school share is sufficiently low, non-native students presence is not able to generate negative peer effects on natives' outcomes. Thus, the 'integration model' is more consistent with the empirical findings because it predicts that for

[6] Data from Italian Ministry of Education generally only distinguish between *Italian* and *non-Italian* students, thus referring to a pure citizenship criterion. In the reminder of the paper we define to as 'non-native' student an individual enrolled in the Italian school system and having both parents without Italian citizenship. This definition coincides with the definition of the Italian Ministry of Education Statistical Service (MIUR 2009a) of 'non-Italian students'. Notice that if a student has one of the parents who is Italian, he automatically gains the Italian citizenship (because of the *ius sanguinis* rule) and so he is defined as 'native student' independently from the country of birth.

[7] 8th grade students, i.e. students finishing their third year of the Italian middle grade comprehensive school. The Italian 'Junior High School Diploma' corresponds to ISCED level 2.

[8] This hypothesis can be justified in a number of ways, for instance, non-native students are more likely to interrupt the class learning process because they typically need more help from teachers.

‘sufficiently low’ values of non-native school share, non-natives students’ disruption is not able to hurt the educational production process because non-native are more integrated with native peers. From the empirical point of view, solving serious problems of sorting and omitted variables bias is crucial in the correct identification of the effect. Our identification strategy exploits the within school idiosyncratic variation in non-native share between adjacent cohorts. It is based on school-level averages in order to sidestep the non-random allocation of non-native students across classes, school fixed effects and selection on observables to control for across school sorting and non-native students endogenous placement (Hoxby, 2000; Gould *et al.* 2009; Brunello and Rocco, 2011).

This paper contributes to the existing literature in a number of ways. It provides new evidence on peer effects between native and non-native students linking the empirical results to a clear theoretical framework in order to understand which possible mechanisms and which channels peer effects are following and shed light on the interpretation of the results. Thanks to its wide and original dataset, it overcomes problems of under-representation of immigrant shares typical of survey data. Moreover, to our knowledge, it is the first study on peer interactions in the Italian junior-high schools contexts, and one of the few studies in the European contexts[9]. Our results show that non-native school share has small and negative impacts on Language test scores of natives’ peers, while it does not significantly affect Math test scores. Negative effects on natives’ test scores are significantly different from zero only for sufficiently high values of non-native school-share and characterized by a convex relation (i.e. marginally increasing with respect to non-native school share). To give a numerical intuition of these results, we estimate that, if in each class there are up to two or three non-native students, the ‘disruption’ mechanism is not strong enough to affect natives’ attainment.

The rest of the paper is organized as follows: Section 2 presents a review of the literature; Section 3 explains the theoretical framework, Section 4 describes the econometric model and identification strategy designed to test the stylized predictions of the theoretical framework; Section 5 discusses the main characteristics of the dataset and provides general descriptive evidence; Section 6 and Section 7 discuss the results

[9] Evidence on educational peer effects and social interactions in Italy is also limited, and focuses on high school (Cipollone and Rosolia, 2007) or university contexts (Brunello, De Paola and Scoppa, 2010; De Paola and Scoppa 2010; De Giorgi, Pellizzari and Redaelli 2010; De Giorgi and Pellizzari, 2010).

and conduct sensitivity checks. Section 8 concludes and derives some policy implications.

2. Literature

Empirical literature in the U.S. traditionally focused on achievement gaps between black (or other minority students) and white students, and only in the last decade peer interaction has started to be seen as one of the possible causes of many observed different behaviours between white and black students (Heckman, 2011)[10]. Early contributions were given by Evans, Oates and Schwab (1992) and Cutler and Glaeser (1997), while Hoxby (2000), Hanushek *et al.* (2009) and Hanushek and Rivkin (2009) are the first to define 'racial peer effects' as a particular group of social interactions taking place between students belonging to different ethnic groups. Hoxby (2000) exploits idiosyncratic variation in the racial and gender composition of adjacent cohorts within the same grade and within the same school to estimate the effects of exposure to minority school share on achievement of both white and minority students. Her results show that immigrant school share has weak effects on students' achievement, but these effects are generally higher within students of the same ethnic group than between students belonging to different ethnic groups. Hanushek *et al.* (2009) and Hanushek and Rivkin (2009) base the estimation strategy on individual fixed effects retrieved tracking the same students and cohorts over time: the estimation of peer group effects relies therefore on cohort differences in the changes in racial composition as students' progress through school. They find that black students test scores are strongly decreasing in the black school share: their estimates imply that excess exposure of black students to black grade mates causes the black-white test score gap to grow by 0.07 standard deviations with each year in school, but no effects on white students. Card and Rothstein (2007) address the endogeneity of school and

[10] The empirical analysis of the effects of non-native students' on native peers educational outcomes stems from the 'desegregation' literature, which examines the effect of minority students on the achievements of the other students in the U.S. schools. Early desegregation literature proposes a variety of analyses on the relationship between ethnic origins and achievement (among the others: Armor, 1995; Cook, 1984; Crain *et al.* 1978), but does not consider social interactions between native and non-native students as a potential educational input to explain the persistent attainment gap. For decades economists and sociologists studied the effects of desegregation plans imposed by U.S. Courts, starting from *Brown vs. Board of Education*, 347 U.S. 483 (1954). The ruling in *Brown v. Board of Education* (1954) held that 'separate but equal', while not inherently unconstitutional in all areas, was unconstitutional in the case of education because separate education for blacks and whites could not be equal. This ruling led to dramatic changes in schools throughout the country (Hanushek *et al.*, 2009).

neighbourhood choice by aggregating to the metropolitan level and relating the black–white achievement gap in different cities to the degree of racial segregation in the area, as measured by the black–white difference in relative exposure to minority neighbours and schoolmates. They reach two main conclusions. First, there is a robust and quantitatively important negative relationship between black relative test scores and the degree of segregation in different metropolitan areas. Second, neighbourhood segregation seems to matter more than school segregation. They estimate that the move from a highly segregated city to an integrated city is associated with a 45 point narrowing of the black–white SAT Test score gap, which corresponds to about one quarter of the raw differential

Outside the U.S., empirical evidence is still quite limited and generally points to a negative effects of non-native school shares on native students attainments. In order to identify the causal link of the immigrant concentration on the outcomes of natives, Gould *et al.* (2009) exploit the variation in the number of immigrants in 5th grade conditional on the total number of immigrant students in grades 4 to 6. The approach is interesting and new under two main aspects: first, they use quasi-experimental evidence claiming that early '90 immigration waves in Israeli can be considered as an exogenous variation in immigrants' flows; second, they focus on long-term outcomes (rather than contemporaneous peers' outcomes effects). Their results point to a strong adverse effect of immigrant concentration on native outcomes. Jensen and Rasmussen (2011) analyse the effect of school ethnic concentration on children cognitive outcomes. They use a rich dataset for Danish ninth-grade students, based on PISA test scores matched with administrative and census information. In order to correct for the endogeneity in school ethnic concentration authors apply school fixed-effects and IV, using as instrumental variable the ethnic concentration in a larger geographical area where school is located. Results show that there is a negative effect of ethnic concentration on students' outcomes, and that this is significant only for the native Danish children. Brunello and Rocco (2011) study whether a higher share of immigrant pupils affects the school performance of natives using aggregate multi-country data from PISA, and find a negative but small effect. The analysis is conducted exploiting aggregation at the country level to avoid sorting problems of immigrant students within each country, while fixed effects and country socio-economic indicators are used to solve the problem of across country sorting and time trends in immigrants residential choices. They also find evidence that, conditional on the average share of immigrant pupils, a reduction of the dispersion of this share between schools would have small positive effects on the test scores of natives.

Theoretical literature on peer effects is still limited although, as outlined by De Giorgi and Pellizzari (2011), focusing on the mechanisms of educational social interactions is crucial in order to provide consistent interpretations of the empirical evidence. One notable exception is Cooley (2009) who defines and estimates a structural model to explain the achievement gap between black and white students. Estimating the model using data from North Carolina elementary schools and an exogenous variation due to the a policy implementation, she finds that endogenous peer effects within the peer groups are much stronger than between effects. The simulation of a desegregation policy with the estimated coefficients shows that desegregation does not have strong average effects on educational achievement, while it has substantial distributional consequences in narrowing the gap at lower percentiles of the achievement distribution.

3. Theoretical framework

Exploiting and education production function (EPF) à la Lazear (2001), we propose two possible mechanisms of social interactions between native and non-native students. The simple 'disruption' model predicts marginally decreasing negative externalities due to the presence of 'disruptive type': just one non-native student (the 'more disruptive type') determines large negative effects on all students' attainment (Lazear, 2001). On the other hand, the 'integration model' embeds the 'subcultural model' of interaction between white and blacks students proposed in the U.S. sociological literature (Fordham and Ogbu, 1986; Steele and Aronson, 1998): non-native students are more likely to be integrated with native peers if they are relatively isolated, so that they are forced to interact to natives and natives do not bear high 'effort costs' in integrating them. From a general perspective, in the 'subculture model' the native student (majority type) makes effort to integrate non-native students (minority type) as long as the latter is relatively isolated (Hoxby and Weinghart, 2006). When, minority students become prevalent enough to form a critical mass, the majority type rejects them. The 'subculture' model can also explain the evidence of 'acting-white' behaviours recently found in U.S. schools (Austen-Smith and Fryer, 2005; Fryer and Torelli, 2010).

3.1 The 'disruption' model

Disruption is a possible mechanism of peer interaction that directly influences the learning process and the attainment levels through externalities caused by peers' behaviour[11]. The basic assumptions we made are two: (*i*) one child's disruption hurts the learning process of all students (including the disruptive one); (*ii*) non-native students have a higher propensity to cause interruptions during the learning process. Indeed, the 'disruption mechanism' of peer interaction may actually follow many different channels and should not be necessarily associated to non-native students' 'bad' behaviour. For instance, it could be simply thought as non-native students' need of additional help which causes the teacher to slow down the activity of the entire class, as well as non-native students' propensity to interrupt the teachers because of more difficulties to understand due to poorer language skills. This basic assumption does not concern the 'unobserved ability' of the types of students, which is indeed the same. It represents a stylized assumption on the different 'behaviours' in the class which distinguishes the two types. The descriptive evidence and discussion in Section 5 corroborate these hypotheses.

Formally, we implement an education production function à la Lazear (2001) where two types, with different propensity to disrupt or to interrupt the lessons (native and non-native students), interact in the school so that the misbehaviour of the 'more disruptive' type determines negative externalities on the learning production process which are captured by negative peer effects on per student outcome. Define p as the probability that any student is not hurting his own learning or other's learning at any moment in the time spent at school, and $(1 - p)$ as the probability that any given student initiates a 'disruption'. Given a class size of n, the probability that disruption occurs at any moment in time t is $(1 - p^n)$. Define V as the value of a unit of learning, which is influenced by the likelihood that a student is not engaged in a disruptive behaviour in the given instant t, and Z the total number of student in the school. Then, the total output for each school is given by $Y=ZVp^n$, and the output per student by $y=Vp^n$. As discussed above, we assume that non-native students ($j=F$) tend to interrupt more frequently (on average) with respect to native peers ($j=N$), so that we can identify to types of students

[11] De Giorgi and Pellizzari (2011), Epple and Romano (2011) and Sacerdote (2010) point to Lazear (2001) model as one of the potential model of peer interaction in the classroom, as well as Hoxby and Weinghart (2006) include the 'Bad Apple model' in their analysis of possible model of peer interaction in the classroom.

($j=N, F$) according to different values of p_j, being $p_N > p_F$. Finally, define as $\theta<0.5$ the proportion of non-native students in each school so that type F is the 'minority type'. Normalizing V to 1 and holding n constant, per-student-output in schools with mixed classes (y) will be equal to:

$$y^D = p_N^{(1-\theta)} p_F^{\theta} \quad [1]$$

Notice that disruptive behaviour is assumed to hurt in the same way both types of students, as any interruption may cause negative effects on the general learning production of the class ($y = y_N = y_F$). The 'disruptive model' predicts that per student output (y) is a decreasing and concave function of non-native student school share (θ). This can be easily seen from the first and second derivative of per student output (y) with respect to non-native school share (θ):

$$\frac{\partial y^D}{\partial \theta} = \left[p_N^{(1-\theta)} p_F^{\theta} \right] \ln\left(\frac{p_F}{p_N} \right) = y^D \ln\left(\frac{p_F}{p_N} \right) < 0 \quad [2]$$

$$\frac{\partial^2 y^D}{\partial \theta^2} = \frac{\partial y^D}{\partial \theta} \ln\left(\frac{p_F}{p_N} \right) > 0 \quad [3]$$

Expression [2] is negative as long as the assumption that $0 < p_F < p_N < 1$ holds. The intuition behind this result is the following: non-native students 'disruptive' behaviour generates negative spill-overs on natives' attainment levels, while concave relation between natives outcome and non-native school share determines a negative decreasing marginal effect. The classical argument hinges upon the 'bad-apple principle' which is incorporated in the EPF [1]: one disruptive student is enough to generate negative peer effects on all classmates, whereas if the share of non-native students increases, then the class becomes more segregated so that the negative effects on per student attainment marginally decreases (Figure 3).

3.2 The 'integration' model

Lazear (2001) demonstrates that as long as the assumption $0 < p_F < p_N < 1$ holds, school total output (Y) is maximized when students are segregated by type. However, peer interactions could intervene to reduce non-natives' disruption probability

$(1-p_F)$ as far as native students' behaviour could exert positive spillovers on non-natives through an 'integration mechanism'. Native students behaviour (i.e. less disruptive types' behaviour) could have a positive impact on non-native peers and, as a consequence of the integration process, the gap between the 'attitude to disrupt' reduces ($p_F \rightarrow p_N$). Integration, however, has some cost which we assume to be the effort made by native students to integrate non-native peers. Intuitively, if non-native students are relatively isolated, then the integration mechanism is less costly for native students, whereas anytime non-native students become prevalent enough to form a critical mass, the native type rejects them because the effort of integration becomes too high. Actually, the rejection may be due to different reasons: natives may be willing to make sufficient effort to include a few minority members but unwilling to make the effort to include numerous non-native schoolmates and but also unwilling to include some non-native students while rejecting others (Hoxby and Weingarth, 2005). Also a specular argument for non-native students is true: when non-native students are relatively more isolated they are forced to interact with native peers.

The formalization of this 'integration mechanism' makes p_F endogenous[12] and, more precisely, a decreasing function of the proportion of non-native students θ. The EPF incorporating the integration mechanism takes the following form:

$$y^I = p_N^{(1-\theta)}\left[p_F(\theta)\right]^{\theta} \quad [4]$$

where $p_F(\theta)$ satisfies the following properties[13]:

$$p_F(\theta) = \begin{cases} p_N \text{ if } \theta = 0 \\ \overline{p}_F < p_F(\theta) < p_N \text{ if } \theta \in (0;0.5) \\ \overline{p}_F < p_N \text{ if } \theta = 0.5 \end{cases}$$

Under standard regularity conditions (i.e. $p_F(\theta)$ continuous and twice differentiable), we have that:

[12] Notice that Lazear (2001) suggests this solution in order to make the 'integration mechanism' play a role.

[13] The function $p_F(\theta)$ can be also defined according to an integration index $I(\theta) = \theta/(1-\theta)$ representing the ratio between the number of non-native and native students. The model is robust to this alternative specification.

$$p_F^{'}(\theta)=\frac{\partial p_F(\theta)}{\partial\theta}=\begin{cases}0 \text{ if } \theta=0\\ \overline{p}_F < p_F^{'}(\theta)<0 \text{ if } \theta\in(0;0.5)\\ \overline{p}_F^{'}<0 \text{ if } \theta=0.5\end{cases}$$

And, in particular, notice that:

$$\begin{cases}\text{if } \theta\to 0^+ \Rightarrow p_F(\theta)\to p_N \text{ and } p_F^{'}(\theta)\to 0\\ \text{if } \theta\to 0.5^- \Rightarrow p_F(\theta)\to \overline{p}_F \text{ and } p_F^{'}(\theta)\to \overline{p}_F^{'}\end{cases} \quad [5]$$

The ‘integration mechanism’ determines important differences in the predicted effects due to non-native students school share with respect to the simple ‘disruption model’. In fact, notice that the externalities generated by non-native school shares are no longer always negative:

$$\frac{\partial y^I}{\partial\theta}=y^I\left\{\ln\left[\frac{p_F(\theta)}{p_N}\right]+\frac{\theta}{p_F(\theta)}p_F^{'}(\theta)\right\}\leq 0 \quad [6]$$

In particular, the role for the ‘integration mechanism’ makes the non-native peers’ negative spillovers due to the disruption mechanism decrease for sufficiently low values of non-native school share:

$$\begin{cases}\text{if } \theta\to 0^+ \Rightarrow \dfrac{\partial y^I}{\partial\theta}\to 0\\ \text{if } \theta\to 0.5^- \Rightarrow \dfrac{\partial y^I}{\partial\theta}\to k<0\end{cases} \quad [7]$$

The basic intuition of the EPF with integration mechanism follows the predictions of the ‘subcultural model’ showing that the minority type can be integrated by the majority type as long as this does not entail high cost. As demonstrated by Lazear (1999, 2001) this ‘integration or cultural acquisition’ mechanism that cancels out the distinction between the two types ($p_F \to p_N$) is more likely to occur when the presence of non-native students in each school is below a certain 'critical mass value'[14] (Figure 4, analytical derivations in Appendix C).

To sum up, the two hypothetical mechanisms embedded in the EPF proposed entail two different predictions about the type of peers' externalities on students' achievement originating from the social interactions between native and non-native students. The 'disruption mechanism' predicts negative and marginally decreasing effects on per-student outcome, while the 'integration mechanism' mitigates these heavy negative effects and predicts 'non-linear effects' with respect to non-native school share which are close to zero as long as non-native school share is 'sufficiently low'. We test these theoretical prediction in the empirical applications on the Invalsi IC data.

4. Empirical strategy

In the specific case of the estimation of peer effects between native and non-native students, there are different types of students' sorting at work. First of all, one must account for the endogenous placement of immigrants into some geographical areas that are usually more likely to be populated also by lower-achieving native students, regardless of the local level of immigrant concentration (Gould *et al.*, 2009)[15]. As a consequence, non-natives' concentration in the schools may be endogenous because of parents' housing decisions: individuals sort into neighbourhoods because they want - or do not want, or they are forced - to live in a 'ghetto' area, or in areas where an occupation is more likely to be found, or in areas where renting houses is less expensive, and so on. Second, the peer group can be the result of individual choices: for example, given the residential choice of the household, individuals living in a given area choose a certain school on the basis of some (perceived) school quality. Third, given the school choice, the allocation of non-native students among the classes within a certain school is not random, but usually depends on school staff choices, previous school path

[14] Lazear (1999) presents a model of 'cultural acquisition' and shows that "[…] incentives to be assimilated into the majority culture depend on the size of the relevant groups. The smaller is the minority relative to the majority, the greater is the incentive of a minority member to acquire the culture of the majority" (Lazear, 2001, p. 791).

[15] As widely recognized in the literature, the vast majority of cross-sectional variation in students' peers is generated by selection: students self-select into schools based on their family background and income, parents' job locations, residential preferences, school rules, educational preferences and even ability (Hoxby, 2000).

and law or compulsory regulations[16]. Besides self-selection issues, the estimation of a reduced form model retrieving the peer effect parameters is also hard because of the problems arising from the presence of the correlated effects that will give rise to a bias if they are correlated with peer group composition (Manski, 1993).

The sorting processes described and the difficulty to control for all possible correlated effects may lead to a negative spurious correlation between attainments levels of native students and non-native school share, independently from the fact that non-native students actually cause some bad or good externalities on natives'. Our estimation strategy relies on the basic assumption that changes in non-natives school shares[17] between adjacent cohorts within the same school are not correlated with pupils' unobservable characteristics that may be relevant in the educational production process. The strategy implemented rests on averaging procedures and selection on observables to solve the sorting mechanisms described above (sorting across classes in the same school, sorting across schools in the same areas and endogenous placement across areas) and school fixed-effects to limit possible bias due to omitted variables in correlated effects. Given that the focus of this work is on peer effects on natives' attainment due to non-native peers' (negative) spill-overs caused by the disruption mechanism, in the empirical specification we use as outcome variable natives' per student outcome (y^N).

4.1 Baseline empirical model

Non-native students are not randomly allocated across classes in the same school (see the institutional regulatory framework, Appendix A)[18]. We solve sorting of non-native students across classes within the same school using school level averages[19] (Card and Rothstein, 2007) and we identify the effect of non-native school share on

[16] In Italy, Heads, School Boards and Municipalities must collaborate to allocate non-Italian students within schools and within classes in such a way to avoid segregation problems.

[17] In the reminder of the paper we generally label as non-native school share our variable of interest (P_{st}^F).However, we only focus on three subsequent cohorts of 8th grade students, so that P_{st}^F corresponds to the share of 8th grade non-native students in school *s* and year *t*, i.e:

$$P_{st}^F = \left(\frac{\text{No. of Non-native students in grade 8 in school s}}{\text{Total No. of students in grade 8 in school s}} \right) * 100$$

[18] This is actually common in most European country. Ammermueller and Pischke (2009) provide evidence of the non-random assignment of non-natives students within school and within classes in some European country.

[19] This is true as long as we assume that: (*i*) the class-specific error component averages to zero across all classes in the school; (*ii*) the individual-specific error component are mean zero for all natives in each school.

natives' attainment by exploiting school by time variations in the data, using the following empirical specification:

$$y_{st}^{N} = \beta P_{st}^{F} + X_{st}^{N}\alpha + \varphi_s + \varphi_t + \eta_{st}^{N} \quad [8]$$

where y_{st}^{N} represents the school mean test score of all 8th grade native (j=N) students in school s and year t, P_{st}^{F} is the share of 8th grade non-native students in school s and year t (that in the reminder of the paper we simply label '*non-native school share*'), X_{st}^{N} is a vector containing mean characteristics of native students in school s and year t, φ_s are school fixed-effects and the term φ_t includes time and territorial fixed-effects[20]. The intuition behind this procedure is that, at the individual level, any non-randomness due to across classes sorting would give rise to a class-specific error term correlated with the observed variables which potentially bias OLS estimates of β and $\rightarrow$ from individual-level data. Conducting our analysis at the school level, thus, solves the sorting of non-natives across classes in the same school as long as we assume that: (*i*) the class-specific error component averages to zero across all classes in the school; (*ii*) the individual-specific error component are mean zero for all natives in each school (Card and Rothstein, 2007). Moreover, given that it would be unlikely be able to control for all school level characteristics which may influence native attainments: school fixed effects solve all possible omitted variable bias in individual mean characteristics and school mean characteristics which may influence native attainments (i.e. the correlated effects). An additional nice feature of this specification is that it can be easily reconducted to a reduced-form linear-in-means model for peer effects estimation where both endogenous and exogenous effects arising from exposure to non-native peers are incorporated in β (Card and Rothstein, 2007; Manski, 1993)[21].

Another important source of endogeneity that must be addressed in our empirical model is across schools sorting of non-native students. School fixed-effects and

[20] Territorial fixed-effects include five territorial dummies (North West, North East, Centre, South, Islands) interacted with year dummies for the three Invalsi IC waves.

[21] However, we cannot distinguish whether β reflects the exogenous effects of student's peers characteristics or the endogenous effects operating through student's peers achievement (i.e. the well-known 'Reflection Problem'). Anyway, finding evidence of the 'social effects' (i.e. both endogenous and exogenous) is still of substantial policy interest (Ammermüller and Pischke, 2009; Hoxby, 2000) and still hard in practice because of endogenous sorting, selection issues and omitted variables bias (Hanushek et al. 2003).

geographical area fixed effects[22] should already capture part of this sorting. However, we exploit the original features of our dataset and add to the specification in eq. [8] a set of school by year variables (W_{st}) which capture the socio-economic characteristics of each school catchment-area[23]. Catchment area variables are school-specific, so that even two schools in same municipality might have partially overlapping catchment areas and different values of these socio-economic indicators, and this is particularly relevant for big municipalities. The socio-economic variables are chosen in order to select characteristics of the catchment-area that could have attracted immigrant families in the past, and thus influence the actual non-native school shares. For example, we include male and female occupation rate, population density, indicators for poor housing conditions. We also include the number of non-Italian residents in each school catchment area in 2001 (i.e. at the beginning of the sharp increase in the Italian immigration trend) which can be shown to be a strong predictor of the actual non-natives school shares and thus control for non-natives' sorting across schools.

A final concern may arise if we observe that the variation of non-natives shares across subsequent school years could be potentially endogenous if some sort of 'native flight' or underlying time trends are present (Betts and Fairlie 2003, Hoxby 2000 among others). To solve this issue we apply the same strategy used by Gould *et al.* (2009) and Brunello and Rocco (2011) conditioning on the total stock of non-native students in the school (i.e. the total number of non-native students in grade 6, 7 and 8) and on the total school size (i.e. the total number of students in the school) (S_{st}). Therefore, conditioning on these variables, the share of non-native students who are attending the 8th grade in each school can be considered as good as random, while any residual correlation between non-native shares and school characteristics is captured by the school fixed-effects. Thus, we estimate the following equation:

$$y_{st}^{N} = \beta P_{st}^{F} + X_{st}^{N}\alpha + W_{st}\delta + S_{st}\gamma + \varphi_s + \varphi_t + \eta_{st}^{N} \quad [9]$$

Table 5 contains the complete list and description of the variables included in the X_{st}, W_{st} and S_{st} vectors. The estimation of ↓ in eq. [9] allows a causal interpretation of

[22] Geographical area FE are in the form of interaction variables between five territorial dummies and year dummies. In the sensitivity analysis we shoe that results are robust even introducing up to 103 territorial dummies corresponding to school-districts (or province level).
[23] See Appendix B for detailed description on how catchment-area are built.

the effect of non-native school share on natives' attainment which we interpret as non-natives' peer effects on natives' attainment. If ↓ < 0 we might conclude that the presence of non-native students causes negative peer effects on the attainment of native peers and that a possible 'disruption mechanism' is at work.

4.2 Non-linear effects: 'disruption' vs. 'integration' mechanism

The theoretical framework predicts that in case the 'integration mechanism' plays a substantive role, the effects of non-native share are non-linear, and rather vary with respect to different levels of P_{st}^{F}. Therefore, to distinguish which of the two possible mechanisms is at work it is crucial to test for possible non linearity in the peer effects. To this purpose, we introduce a linear spline functional form in the non-native school share dividing the percentage range [0; 1] into two intervals with boundaries $\underline{\theta}$, $\tilde{\theta}$ and $\overline{\theta}$, where $\underline{\theta}$ and $\overline{\theta}$ correspond, respectively, to 0 and 1:

$$y_{st}^{N} = \beta_1 P_{st}^{F1} + \beta_2 P_{st}^{F2} + X_{st}^{N}\alpha + W_{st}\delta + S_{st}\gamma + \varphi_s + \varphi_t + \eta_{st}^{N}$$

where: [10]

$$P_{st}^{Fi} = \begin{cases} \theta_{st} & \text{if } 0 \le \theta_{st} < \tilde{\theta} \\ 1-\theta_{st} & \text{if } \tilde{\theta} \le \theta_{st} < 1 \end{cases}$$

Following the theoretical framework, we accept the hypothesis that a simple 'disruption mechanism' is at work if $\downarrow_1$<0 and $\downarrow_2$<0 for every value of $\tilde{\theta}$. Moreover, the strictly concave relation between non-native school share and native educational outcome stemming from the 'bad apple principle' implies that the estimated peer effects (↓) should be greater for lower values of non-native school shares so that $|\downarrow_1| > |\downarrow_2|$. On the other hand, we accept the hypothesis that an 'integration mechanism' is at work if $\downarrow_1$=0 and $\downarrow_2$<0 for 'sufficiently low' values of $\tilde{\theta}$. The 'integration mechanism' also entails a convex relation between non-native school share and native educational outcome (at least) as $\theta \rightarrow 0$. Thus, $|\downarrow_1| < |\downarrow_2|$ for 'sufficiently low' values of $\tilde{\theta}$.

5. Data and descriptive statistics

We exploit a unique dataset that combines the *Invalsi First Cycle Final Exam* data[24], administrative records from *Ministry of Education Statistical Office*, and the *Italian Population Census Survey 2001*[25]. *Invalsi First Cycle Exam* (from now on 'First Cycle' or 'Invalsi IC') data are the first experience of testing attainment levels of all students enrolled in Italian junior high schools. The census dimension of Invalsi IC tests allows us to overcome problems of underrepresentation of immigrant individuals and measurement errors in sample surveys (Aydemir and Borjas, 2010). Additional information about socio-economic family background are obtained as school-level averages of Census variables linked to each school using an original matching technique that identifies for each junior high school its 'catchment area'. To our knowledge, this is the first time that a dataset with such a variety of information and covering the universe of 8th graders students is made available for the Italian school system.

In detail, Invalsi IC dataset contains school level information, Math and Language test scores results and individual information for each 8th grade student enrolled in a public or private Italian junior high school[26]. Three waves are available, corresponding to 2007-08, 2008-09 and 2009-10 school years final exams (about 500,000 students per wave). Individual information covers year of birth, gender, citizenship (Italian, non-Italian), place of birth; how long the student is in Italy if born abroad (from primary school, for 1-3 years, less than 1 year); mother's and father's place of birth (Italy, EU, European but non-EU, other non-European country), grade retention (if the student is 'regular' i.e. if he/she is 14 years old at the end of the school year; 'in advance' i.e. younger than 'regular' students, or 'retained' i.e. older than 'regular' students), school identifier[27]. Administrative records from Ministry of Education Statistical Office provide general information about school characteristics (i.e. type of school, public vs. private, number of students enrolled and number of teachers, average class size) matched to Invalsi First Cycle data through an anonymous school identifier. Finally, Census 2001 contains information about resident population

[24] INVALSI (*Istituto Nazionale per la Valutazione del Sistema Educativo di Istruzione e di Formazione*) is the independent public institute carring out the evaluation of Italian school system and test students' attainment levels.

[25] Many people collaborate to make available the dataset used. We thank: Claudio Rossetti (Luiss), Patrizia Falzetti (Invalsi) and Marco Mignani (Invalsi) for their work in merging Census and Miur data with the Invalsi IC datasets; Paolo Sestito (Bank of Italy), Piero Cipollone (Invalsi and Bank of Italy) for fruitful discussions and data support.

[26] Test scores range from 0 to 100 and refer to the fraction of right answers for each of the two subjects.

[27] Data do not contain class identifiers so that it not possible to build a panel based on classes (or sections) within the same school to implement an identification strategy based on a teacher fixed effects.

in Italy in 2001. Each school is matched to a group of census divisions through an original matching technique designed to associate to each junior high school a group of census cells constituting its 'catchment area' (Barbieri, Rossetti and Sestito, 2010)[28]. This procedure allows matching to each junior high school more than two hundreds variables from 2001 Italian Population Census Survey covering a great variety of demographic and socio-economic information on resident population (gender, age, ethnic origins, education, labour force participation, occupation, households' composition and houses characteristics).

5.1 Descriptive statistics

We exploit the panel dimension of the dataset constituted by 5771 junior high schools[29] (*s=1…5771*) and three school years (*t=2008, 2009, 2010*). Mean test scores and mean individual characteristics are obtained from all 8th grade students enrolled in all Italian junior high schools[30] in 2007-08, 2008-09 and 2009-10 (1,504,286 individuals), while school characteristics are matched from Census and administrative school records as explained above.

Table 1 describes general characteristics of the junior high schools in the dataset (percentage of public schools, non-native school share, average school size, average class size) with respect to macro-area and Invalsi IC wave, while Figure 2 shows the average percentage of non-native students per school (i.e. 'school shares'). The distribution of non-native students across Italian territory is highly not homogenous: Northern and Centre regions experience the highest average school share of non-native students (10.01% and 9.18% in 2010), while it dramatically falls in the South (1.97%), while school characteristics, such as average school and class size are generally equally distributed. Table 2 shows school average and standard deviation of test scores results according to the native/non-native partition of each school population: gaps between mean test scores for natives and non-natives are large and statistically significant. Descriptive evidence confirms general results common in the European literature: first, non-native students perform worse than their native peers; second, gaps are greater in Language and lower for Math. The distribution of school mean test scores is also

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[28] See Appendix B for a detailed description of data and matching techniques used.
[29] From the original population of 6290 schools, almost 5% are dropped because they appear in only one wave.
[30] We exclude all individuals who did not sit either Maths or Italian Language test (0.73% of the total students population).

different: non-native students' test score distribution is more similar to a normal distribution, and shows a higher variance.

We focus on the test score gap between native and non-native students at the individual level in Table 3 where we report the coefficient of the dummy variable '*being non-native*' obtained running descriptive (pooled) OLS regressions on the whole sample of IC 2009 and 2010 students. We first show the row coefficient, i.e. the unconditioned attainment gap: non-native students have test score results lower than native peers by 21.21% in Language, and 15.08% in Math. Then, we progressively add controls for individual characteristics (gender, retention, parents' origins, time spent in the host country since birth), school characteristics (ownership, type, size, average class size, pupil-teacher ratio, support teacher-pupil ratio) and territorial dummies[31]. The conditioned gaps turn out to be smaller than the unconditioned one, but still significantly different from zero: *coeteris paribus*, being non-native implies a 7% lower test score in Language and 4% in Math.

The behavioral assumption of the theoretical model ($p_N > p_F$) is actually corroborated by a variety of international studies (see, among others, OECD 2010, NESSE 2008, Stanat and Christensen 2006, Schnepf 2007) which underline how language, culture and previous school path influence non-native students' behaviour at school and contributes to affect negatively non-natives' school performance. In order to bring additional evidence, Table 4 contains an elaboration from PISA 2006 mean test scores results which tested Science skills of 15-years-old students in OECD countries. Mean test scores are shown by country and with separate indication of native, first and second generation students (where the distinction is possible). Although there are sharp differences in the native-non-native gap depending on the specific immigration history of each country, non-native students always perform worse than their native mates. Moreover, second generation students show, on average, better results than first generation students and one may argue that this is driven by an higher degree of integration (in terms of language and culture, especially) with the hosting country language (Stanat and Christensen, 2006).

In the above mentioned studies, immigrant students' lower educational attainment is interpreted as a proxy for unobserved behavioural attitudes of non-natives which make them face more difficulties at school (Cooley, 2010). However, there is

[31] For the complete list and explanation of control variables used see Table 5.

also direct evidence of the fact that minority students tend to show lower discipline with respect to natives. For instance, Kinsler (2010) exploits rich dataset on North Carolina schools containing detailed information on students discipline and behaviour in the class. He finds that discipline has an overall positive influence on student performance and a substantive part of the attainment gap between white and minority students is explained in his model by differences in behaviours. Descriptive statistics also show that minority students tend to suffer suspensions or discipline punishments more frequently than white students. Concerning the Italian context, data from a survey on non-native adolescent integration in society (CNEL, 2011) confirms that non-native have more difficulties at school, and shyness, language and discipline are important factors determining these difficulties. The representative sample of 414 non-natives interviewed declared to have had attainment difficulties at school (43.3%), difficulties in interactions with classmates (33.3%) and teachers (24%), difficulties in interactions due to language (30.2%), integration (28%) and discipline problems (44.5%)[32] (CNEL, 2011).

Summing up, two main results may be drawn from these general descriptive evidence. First, there exists a sizable gap in test scores results between native and non-native students, and this attainment gap seems to be more critical in Language rather than in Math skills. Second, even after taking into account individual characteristics, parental background, school characteristics and territorial differences, the attainment gap is reduced but still persists. Moreover, given that the gap does not disappear controlling for usual school and family background inputs, it is plausible to think that 'social' inputs and peers' externalities may play a crucial role in explaining these gaps (Akerlof and Kranton 2000, 2002; Zenou and Patacchini 2006; Heckman 2011; Freyer 2011, among others). Finally, Italian and international descriptive evidence supports the basic assumption of the theoretical framework: *coeteris paribus*, non-native students may cause more occasions of interruption in the classroom compared to native peers ($p_N > p_F$) for many reasons. For instance, given of lower attainments levels (on average) and poorer language skills, they tend to interrupt more and need more help from teachers slowing down the class learning process.

6. Results

[32] These percentages are statistically different (at 5 or 10% level) with respect to the same answers given by a control group of 337 natives.

In this section, we first present the baseline model results and then we test for non-linear effects in order to find evidence to support or reject the theoretical models illustrated in Section 3. As already outlined, the variable of interest is the non-native school share (P_{st}^{F}) and the parameter ↓ captures both the exogenous effects operating through student's peers characteristics and the (pure) endogenous effects operating through students' peers achievement.

6.1 Baseline model results

Table 6 contains the results for the estimation of the parameter of interest from eq. [8] and [9]. The dependent variable is the log of the Invalsi IC school mean test score for native students (from now on, SMT), and we conduct our analysis separating the Language from the Math test score. The rationale for doing it being that we expect peer effects to have greater impact on Language tests as long as language skills are directly influenced by the use of Italian language with native peers in the classroom. We progressively add school variables controls (S_{st}) in columns (II), and catchment-area socio economic variables (W_{st}) in columns (III)[33]. Thus, the coefficients estimated in columns (I) correspond to eq. [8], while the ones estimated in columns (III) to eq. [9]. Adding school and catchment-area controls significantly influences the estimates, improving the school fixed-effects basic framework and limiting the possible biases due to across school sorting. In fact, focusing on the estimates of ↓ from eq. [9] (columns III) we have small and negative effects, statistically different from zero only for Language test score. Thus, increasing non-native school share by 1% determines a decrease of 6.5% in native peers' Language test score, and no significant effects in Math.

A first important result can be derived from the baseline model estimations: the 'disruption model' cannot be accepted in general terms. Negative effects are small and only concentrated in Language skills, while for Math test scores there are not significant negative spillovers. Thus, there does not seem to be negative peer effects working through disruption and interruption mechanisms in the education production of Math skills. This is somehow reasonable in our view, given that mathematical skills are more intuitive and based on a 'universal numerical alphabet'. These results are in line with

[33] See Table 4 for the complete list of variables and description.

the evidence from U.S. (Hoxby, 2000; Hanushek and Rivkin, 2009; Hanushek *et al.* 2009) which generally highlights small and non-significant effects of black school shares on white test scores results. The limited evidence from literature on peer effects between immigrants and native students in EU context makes comparisons more difficult. Our results are similar to Brunello and Rocco (2011) who exploit cross-country variation in PISA data for a panel of OECD countries, although they cannot distinguish among the subjects tested due to the PISA survey structure. They find that a one percentage point increase in the share of immigrants students is expected to reduce the average test score of natives by 0.27%[34]. Jansen and Rasmussen (2011) estimate effects of immigrant school concentration on test scores both of native and non-native students in Denmark using individual level data with an IV identification approach and distinguishing between mathematical and language skills. Their evidence is less consistent with our analysis as they find negative and significant effects only in Math, while the pattern of the results is not clear for Language skills: they find that a 10% increase in immigrant school concentration reduces child's Math score by 8.6 points and 2.7 in Reading. The difference in the results can be attributed to country specific characteristics as well as to differences due the identification approach and the use of individual level data.

6.2 Disruption vs. integration mechanism

We test for non-linarites in the effects of non-native school share on natives' test scores estimating $\downarrow_1$ and $\downarrow_2$ in eq. [10] with a spline linear function with one break point ($T=\tilde{\theta}$). To seek for structural changes in the effect we use different values of the break and report the results in Table 7. This allows showing in a flexible way how effects are different above and below any given threshold, and if they are statistically significant while in the sensitivity analysis (Section 7) we present several results testing non-linear effects in non-native school share implementing different methods (i.e. higher order terms of θ), and showing estimation results of spline functional forms with percentiles and deciles intervals.

The effects are highly non-linear: we always reject the null that $\downarrow_1 - \downarrow_2 = 0$. For instance, setting the threshold at the mean of the non-native school share distribution (T=0.065) we have that increasing by 1% the non-native share has not significant

[34] Brunello and Rocco (2011) also find that the attenuation bias correction à la Aydemir and Borjas (2010) does not significantly change the size of the effect.

effects if the non-native school share is below 6.5% (T), while it decreases natives' language test scores by 7.6% if the share is above 6.5%. Thus, both in Language and Math, the general pattern of the results shows that the increase of non-native share has negative and significant effects only for sufficiently large values of $\tilde{\theta}$. To be more precise, we cannot reject the null that $\downarrow_1=0$ and $\downarrow_2<0$ for $T<0.20$, while, if $T>0.20$ $\downarrow_1$ and $\downarrow_2$ are both negative and significant for Language. Concerning the magnitude of the effects, it is clear that effects are greater for greater values of non-native school share, thus rejecting the implication $|\downarrow_1| > |\downarrow_2|$. We observe that the concave relation embedded in the 'disruption model' in is not found in the empirical estimation of the effects, which seem driven, on the contrary, by a non-linear convex relation: negative marginal effects are present only for high levels of non-native school share and are generally increasing with respect to non-native school share.

We go deeper into the analysis introducing a spline function with two break points, where the first one is fixed at 10% ($T_1=0.10$) and we set different values for the second (T_2). The rationale is the following: with one break point we exclude that the structural break ($\tilde{\theta}$) is greater than the threshold of 10%, indeed the effects above 10% are still unclear. Table 8 shows the results for three possible break points for $T_2=0.20$; 0.25; 0.30[35]. Results for Math test score do not show clear patterns, while for Language we always find negative and significant effects between 10% and 20, 25 and 30% levels of non-native school share.

Summing up and interpreting together the results from Table 8 and Table 7, we have that non-linear effects are stronger for Language test score, while less clear for Math, and the hypothesis of concave relation is rejected by the data. In details: for the Language test, we cannot reject the null that $\downarrow_1=0$ and $\downarrow_2<0$ for $\tilde{\theta} < 0.10$, while for Math the same result holds for $\tilde{\theta} < 0.20$. To give a numerical intuition, we calculate that, on average, a non-native school share of 10% corresponds to nine non-native students in the school, or, equivalently, two or three non-natives students in each class, on average. Thus, if in each class there are up to one or two non-native students, the 'disruption' mechanism is not strong enough to affect natives' attainment. These findings are consistent with the theoretical predictions of the 'integration model' of peer interaction. Interestingly, this result is stronger for language skills, where the

[35] Additional robustness checks for other thresholds between 0.20 and 0.30 are always consistent with these results.

‘disruption’ occurs more frequently given the greater difficulties to learn a non-mother-tongue for non-natives.

7. Robustness checks

We test the robustness of our results under three main dimensions. First, we test the robustness with respect to missing values in school and catchment-area variables due to the dataset construction. Then we test for possible concerns due to the main source of endogeneity (across school sorting) and the underlying phenomenon of ‘native flight’. Finally, we show further evidence on non-linear effects

7.1 Missing values in school and catchment-area variables

Missing values in school and catchment-area variables are due to the construction of the dataset. This fact causes the number of schools in the regression estimates to shrink from 6,289 in the estimation of eq. [8] to 4827 in the estimation of eq. [9] (Table 6). We test the robustness of the baseline results controlling for missing values and correcting missing values with some approximations, where possible, to verify that the results are not driven by any kind of sample selection or attrition. Indeed, a preliminary analysis with probit regressions excludes any particular pattern in missing values due to geographical school location.

The variable containing the information about the ‘stock of non-native students’ in the school is missing for 16% of schools due to school register data missing. We correct this variable in two possible ways: *(i)* setting missing values to zero and creating an indicator variable taking value 1 when this information was corrected; *(ii)* replacing the missing values with the total stock of 8th graders non-natives students, one year lagged from Invalsi data sources. Catchment-area variables are missing because the matching procedure between the school identifier and the census cells failed due to some non-perfect overlapping between the school identifier in the Invalsi data and the one in the Census data. However, for more than half of them we can replace the missing values of the socio-economic variables of the school catchment-area with the average value of the same variables taken from the schools which are located in the same municipality. This correction procedure shrinks missing data on catchment-area variables from 6.3% to 4.6% of schools. Table 9 shows that implementing the correction procedures allows keeping all the observations but does not modify previous results, which, in turn, are not due to some selection pattern in the missing data.

7.2 Robustness to across schools sorting and 'native flight'

The identification strategy implemented by eq. [9] is designed to control for across school sorting through school fixed-effects, territorial by year fixed effects and school specific catchment-area socio economic variables. To test that the identification strategy is suitable to capture this main source of endogeneity, we split the sample of schools into two groups according to school location in big or small municipalities. We define to as 'big municipalities' those having three or more junior high schools in their territory, while 'small municipalities' have one or two junior high schools. The enrolment rules are based on residency criteria, therefore students have to attend the junior high school in the same municipality where they live with their family. If there is more than one school, then families usually have to enrol the child to the school of the area where they reside, otherwise they are allowed to enrol the child to another junior high school of the municipality, if free slots are available.

Thus, the enrolment institutional framework limits per se across school sorting, however this is still possible and more likely to happen in big municipalities, where there is a sufficiently large number of junior high schools and families have some degree of 'choice'. Moreover, 'big municipalities' are the ones located in more urbanized areas, which benefit from higher public transportation means that could favour, to some extent, the commuting process from the residency place to a distant junior high school, alternative to the one nearby home. Thus, we run separately eq. [2] on the subsample of small and big municipalities. If across school sorting is at work, the estimations should differ substantially in the two groups of schools inducing a negative spurious correlation between natives' mean test scores and non-native shares, and downward bias in the estimation of ↓. Given that across school sorting is more likely to happen in urban areas (i.e. big municipalities group), concerns for across school sorting would then arise if we systematically find that $\left|\beta_{big\_municip}\right| > \left|\beta_{small\_municip}\right|$. Estimations in Table 10 reject this hypothesis: effects are similar in the two subsamples, though slightly larger, in absolute terms, in small municipalities.

An additional sensitivity check was carried out using instead of the five areas territorial dummies (North East, North West, Centre, South, Islands), 103 territorial dummies corresponding to junior-high school districts (which also correspond to Italian Provinces, NUT5). School districts by year fixed-effects and school fixed-effects would capture any kind of across-school sorting within each school district. Table 11 shows that the effects do not change with respect to the baseline specification. Thus we can conclude that across schools sorting is not a huge concern in our data and it seems adequately captured in our empirical model.

7.3 Tests for non-linear effects in non-native school share

In order to bring further evidence on non-linear effects between non-native school share and natives' attainments, we progressively add to the baseline model higher orders terms non-native school share in order to test the possible concave relation predicted by the 'disruptive model' or even any cubic or quadratic relevant relationship. Table 12 shows that higher order terms do not have statistically significant coefficients neither for Language nor for Math. Focusing our attention on the coefficient of the quadratic term, although not significant, it is also negative thus rejecting the hypothetical concave relation predicted by the 'bad apple principle' in the 'disruptive model'. However, as the analysis using the spline function shows, effects are highly non-linear. This finding also emerges from Table 13 and Table 14 where we use the spline functional form with very tiny intervals in the non-native school share values distribution to test whether it is possible to find evidence of statistically significant effects for some thinner intervals of the distribution of θ. We let spline thresholds coincide with the 20^{th}, 40^{th}, 60^{th} and 80^{th} percentiles in Table 13, and with the first up to the 9^{th} decile in Table 14. This test increment the robustness of the findings concerning the use of only one threshold exogenously determined as results show once more that the only negative and significant effects are concentrated in the upper percentiles or deciles of the distribution of non-native school share.

8. Conclusions

This paper shed light on peer interaction between native and non-native students contributing to the existing literature in three main aspects. First, we provide a theoretical framework to interpret possible underlying social mechanisms that work through peer interactions; second, we estimate the effect of non-native school share on natives' attainments identifying the social interaction parameter (↓); third, allowing for non-linear effects, we provide empirical evidence to test the stylized predictions of the theoretical framework. The estimation results are of substantial interest *per se*, given the limited evidence in European setting of peer effects between natives and immigrants, and given the growing relevance of the immigration phenomenon and its impacts, not only on the labour markets, but also on the school system. Increasing non-native school share by 1% determines a decrease of 6.5% in native peers' Language test score, and no significant effects in Math. These results are in line with the limited evidence from European literature on peer effects between immigrants and native students (see Brunello and Rocco, 2011), and with evidence from U.S. (Angrist and Lang, 2004; Hoxby, 2000; Hanushek and Rivkin, 2009; Sacerdote, 2010) which finds limited evidence of negative 'between-groups' effects.

However, introducing non-linearity in the effects and rooting our analysis on the comparison between the 'disruptive' and the 'integration' model of education production proposed in the theoretical framework allows us to interpret the results in a more precise way. Therefore, if, in general, the 'disruptive' behaviour of non-native peers *causes* only small negative externalities on natives' Language test scores, introducing non-linearity shows that negative effects are concentrated only in schools with sufficiently high values of non-native school-share and characterized by a non-concave relation (i.e. the negative effects are not marginally increasing with respect to non-native school share). To give a numerical intuition, we calculate that, on average, a non-native school share of 10% corresponds to 9 non-native students in the school, or, equivalently, 2 or 3 non-natives students in each class. Thus, if in each class there are up to two or three non-native students, the 'disruption' mechanism is not strong enough to affect natives' attainment. Interestingly, this result is stronger for language skills, where it is likely that 'disruption' occurs more frequently given the greater difficulties to learn a non-mother-tongue for non-natives. The overall pattern of these findings is more consistent with the 'integration model' of peer interaction and robust under many dimensions.

Our work also suggests important policy implications concerning allocation rules of non-native students across classes and across schools. Notice that policy implications are different according to the mechanism that is at work. The simple 'disruption mechanism' would entail average outcome to be maximized when schools are totally segregated by type of student. On the contrary, the 'integration mechanism' let allocation rules play a substantive role in minimizing the negative externalities and fostering the integration processes. In fact, according to the ‘integration mechanism’ any allocation rule should be constructed so to avoid any concentration of non-native students in the same class or school, and rather distribute them equally or according to some thresholds empirically determined. As our empirical results support this latter mechanism of social interactions between native and non-native students, we can posit a relative isolation of non-native students from other non-native peers is beneficial for natives as it forces the integration mechanism between the two peer groups. A non-native school share below 10% in each school would ensure the ‘integration mechanism’ to be at work. For instance, a recent regulation act from the Italian Ministry of Education imposes a cap threshold of 30% to non-native share in each class[36]. According to our findings, this threshold would be inefficiently high and may not have any effect to the educational production in the classroom. Indeed, more research has to be undertaken to study peer effects within the peer group of non-natives students, to understand to which extent their concentration in the school or in the class could harm themselves and induce their clustering.

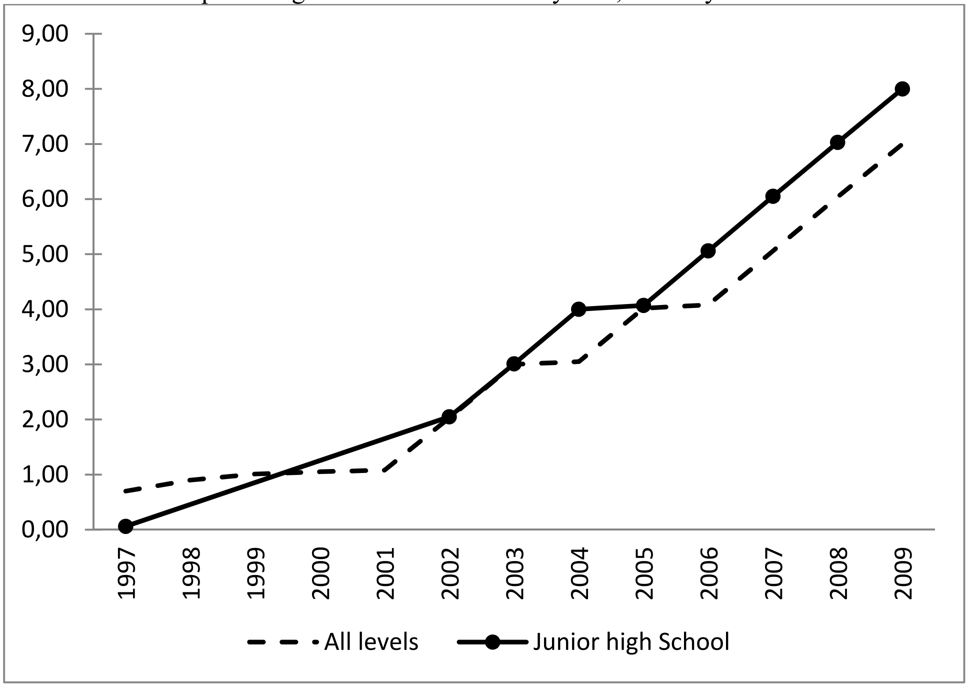
To sum up, we can conclude that the ‘disruptive mechanism of native/non-native students peer interactions’ is able to explain only a part of the empirical evidence. The most critical aspect concerns the convex relation which is not embedded in the education production function à la Lazear (2001). This is because the original Lazear model is based on the underlying ‘bad apple principle’: one disruptive student is enough to generate bad spill-overs on all the class, and the greater is the concentration of more disruptive types, the lower will be the negative effects. This mechanism is rejected by the empirical analysis proposed, which rather shows that, as long as non-native school share is sufficiently low, non-native students presence is not able to generate negative peer effects on native outcomes and rather support the ‘integration model’. A possible interpretation of the results is that the negative effects seem to be concentrated in schools where non-native students are enough to form a ‘critical mas’ so that they tend to cluster and do not change their behaviour thanks to the integration process. This interpretation is also in line with the general evidence of ‘acting white’ behaviours in the U.S. schools. The ‘integration effects’ of native students seems to work only if non-native share is ‘sufficiently low’ so that it is not too costly for natives to make effort to

[36] “*Indicazioni e raccomandazioni per l’integrazione di alunni con cittadinanza non italiana*”, MIUR, Circolare Ministeriale No. 2/2010 (C.M. 8/1/2010, n. 2).

interact and integrate non-native peers, and, in the other way round, non-natives are somehow ‘forced’ to interact with native peers. Interestingly, all the results are stronger for Language test scores, confirming that Language skills are more influenced by peer interaction between native and non-natives, rather than Mathematical skills.

Figures

Figure 1. Non-native students percentage in the Italian school system, from s.y. 1996-07 to 2008-09.



Source: own elaboration on MIUR (2009) data.

Figure 2. Average percentage of non-native student per school (i.e. 'school share') by macro-area and school year (Invalsi IC data).

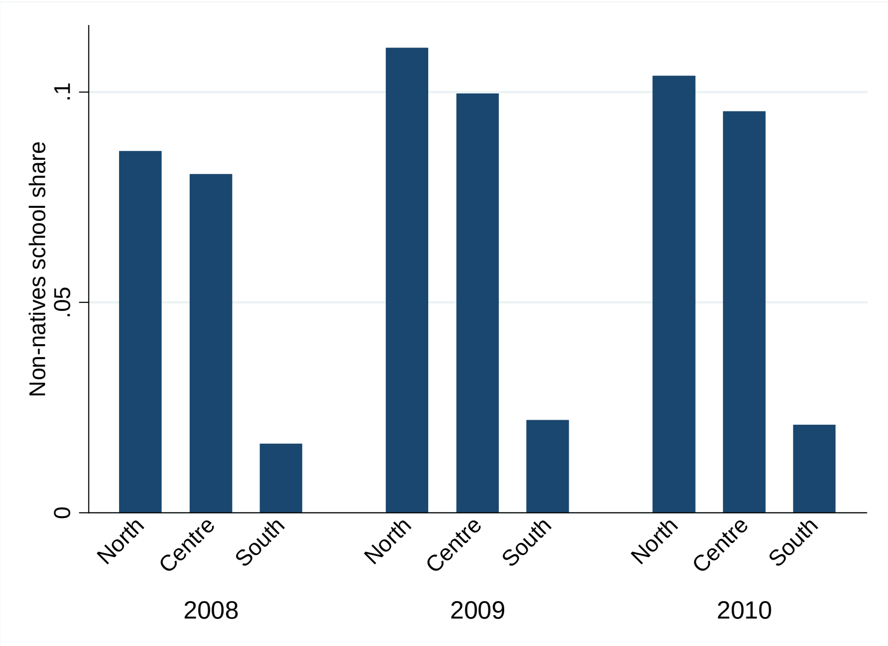


Figure 3. The 'disruption model': concave relation between non-native school share (θ) and per student output (y) (the 'bad apple principle').

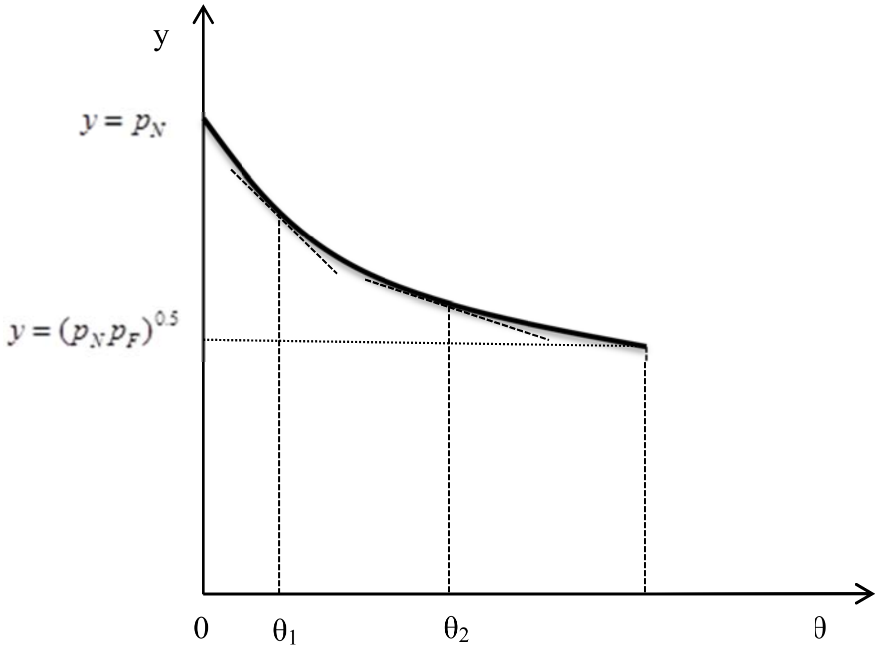
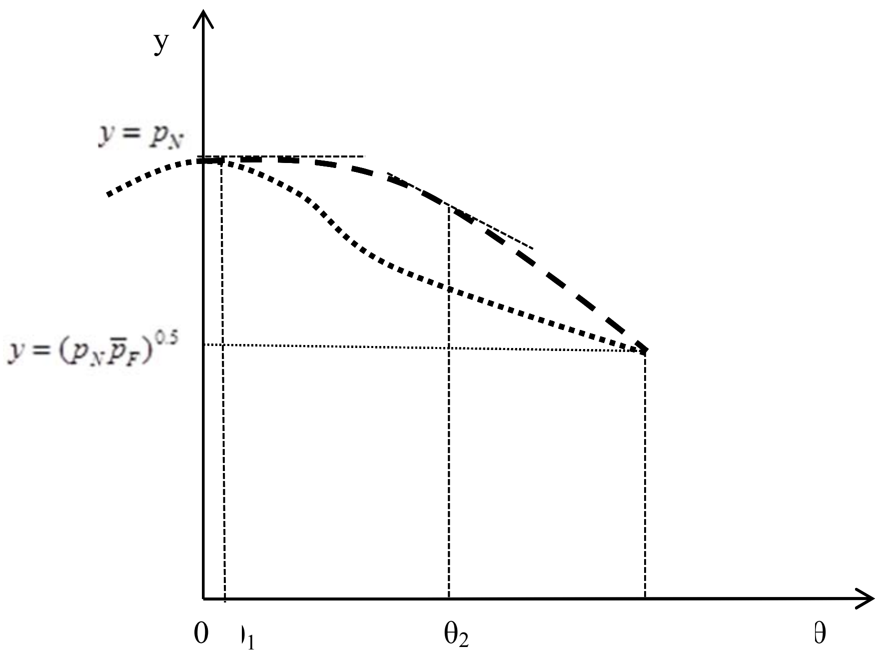


Figure 4. The 'integration model': examples of possible shapes of the relation between non-native school share (θ) and per student output (y) consistent with the assumption on $p_F(\theta)$**.**



Tables

Table 1. School level descriptive statistics.

Wave Invalsi IC	*Area*	*No. Students*	*No. Schools*	*% Public Schools*	*% Non-native students*	*Avg. No. Students per School*	*Avg. No. Students per Class*	*% Schools linked to Catchment Area Info.*
2007-08	North	201,650	2313	83.48	9.49	295.32	21.08	95.72
	Centre	89,870	998	85.77	8.07	301.62	20.68	94.99
	South	204,339	2388	95.27	1.48	287.48	19.36	93.34
	Tot.	*495,859*	*5699*	*88.82*	*5.95*	*293.11*	*20.28*	*94.59*
2008-09	North	211,567	2359	83.59	11.20	341.94	21.20	94.82
	Centre	93,440	1017	86.52	8.97	342.03	20.83	94.00
	South	205,856	2427	95.09	1.83	298.58	19.75	93.08
	Tot.	*510,863*	*5803*	*88.91*	*7.04*	*322.21*	*20.48*	*93.95*
2009-10	North	206,530	2368	83.78	11.24	306.61	21.30	93.12
	Centre	91,629	1009	86.72	9.28	315.50	21.00	92.86
	South	199,405	2356	95.33	1.84	291.01	20.08	91.85
	Tot.	*497,564*	*5733*	*89.04*	*7.12*	*301.72*	*20.74*	*92.55*

Table 2. Mean and standard deviation of Invalsi IC average school test scores for native and non-native students.

MEAN						
	Language			Math		
Wave Invalsi IC	Natives	Non-natives	Delta	Natives	Non-natives	Delta
2007-08	68.73	59.44	9.29***	54.15	47.65	6.50***
2008-09	67.01	53.39	13.62***	66.11	56.28	9.83***
2009-10	65.24	55.80	9.44***	55.74	49.82	5.92***
SD						
	Language			Math		
Wave Invalsi IC	Natives	Non-natives	Ratio	Natives	Non-natives	Ratio
2007-08	6.36	11.77	0.54***	8.79	12.55	0.70***
2008-09	8.22	15.01	0.55***	9.43	15.51	0.61***
2009-10	7.05	11.11	0.63***	8.16	11.07	0.74***

Notes. Test scores range from 0 to 100 (percentage of right answers). Delta indicates the difference between test score means of (native – non-native); *** indicates whether Delta>0 (ttest, p.val≤0.001); Ratio indicates the ratio between test score sd of (native / non-native); *** indicates whether Ratio<1 (p.val≤0.001).

Table 3. Gap in individual test scores between native and non-native students (Invalsi IC 2009-2010).

	Dep. Var.: individual test score			
	Italian Language test score			
Non-native (dummy)	-0.2121***	-0.0685***	-0.0773***	-0.0716***
	(0.0025)	(0.0039)	(0.0039)	(0.0038)
	Math test score			
Non-native (dummy)	-0.1508***	-0.0455***	-0.0483***	-0.0405***
	(0.0025)	(0.0047)	(0.0042)	(0.0040)
Clusters	6215	6190	5513	5513
N	994593	852099	794896	794896
Controls:				
Year Dummies	*X*	*X*	*X*	*X*
Individual Characteristics		*X*	*X*	*X*
School Characteristics			*X*	*X*
Province FE				*X*

*(Robust Std. Errors in parenthesis, Clustered at the School level). Significance level: * p<0.1, ** p<0.05, *** p<0.01*

Notes. Coefficients are obtained from the dummy variable 'being non-native' through pooled OLS regressions performed at the individual level. For detailed description of control variables included in the individual and school characteristics see Appendix B, Table B.1. Province fixed-effects (*Province FE*) include 103 territorial dummies.

Table 4. Differences in test scores between native and non-native students, in some OECD countries.

	Native students		*Second-generation students*		*First-generation students*	
	Mean	S.E.	Mean	S.E.	Mean	S.E.
Australia	529	(2.0)	528	(5.7)	527	(5.7)
Austria	523	(3.5)	431	(13.4)	435	(10.9)
Belgium	523	(2.4)	443	(7.3)	430	(8.3)
Canada	541	(1.8)	528	(4.8)	519	(5.2)
Denmark	503	(2.9)	418	(11.0)	414	(8.0)
France	505	(3.5)	456	(10.4)	438	(10.1)
Germany	532	(3.2)	439	(8.7)	455	(8.8)
Greece	478	(3.2)	-	-	428	(10.3)
Ireland	510	(3.0)	-	-	500	(14.6)
Italy	479	(2.0)	-	-	418	(8.2)
Luxembourg	511	(1.6)	445	(3.0)	445	(3.7)
Netherlands	534	(2.3)	455	(11.2)	467	(10.2)
New Zealand	536	(2.6)	508	(8.0)	526	(6.6)
Norway	493	(2.5)	-	-	433	(11.2)
Portugal	479	(2.9)	-	-	412	(11.1)
Spain	494	(2.4)	-	-	428	(7.2)
Sweden	512	(2.3)	464	(6.0)	434	(8.1)
Switzerland	531	(2.9)	462	(4.8)	436	(6.9)
United Kingdom	519	(2.0)	493	(8.9)	479	(14.7)
United States	499	(4.3)	456	(6.7)	442	(7.9)
OECD average	506	(0.5)	466	(2.2)	453	(2.1)

Source: PISA 2006, test scores in Science.

Table 5. Control variables used, description and source.

Type	*Name*	*Description*	*Source*
Individual (X)	*female*	Fraction of native females in school s (grade 8)	Invalsi / MIUR
	late	Fraction of native retained students in school s (grade 8)	
	father place of birth	Fraction of native students in school s and grade 8 with father born abroad	
	always_italy	Fraction of native students in school s grade 8 in Italy since birth	
	mother place of birth	Fraction of native students in school s and grade 8 with mother born abroad	
School (S)	*Non-native school share*	Fraction of 8 grade non-native students in school s	
	nonnatives_stock	Total number of non-native students in the school (6, 7 and 8 grade)	
	school_size	School size, given by the total number of students in the school (6, 7 and 8 grade).	
	High_cheating_dummy (subject specific)	Dummy equal 1 if the school is in the 9th decile of the school cheating coefficient distribution	
Catchment Area (W)	*lpop*	Log of total resident population	Census 2001
	illiterate	Fraction of illiterate pop.	
	university_edu	Fraction of pop. with university level education	
	m_occup_rate	Male occupation rate	
	f_occup_rate	Female occupation rate	
	foreign_citizens	No. of non-Italian residents	
	agri_oc	Fraction of workers occupied in agriculture	
	self_empl	Fraction workers self-employed	
	commuter	Fraction of resident commuting every day for school or working reasons	
	avg_family_members	Average number of family members	
	house_poor	Fraction of houses without clean water	
	house_new	Fraction of houses built after 1980	
	avg_rooms	Average number of rooms per house	

Table 6. Baseline model results with school fixed-effects.

	Dep. Var.: School Mean Log Score for NATIVE students					
	Language			Math		
	(I)	(II)	(III)	(I)	(II)	(III)
Non-native SS	-0.0867***	-0.0584**	-0.0653**	-0.0866**	-0.0428	-0.0499
	(0.0230)	(0.0249)	(0.0253)	(0.0345)	(0.0336)	(0.0344)
R sq.	0.172	0.289	0.302	0.462	0.587	0.589
Adj.R sq.	0.171	0.288	0.300	0.461	0.587	0.587
Clusters	6289	5115	4827	6290	5115	4827
N	17198	14368	13851	17199	14368	13851
Controls						
Individual Charact. (X), school and year FE	X	X	X	X	X	X
School variables		X	X		X	X
Catchment Area*Year FE			X			X
(Robust Std. Errors in parenthesis, Clustered at the School level). Sig. level: * p<0.1, ** p<0.05, *** p<0.01						

Table 7. Non-linear effects: spline linear functions with one structural break (T)

	Dep. Var.: School Mean Log Score for NATIVE students				
	Language				
	T=0.04 (med)	T=0.065 (mean)	T=0.10 (P75)	T=0.20 (P95)	T=0.25 (>P95)
Share < T ($\downarrow_1$)	-0.0648	-0.0239	-0.0185	-0.0469*	-0.0478*
	(0.1080)	(0.0686)	(0.0452)	(0.0278)	(0.0259)
Share > T ($\downarrow_2$)	-0.0628**	-0.0764**	-0.0954**	-0.1199*	-0.1615*
	(0.0291)	(0.0319)	(0.0379)	(0.0728)	(0.0949)
R sq.	0.300	0.300	0.300	0.300	0.300
Adj.R sq.	0.298	0.298	0.298	0.298	0.298
Clusters	4825	4825	4825	4825	4825
N	13576	13576	13576	13576	13576
	Math				
	T=0.04 (med)	T=0.065 (mean)	T=0.10 (P75)	T=0.20 (P95)	T=0.25 (>P95)
Share < T ($\downarrow_1$)	-0.0844	-0.0047	0.0234	-0.0078	-0.0147
	(0.1448)	(0.0939)	(0.0620)	(0.0381)	(0.0350)
Share > T ($\downarrow_2$)	-0.0405	-0.0612	-0.0977*	-0.1840*	-0.2536*
	(0.0397)	(0.0440)	(0.0528)	(0.1084)	(0.1417)
R sq.	0.589	0.589	0.589	0.589	0.589
Adj.R sq.	0.588	0.588	0.588	0.588	0.588
Clusters	4825	4825	4825	4825	4825
N	13576	13576	13576	13576	13576
All Controls	X	X	X	X	X
(Robust Std. Errors in parenthesis, Clustered at the School level). Significance level: * p<0.1, ** p<0.05, *** p<0.01					

Table 8. Non-linear effects: spline linear functions with two break points (T1=0.10 and T2=0.2, 0.25, 0.3).

	Dep. Var.: School Mean Log Score for NATIVE students					
	Language			Math		
	T1=0.10 T2=0.20	T1=0.10 T2=0.25	T1=0.10 T2=0.30	T1=0.10 T2=0.20	T1=0.10 T2=0.25	T1=0.10 T2=0.30
Share < T1 ($\downarrow_1$)	-0.0215	-0.0241	-0.0249	0.0087	0.0095	0.0136
	(0.0465)	(0.0459)	(0.0456)	(0.0630)	(0.0624)	(0.0622)
T1<Share<T2 ($\downarrow_2$)	-0.0820*	-0.0723*	-0.0697*	-0.0304	-0.0397	-0.0577
	(0.0471)	(0.0397)	(0.0388)	(0.0639)	(0.0528)	(0.0514)
Share > T2	-0.1114	-0.1544	-0.2133*	-0.1785	-0.2463*	-0.2812
	(0.0741)	(0.0952)	(0.1222)	(0.1104)	(0.1418)	(0.1785)
R sq.	0.300	0.300	0.301	0.589	0.589	0.589
Adj.R sq.	0.298	0.298	0.298	0.588	0.588	0.588
Clusters	4825	4825	4825	4825	4825	4825
N	13576	13576	13576	13576	13576	13576
All Controls	X		X		X	X

(Robust Std. Errors in parenthesis, Clustered at the School level). Significance level: * p<0.1, ** p<0.05, *** p<0.01

Table 9. Sensitivity analysis to missing variables.

	Dep. Var.: School Mean Log Score for NATIVE students			
	Language			
	(I)	(II)	(III)	(IV)
Non-native SS	-0.0639**	-0.0616**	-0.0718***	-0.0732***
	(0.0253)	(0.0250)	(0.0237)	(0.0229)
R sq.	0.302	0.300	0.276	0.272
Adj.R sq.	0.299	0.298	0.274	0.270
Clusters	4827	4992	5557	6150
N	13855	14142	16114	16919
	Math			
	(I)	(II)	(III)	(IV)
Non-native SS	-0.0512	-0.0450	-0.0534	-0.0581*
	(0.0344)	(0.0340)	(0.0329)	(0.0330)
R sq.	0.589	0.589	0.573	0.574
Adj.R sq.	0.587	0.588	0.571	0.573
Clusters	4827	4992	5557	6151
N	13855	14142	16114	16920
All Controls	X	X	X	X
Catchment Area Missing Correction		X		X
School Variable Missing Correction			X	X
(Robust Std. Errors in parenthesis, Clustered at the School level). Sig. level: * p<0.1, ** p<0.05, *** p<0.01				

Table 10. Sensitivity analysis: big vs. small municipalities.

	Dep. Var.: School Mean Log Score for NATIVE students			
	Language			
	Big Municipalities	Small Municipalities	Big Municipalities	Small Municipalities
Non-native SS	-0.0561*	-0.0808	-0.0559**	-0.0983**
	(0.0288)	(0.0522)	(0.0281)	(0.0403)
R sq.	0.305	0.316	0.301	0.242
Adj.R sq.	0.302	0.306	0.298	0.236
Clusters	3757	1070	3949	2201
N	10873	2984	11342	5577
	Math			
	Big Municipalities	Small Municipalities	Big Municipalities	Small Municipalities
Non-native SS	-0.0386	-0.0938	-0.0344	-0.1049
	(0.0375)	(0.0796)	(0.0366)	(0.0656)
R sq.	0.595	0.579	0.596	0.538
Adj.R sq.	0.593	0.572	0.594	0.534
Clusters	3757	1070	3949	2202
N	10873	2984	11342	5578
All Controls	X	X	X	X
Corrected Missing			X	X
(Robust Std. Errors in parenthesis, Clustered at the School level). Significance level: * p<0.1, ** p<0.05, *** p<0.01				

Table 11. Sensitivity analysis: school district fixed-effects (province * Year).

	Dep. Var.: School Mean Log Score for NATIVE students			
	Language		Math	
Non-native SS	-0.0492*	-0.0636***	-0.0410	-0.0533
	(0.0252)	(0.0228)	(0.0344)	(0.0332)
R sq.	0.340	0.311	0.604	0.588
Adj.R sq.	0.328	0.301	0.597	0.582
Clusters	4827	6150	4827	6151
N	13857	16917	13857	16918
All Controls	X	X	X	X
Province * Year FE	X	X	X	X
Corrected Missing		X		X

(Robust Std. Errors in parenthesis, Clustered at the School level).
Significance level: * p<0.1, ** p<0.05, *** p<0.01

Table 12. Sensitivity analysis: non-linear effects adding higher order polynomials of non-native school share.

	Dep. Var.: School Mean Log Score for NATIVE students		
		Language	
Non-native SS (θ)	-0.0114	-0.0332	-0.0594
	(0.0456)	(0.0743)	(0.1047)
θ^2	-0.1833	-0.0319	0.2683
	(0.1488)	(0.4448)	(0.9582)
θ^3		-0.2198	-1.1925
		(0.6692)	(3.0710)
θ^4			0.8719
			(2.9342)
R sq.	0.300	0.300	0.300
Adj.R sq.	0.298	0.298	0.298
Clusters	4826	4826	4826
N	13576	13576	13576
		Math	
Non-native SS (θ)	0.0178	0.0172	-0.0317
	(0.0695)	(0.1032)	(0.1415)
θ^2	-0.2638	-0.1596	0.4001
	(0.2300)	(0.6247)	(1.3042)
θ^3		-0.2637	-2.0773
		(0.9547)	(4.2211)
θ^4			1.6258
			(4.0370)
R sq.	0.519	0.519	0.519
Adj.R sq.	0.517	0.517	0.517
Clusters	4826	4826	4826
N	13576	13576	13576
All Controls	X	X	X

(Robust Std. Errors in parenthesis, Clustered at the School level).
Significance level: * p<0.1, ** p<0.05, *** p<0.01

Table 13. Sensitivity analysis: spline functions with intervals of five percentiles.

	Dep. Var.: School Mean Log Score for NATIVE students	
	Language	**Math**
pc1 (θ)	0.00	0.00
pc2 (θ)	-0.3092	-0.3747
	(0.1999)	(0.2598)
pc3 (θ)	0.1306	0.1399
	(0.1195)	(0.1636)
pc4(θ)	-0.0450	0.0865
	(0.0648)	(0.0898)
pc5(θ)	-0.0991**	-0.1440**
	(0.0436)	(0.0615)
R sq.	0.300	0.588
Adj.R sq.	0.298	0.587
Clusters	4826	4826
N	13576	13576
All Controls	X	X

(Robust Std. Errors in parenthesis). Sig. level: * p<0.1, ** p<0.05, *** p<0.01

Table 14. Sensitivity analysis: spline functions with intervals of ten percentiles.

	Dep. Var.: School Mean Log Score for NATIVE students	
	Language	**Math**
pc1 (θ) - pc2 (θ)	0.00	0.00
pc3 (θ)	-0.6259	-1.4945
	(0.6816)	(0.9318)
pc4(θ)	-0.1320	0.3666
	(0.4543)	(0.6064)
pc5(θ)	0.1468	-0.1010
	(0.3870)	(0.5002)
pc6 (θ)	0.0364	0.1794
	(0.2444)	(0.3361)
pc7 (θ)	0.0932	0.1549
	(0.1781)	(0.2515)
pc8 (θ)	-0.1659	0.0003
	(0.1350)	(0.1820)
pc9(θ)	-0.0309	-0.0840
	(0.0971)	(0.1332)
pc10(θ)	-0.1137*	-0.1577*
	(0.0619)	(0.0906)
R sq.	0.300	0.589
Adj.R sq.	0.298	0.587
Clusters	4826	4826
N	13576	13576
All Controls	X	X

(Robust Std. Errors in parenthesis). Sig. level: * p<0.1, ** p<0.05, *** p<0.01

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Appendix A. Institutional framework

Non-native students in the Italian school system: the existing normative framework and the 'Gelmini rule'

Only in the last decade the total number and the percentage of non-native students enrolled in the school system has dramatically risen (Table A1, Figure A1). Concerning the general time trends, Table A.2 shows that the percentage variation in non-native students' population is now decreasing, after the peaks at the end of the Nineties and at the beginning of the present decade.

Table A1. Non-native students, school level detail.

School Year	*All Levels*		*Kindergarten*		*Primary*		*Lower Secondary*		*Upper Secondary*	
	Total No.	%	Total No.	%	Total No.	%	Total No.	%	Total No.	%
1996/1997	59389	0.7	12809	0.8	26752	1.0	11991	0.6	7837	0.3
1997/1998	…	…	…	…	…	…	…	…	…	…
1998/1999	85522	1.1	…	…	…	…	…	…	…	…
1999/2000	119679	1.5	…	…	…	…	…	…	…	…
2000/2001	147406	1.8	…	…	…	…	…	…	…	…
2001/2002	181767	2.3	39445	2.5	84122	3.0	45253	2.5	27594	1.1
2002/2003	232766	3.0	48072	3.0	100939	3.7	55907	3.1	34890	1.3
2003/2004	282683	3.5	59500	3.6	123814	4.5	71447	4.0	52380	2.0
2004/2005	361576	4.2	74348	4.5	147633	5.3	84989	4.7	63833	2.4
2005/2006	424683	4.8	84058	5.0	165951	5.9	98150	5.6	83052	3.1
2006/2007	501445	5.6	94712	5.7	190803	6.8	113076	6.5	102829	3.8
2007/2008	574133	6.4	111044	6.7	217716	7.7	126396	7.3	118977	4.3
2008/2009	629360	7.0	125092	7.6	234206	8.3	140050	8.0	130012	4.8

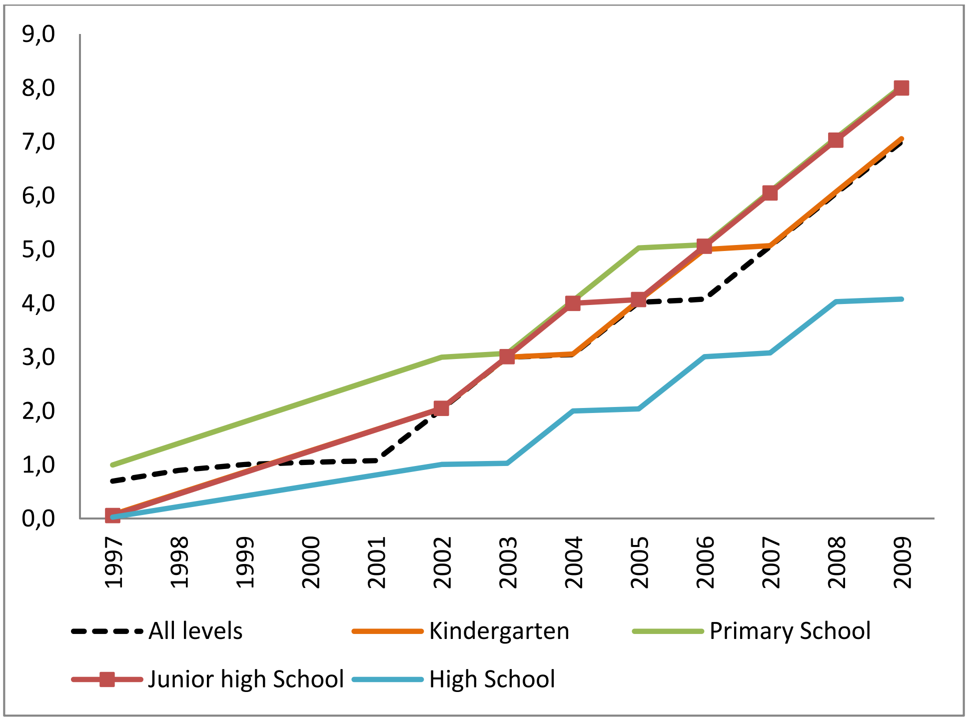
Source: elaboration from MIUR (2009a, 2009b).

Table A2. Variation in non-native students enrolled, school level detail.

School Year	*All Levels*		*Kindtergarden*		*Primary*		*Lower Secondary*		*Upper Secondary*	
	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)	(A)	(B)
1996/1997	100	-	100	…	100	…	100	…	100	…
1998/1999	144	44.00	…	…	…	…	…	…	…	…
1999/2000	202	39.94	…	…	…	…	…	…	…	…
2000/2001	248	23.17	…	…	…	…	…	…	…	…
2001/2002	306	23.31	308	-	314	-	377	-	352	-
2002/2003	392	28.06	375	21.87	377	19.99	466	23.54	445	26.44
2003/2004	476	21.45	465	23.77	463	22.66	596	27.80	668	50.13
2004/2005	609	27.91	580	24.95	552	19.24	709	18.95	815	21.87
2005/2006	715	17.45	656	13.06	620	12.41	819	15.49	1060	30.11
2006/2007	844	18.08	739	12.67	713	14.98	943	15.21	1312	23.81
2007/2008	967	14.50	867	17.24	814	14.11	1054	11.78	1518	15.70
2008/2009	1060	9.62	977	12.65	875	7.57	1168	10.80	1659	9.27

Source: elaboration from MIUR (2009a, 2009b). **Notes:** Column *(A)* contains the increment with respect to 1996-97 school year (=100); column *(B)* contains the percentage increase with respect to the (available) year before.

Figure A1. Time trend in the percentage of non-native students enrolled in Italian schools, by school level.



Source: own elaboration from MIUR (2009a, 2009b).

Students from Romania, Albania and Morocco contribute for almost 45% of the total non-Italian students population, and, in general, students from European countries (EU and non-EU) and from Africa cover more than two thirds of the non-native students population (MIUR 2009a, 2009b). Another element observed in the non-native students population in the last years is the growing number of non-native students born in Italy (so called, 'second generation' immigrants). Only for 2008-09 school year the Statistical Office provides data on this (Table A3): almost 37% of non-Italian students are born in Italy (in some Northern regions - Lombardy and Veneto - the percentage increases up to 40%). Despite the limited evidence available[37], a pattern emerges from Table A.3: the presence of 'second generation' non-Italian students is concentrated in the lowest education levels (i.e. kindergarten and primary school where, respectively, 73.3% and 45% of non-Italian students are born in Italy); the issue is less relevant in lower and upper secondary school (where, respectively, the percentage decreases to 18.8% and

[37] Only recently (starting from the 2008-09 school year) the Ministry of Education Statistical Service has begun to record in a different way non-Italian students born abroad and non-Italian students born in Italy from (both) non-Italian parents, this latter being part of the category of 'second generation immigrants'.

7.5%). The remarkable presence of 'second generation' non-Italian students in the lowest educational level and kindergartens is probably a consequence of the massive migrant flows of the Nineties. Second generation immigrants are children born in households settled in Italy during the last decade, therefore, despite maintaining their foreigner status, they are in Italy since their birth and they are plausibly more integrated than non-native first generation students.

Table A3. Non-native students born in Italy, detail for 2008-09 school year, by school level.

School level	*No.*			*% wrt Total Students Pop.*			*% wrt Non-native Students*		
	Born in Italy	Born abroad	Total	Born in Italy	Born abroad	Total	Born in Italy	Born abroad	Total
Kindtergarden	91647	33445	125092	5.5	2.1	7.6	73.3	26.7	100
Primary	105292	128914	234206	3.7	4.6	8.3	45.0	55.0	100
Lower Secondary	26366	113684	140050	1.5	6.5	8.0	18.8	81.2	100
Upper Secondary	9698	120314	130012	0.3	4.5	4.8	7.5	92.5	100
Total	233003	396357	629360	2.6	4.4	7.0	37.0	63.0	100

Source: elaboration from MIUR (2009b).

During the past twenty years, the Italian Ministry of Education has produced administrative acts[38] concerning the growing phenomenon of the presence of non-native students in the school system, disciplining the basic tools to implement an integration of native and non-native students (the so called 'intercultural education approach'. The Italian normative discipline of migration and migration flows[39] recalls the duty of the schools to implement adequate intercultural education, to preserve and add value to the differences brought by non-native students and their culture. The principles of the law are enforced through the D.P.R. No. 394/1999, which constitutes the reference regulatory framework. The basic elements to recall here are three: first, the right and the duty for every immigrant individual in school age, to be enrolled in the suitable school institution, independently from their legal or illegal status[40]; second, the duty for every school to accept and enrol immigrant students in every moment of the school year;

[38] Among others: C.M. 8/9/1989, n. 301 "*Inserimento degli alunni stranieri nella scuola dell'obbligo. Promozione e coordinamento delle iniziative per l'esercizio del diritto allo studio*", C.M. 22/7/1990, n. 205, "*La scuola dell'obbligo e gli alunni stranieri. L'educazione interculturale*", C.M. 1/3/2006, n. 24, "*Linee guida per l'accoglienza e l'integrazione degli alunni stranieri*".

[39] Legge n. 40/1998, art. 36. The law n. 189/2002 (so-called 'Bossi-Fini') introduced a new regulatory framework to control immigration flows (innovating the previous law n. 40/1998) but did not change in any part the normative framework for the enrollment of immigrant children, established in the D.P.R. No. 394/1999.

[40] The D.P.R. introduces in the Italian legislative framework the content of the *Human Rights Convention* (U.N., 1948) and *International Convention on Children Rights* (U.N., 1989).

third, the competence of the School Board and Head (i.e. *Collegio Docenti* and *Dirigente Scolastico*) to allocate foreign students so to avoid the "constitution of classes where their presence is predominant". Non-native students should be allocated to the grade and class appropriate for their age (so called 'age-rule'), however, the School Board is allowed to allocate non-native incoming students to a lower grade depending on the native country school system, language skills, and type of school path followed in the previous school system. Notice also that students previously enrolled in a school in a EU country should be automatically allocated to the appropriate Italian grade and school corresponding to their age[41].

Table A4. Presence of non-native students per classes.

	Classes with a percentage of Non-Italian students > 30%							
	Primary				Lower Secondary			
	Non-Italian students		Only Non-Italian students born abroad		Non-Italian students		Only Non-Italian students born abroad	
	N.	%	N.	%	N.	%	N.	%
Piemonte	817	11.1	175	12.7	341	10.9	215	13.7
Lombardia	2040	27.4	218	16.6	915	29.3	423	27.0
Veneto	989	13.1	117	8.4	393	12.6	189	12.1
Friuli VG	176	2.4	38	2.9	104	3.3	59	3.8
Liguria	258	3.8	89	6.9	118	3.8	90	5.7
Emilia Romagna	950	12.7	128	9.2	417	13.4	173	11.0
Toscana	567	7.9	90	6.9	236	7.6	115	7.3
Umbira	242	3.3	46	3.4	91	2.9	50	3.2
Marche	307	4.2	57	4.4	124	4.0	49	3.1
Lazio	550	7.4	130	9.7	272	8.7	139	8.9
Abruzzo	79	1.2	43	3.7	20	0.6	11	0.7
Molise	13	0.2	13	1.0	4	0.1	4	0.3
Campania	43	0.6	36	2.7	10	0.3	7	0.4
Puglia	27	0.9	7	0.8	10	0.3	3	0.2
Basilicata	5	0.1	2	0.2	2	0.1	1	0.1
Calabria	84	1.2	77	5.8	19	0.6	17	1.1
Sicilia	117	2.0	53	4.4	42	1.3	20	1.3
Sardegna	15	0.4	6	0.5	4	0.1	3	0.2
Italia	7279	100	1325	100	3122	100	1568	100

Source: MIUR (2010).

In January 2010, the Italian Ministry of Education introduced a new rule for the allocation of non-native students within classes and schools, establishing that class should not contain more than 30% of non-native students (i.e. students with non-Italian citizenship)[42]. The idea behind the implementation of such a threshold is to avoid social segregation in the schools and in the classes within schools, especially in areas where immigrant population, and, as a consequence, the concentration of non-native students enrolled at schools, is particularly high. As a matter of fact, the rules in the D.P.R. No.

[41] D. lgs. n. 297/1994, art. 115-116.
[42] "*Indicazioni e raccomandazioni per l'integrazione di alunni con cittadinanza non italiana*", MIUR, Circolare Ministeriale No. 2/2010 (C.M. 8/1/2010, n. 2).

394/1999 already established that the allocation of non-Italian students within classes in a school should be decided by the School Board and Head in order to avoid the creation of any sort of ‘ghetto-classes’, however, the new regulation seems to reorganize in a less discretional way the general rules for the allocation of non-native students within the classes of the same school and also within schools operating in the same territory introducing the mandatory threshold.

The rule (that we name ‘*Gelmini rule’* form the surname of the Ministry of Education who introduced it) is enforced starting from the first-grade-classes of primary, lower and upper secondary schools of the 2010-11 school year. Its impact is not huge but still relevant, especially in the North and Centre of Italy (Table A.4): in Lombardy, for example, more than 29% of the classes in the lower secondary schools have a concentration of more than 30% of non-native students (the percentage decreases to the 27% if we consider only non-native students born abroad).

Geographical patterns of non-native students distribution across school-districts.

To capture geographical differences in the school population composition, distribution and concentration, we calculate two measures commonly used in residential segregation literature: the dissimilarity (*D*) and the exposure (*E*) index. We calculate the indices referring to the general distinction, based on citizenship criteria, between native and non-native students.

The first dimension we analyse is the *evenness* in the distribution of non-Italian students, as measured by the dissimilarity index, proposed by Duncan and Duncan (1955), Taueber and Taueber (1965), and extensively used in school segregation analysis (among the others, Cutler *et al.* 1999; Clotfelter, 1999; Allen and Vignoles, 2004). Suppose to divide a given area j in N_j sections ($i=1...N_j$), the dissimilarity index (*D*) measures the percentage of a group’s population (in our case, non-native students) that would have to change section for each section to have the same percentage of that group as the whole area (Echenique and Fryer, 2007). Defining the two groups as the non-native (*NI*) and native (*I*) student group, taking as reference area the province (j), and being each section a junior high school of the province ($i=1...N_j$) we obtain the dissimilarity index for each province j measuring the evenness of the distribution of non-native students across all junior high school of the province, in symbols:

$$D^j = \frac{1}{2}\sum_{i=1}^{N_j}\left|\frac{NI_i}{NI_j} - \frac{I_i}{I_j}\right|$$

where NI_i and I_i, and NI_j and I_j represent, respectively, the total number of non-native and native students in school i / in province j. D ranges from 0 (perfectly even distribution, meaning 'no segregation') to 1 (perfectly uneven distribution, i.e. 'maximum segregation'). As elementary and junior high schools students in Italy attend schools following a residential criterion (apart from private institutions, students have to attend elementary and junior high schools in the same municipality where they live), we calculate D for each province (j) according to the non-native students concentration in each school of the province (so, Nj = No. of schools in Province j). The province level is chosen as reference level because school districts authorities in Italy (i.e. *Provveditorati agli Studi*) are partitioned according to provinces geographical boundaries and are coordinated at a regional level by a general office. We also provide D^* as weighted mean of D at regional or geographical macro-area levels, with weights proportional to the total number of students per province (Allen and Vignoles, 2004).

The second dimension we analyze is *isolation*, which is a measure of the extent to which non-Italian students are exposed only to non-Italian peers, rather than to Italian. In particular, the Exposure Index ($E^j_{I/NI}$) is a measure of the exposure of native students to non-native students in each school district (i.e. province) j:

$$E^j_{I/NI} = \frac{\left[\sum_{i=1}^{N_j} I_{ij}\left(\frac{NI_{ij}}{NI_{ij}+I_{ij}}\right)\right]}{\left[\sum_{i=1}^{N_j} I_{ij}\right]}$$

where I_{ij} represents the sum of native students in school i of province j, and similarly NI_{ij} represents the sum of non-native students in school i of province j; N_j is the total number of junior high school in province j. This measure is a refinement of the simple non-native school share and is generally interpreted as the racial composition (percentage of non-native students) enrolled with the average native student (Clotfelter, 1999). As for D, we also provide E^* as weighted mean of E at regional or geographical macro-area levels, with weights proportional to the total number of students per province.

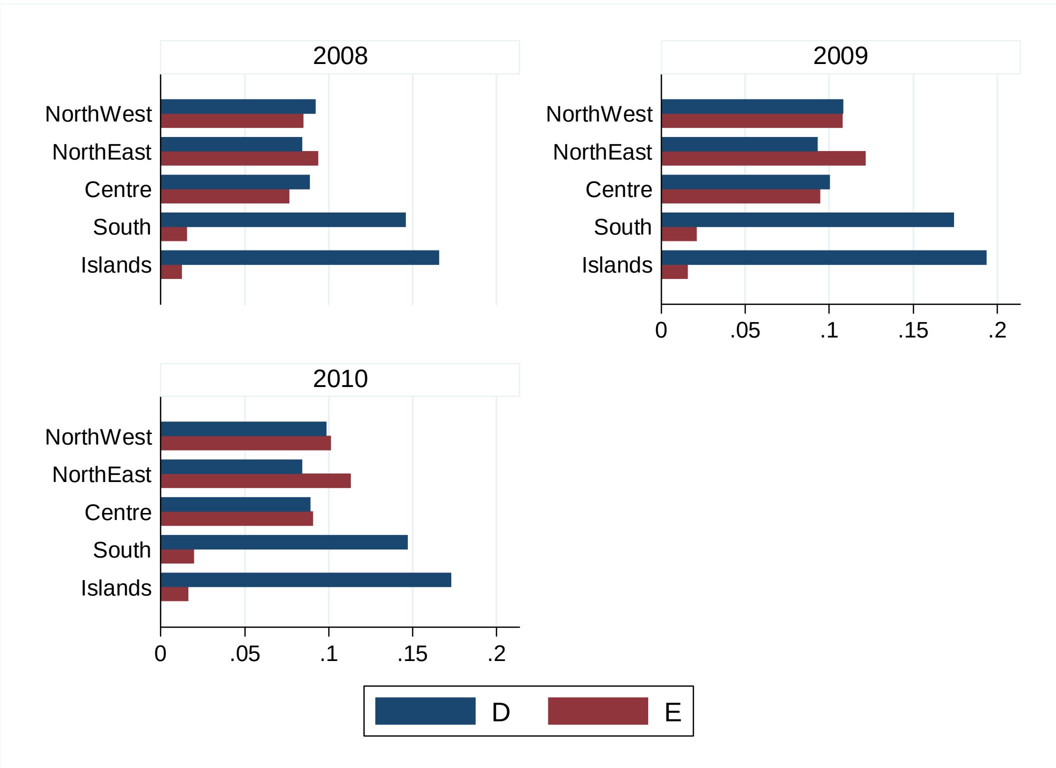
Table A5. School segregation measures: Dissimilarity (D, D*) and Exposure (E, E*) Indices.

Area	*D*	*D**	*E*	*E**
North West	0.0997	0.1107	0.0980	0.0979
North East	0.0871	0.0844	0.1095	0.1103
Centre	0.0926	0.1018	0.0873	0.0784
South	0.1557	0.1652	0.0186	0.0136
Islands	0.1774	0.1797	0.0148	0.0141
Total: Italy	0.1227	0.1297	0.0645	0.0608

Notes. D* and E* represents, respectively, the Dissimilarity and Exposure Index at the regional level as weighted average of D and E at province level, weights equal to the total number of students by province.

Results are constant across the three IC waves (see Appendix B for details on the datasets) and show a clear pattern (Figure A2 and Table A5): Exposure Index is generally inversely related to the Dissimilarity Index in the Southern regions, while they are almost similar in the North and Centre, so that in the areas of the country where the school concentration, and, consequently, the Exposure Index, is low, the Dissimilarity Index is generally high. Thus, in the South non-native students are less but more 'segregated' in some school districts, while in the North and Centre they are generally evenly distributed across schools and school districts.

Figure A2. Dissimilarity (D) and Exposoure (E) Indeces across geographical areas (Invalsi IC data).



Appendix B. Detailed data description, categories definitions and variables used

Detailed data description

We match three datasets containing individual level information on each 8th grade student who attended an Italian junior high school and sit the Invalsi *First Cycle Final Exam* in s.y. 2007-08, 2008-09 and 2009-10, administrative school records from Ministry of Education Statistical Office and information of each school 'catchment-area' collected from Census 2001 matched so to re-create the potential intake territory of each school.

Individual level information. INVALSI *First Cycle Final Exam Data* is a newly available census survey of Mathematics and Italian Language attainment levels for 8th grade students (ISCED 2 level) enrolled in all Italian public and private junior high schools. INVALSI (*Istituto Nazionale per la Valutazione del Sistema Educativo di Istruzione e di Formazione*) is the independent public institute established in 2004 to start a rigorous and objective evaluation of the Italian school system and Italian students' attainment levels. Starting from school year 2009-10, census survey on attainment levels and schools quality are conducted in grade 2 and 5 (primary schools), grade 6 and 8 (junior high schools) and grade 10 and 14 (high schools). As stated in the L. No. 176/2007, the 'First Cycle Final Exam' corresponds to 8th graders test and has been conducted since 2007-08 school year. However, only starting from the 2009-10 s.y., test scores contribute for one sixth of the final junior high school grade, while in previous years the test results did not enter directly in the final grade. Invalsi IC data are the first experience of standardized test scores census survey taken on all Italian students.

The dataset contains test scores and individual information on 1,504,286 8th grade students, aged between 13 and 14, who took the Invalsi standardized tests at the end of the 'first cycle' of compulsory education in the Italian schools[43] (i.e. after five years of primary education and three years of junior high school). Data contain separate test scores for Maths and Italian Language[44] ranging from 0 to 100, as they are expressed as percentage of right answers, and individual information is provided by the

[43] Both Math and Italian Language *First Cycle Invalsi Exam Test* take place in all junior high schools in June. Each part usually lasts one hour and between Language and Math test students have a fifteen minutes break.

[44] Italian Language exam is divided into three parts: narrative text comprehension, expositive text comprehension and grammar. The total Italian Language test score is obtained from the sum of the three parts.

school administrative staff through school administrative records (thus, not directly asked to students). In addition, because of cheating evidence in preliminary data analysis (Invalsi 2008a, b, 2009, 2010), for each student we have both the row and cheating-corrected Maths and Language test score[45]. For each student we know: year of birth, gender, citizenship (Italian, non-Italian), place of birth[46]; how long the student is in Italy if born abroad (from primary school, for 1-3 years, less than 1 year); mother's and father's place of birth (Italy, EU, European but non-EU, other non-European country) [47], grade retention (if the student is 'regular' i.e. if, at the end of 2010, he/she is 14 years old; 'in advance' i.e. younger than 'regular' students, or 'held back/retained' i.e. older than 'regular' students), school and class identifier (so, given a school, we can identify the class attended in that school by each student). Combining this information and following the categorization implemented in OECD Pisa Program, we are able to distinguish between Italian and non-Italian, native and non-native, immigrant and non-immigrant students, and, amongst immigrant students, first and second generation students[48],[49].

School level information. Invalsi and MIUR Statistical Office provided us with additional school level information. The census Invalsi IC Exam covers 5,699 junior high schools in 2007-08, 5,803 in 2008-09 and 5,733 in 2009-10. For each junior high school we know: ownership (i.e. public (state) school or private (recognized)

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[45] Sensitivity analysis confirm that raw and cheated-corrected results coincide once we control for geographical differences (i.e. we introduce in the model macro-area, regional or province dummies). Therefore, we stick on the raw test scores results and add geographical controls and a subject and school specific dummy indicating if the school has an high-cheating evidence based on the cheating coefficients calculated by Invalsi on the basis of a fuzzy-logic correction procedure explained in detail in Invalsi (2010, Appendix 9). In particular, the 'high-cheating dummy' identifies, for each year and subject, the schools in the lowest decile of the distribution of the subject specific cheating coefficient (i.e. the schools with the highest evidence of cheating behaviours). Robustness checks replicate the construction of the 'high-cheating dummy' with different percentiles (1-5, 1-15, 1-20) without showing differences in the results.

[46] For IC 2007-08, and IC 2008-09 the students' place of birth is indirectly obtained through the survey question "*How long is the student living in Italy?*". If the answer is "*Always*", we define that the student's place of birth is "*Italy*", otherwise the student is considered as "*Born abroad*". With respect to previous waves, we only lack the information on students' month of birth, omitted because of Privacy Law restrictions.

[47] Information concerning parents' place of birth is not available for the IC 2007-08 wave.

[48] '*First-generation immigrants*' refers to those persons who were born abroad and whose parents were also born abroad, while '*second-generation immigrants*' refers to persons who were themselves born inside the receiving country but whose parents were born abroad. Together, the first- and second-generation immigrants constitute the '*immigrant students*' group. By contrast, all students born in the receiving country who have at least one parent who was also born inside the country are referred to as '*native*' (OECD, 2010). See Appendix B for details.

[49] Besides being the most recent survey, Invalsi First Cycle 2009-10 wave has more precise information on relevant variables (in terms of missing values). Missing values on relevant variables are due either because they might not be reported by the school administrative staff or because parents decide not to provide it at the time of the student's enrolment. Moreover, cheating problems are less relevant with respect to the previous waves (see Invalsi 2010, Appendix 9).

institution), administrative organization (i.e. whether it is an institute having both elementary and junior high schools – that we define as '*K-8 school*'- or whether it is a simple junior high school, administratively independent from other elementary schools - that we define a '*middle school*'[50]); the province where the school is located; total number of students enrolled in 6, 7 and 8 grade, and the total number of classes for each grade[51]; total number of teachers hired in the school; total number of support learning teachers for students with handicaps or language difficulties; number of students with disabilities for each grade; total number of class making 'normal' (i.e. 30-hours) or 'extended' (i.e. 40-hours) weekly time schedule[52]. Finally, we have the information of the municipality where a school is located only in the case in which the school is located in a municipality with at least three junior high schools[53].

Catchment-area information. For each junior high school we define a 'catchment area' aimed at identifying the area where the majority of school attendants live[54]. Each catchment area is composed by a number of census divisions linked to each school according to a given algorithm. The procedure for the association between school and census divisions assigns for each school the closest divisions (in terms of geographic distance) so that the 'relevant resident population' living in those divisions contains at least $k>1$ times the number of students enrolled in that particular school (Barbieri *et al.*, 2010). The 'relevant population' is defined according to the 10-14 years resident population in the census data, while the multiplicative factor k is set equal to ten and it allows the overlapping of census divisions among different (but geographically not distant) junior high schools. As a result, the matching procedure links each school j with N_j census divisions constituting the school 'catchment area' and for each school j the socio-economic background variables are obtained as average of the socio-economic variables of each school catchment area. Thus, we are able link to each school about two hundreds variables from 2001 Italian Population Census Survey covering demographic and socio-economic information on resident population (gender, age,

[50] The terms *K-8 school* and *middle school* mimic the US traditional distinctions among different types of middle grade schools configurations.
[51] Junior high schools in Italy enroll students from grade 6 to 8. Thus, we have the total number of students enrolled and the number of classes by each grade in each school.
[52] In most of the cases it is also possible to recover the information of whether a given class follows a 'normal' or 'extended' time schedule.
[53] Restriction imposed by Italian Privacy Authority. In the end, we have the municipality information for more than 60% of the schools.
[54] The matching procedure is used in Barbieri *et al.* (2010). See for details Barbieri *et al.* (2010), Appendix A.

ethnic origins, education, labour force participation, occupation), households composition and houses characteristics.

Categories definitions

We partition students of Invalsi IC data into two main categories. The first category refers to the simple student's citizenship, thus we distinguish between *native* and *non-native* students. We recall that Italian citizenship follows a, so called, '*ius sanguinis*' rule: a student is native student if at least one of the parent is an Italian citizen. Data from Italian Ministry of Education generally only make this type of distinction. This first categorization is obtained thanks to the variable 'student citizenship', which distinguishes between Italian and non-Italian students and it is available for all the three IC data waves. The second category distinguishes between *immigrant* vs. *non-immigrant* students: according to Pisa-OECD criteria (see, for example, OECD, 2010), individuals whose both parents were born abroad are defined to as '*immigrants*'. On the contrary, '*non-immigrant*' students have at least one parent born in Italy. This category is obtained through two variables containing the information on the parents' place of birth (Italy or abroad), and have a greater percentage of missing (3.92% of the final student population). Immigrant students are then partitioned according to their place of birth: '*first generation immigrants*' are students born abroad, while '*second generation immigrants*' are students born the host country (Italy). Immigrant status does not depend on citizenship criteria, but only on the student's and parents' place of birth in order to allow international comparisons which must exclude citizenship criteria because citizenship is conferred according to country-specific rules.

Notice that in OECD surveys, the native vs. non-native categorization follows different criteria with respect to the ones we adopt in our analysis[55]. However, the definition we adopt based on the Italian citizenship is useful to allow comparisons and match data with Italian Ministry of Education Statistical Office which generally only divide students according to origins following the citizenship partition, and limit missing data problems. In fact, information concerning parents' place of birth and period stayed in Italy if born abroad – which show the highest percentage of missing data – are not compulsory by law, so that parents can decide not to provide them to the school administrative staff at the moment of the enrolment. Thus, missing data in

[55] Pisa OECD surveys define to as 'native' all students born in the receiving country who have at least one parent who was also born inside the country are referred to as '*native*'. Thus, *native* vs. *non-native* categorization exploits both the information on the student's and parents' place of birth

individual information may be due to different reasons: misreporting of school administrative staff, missing information, or students' parents refusal to provide information at the time of the enrolment. Exploiting the simple citizenship criterion limits these problems.

Descriptive OLS regressions

We perform descriptive pooled OLS regressions on the students population in order to provide a description of the individual determinants of the IC Invalsi test scores results. Table B.1 contains the complete list of the control variables used including a short description. We control for regional differences in the test scores (dummies for 20 Italian regions) and high cheating schools (dummy for cheating coefficient in the 9th decile of the cheating coefficients distribution). Results are reported in Table B2.

Table B1. Control variables description.

Type	*Name*	*Description*	*Source*
Individual (X)	*female*	Fraction of group j females in school s	Invalsi
	late	Fraction of group j retained students in school s	
	father place of birth	Fraction of group j students in school s with father born abroad	
	mother place of birth	Fraction of group j students in school s with mother born abroad	
	always_italy	Fraction of group j students in school s in Italy since birth	
School level (S)	*istituto*	Dummy equal 1 if "K-8 school"	Invalsi
	statale	Dummy equal 1 if State school	
	tot_alunni *tot_alunni2*	School size, given by the total number of students in the school and its square	MIUR / Invalsi
	avg_class *avg_class2*	Average class size in each school and its square	
	handicap_percent	Percent of students with disabilities in the school	
	pt_ratio	Pupil-to-teacher ratio	
	it_ratio	Non-native students-to-support Teacher ratio	
	tl_class_iii	Fraction of 40-hours classes in 8th grade	
	High_cheating_dummy (subject specific)	Dummy equal 1 if the school is in the 9th decile of the school cheating coefficient distribution	
Province by year Fixed Effects	*provyearFE_**	Interaction dummies for provinces (103 dummies) and years (2 dummies)	
Catchment Area (W)	*lpop*	Log of total resident population	Census 2001
	illiterate	Fraction of illiterate pop.	
	university_edu	Fraction of pop. with university level education	
	m_occup_rate	Male occupation rate	
	f_occup_rate	Female occupation rate	
	agri_oc	Fraction of workers occupied in agriculture	
	self_empl	Fraction workers self-employed	
	commuter	Fraction of resident commuting every day for school or working reasons	
	avg_family_members	Average number of family members	
	house_poor	Fraction of houses without clean water	
	house_new	Fraction of houses built after 1980	
	avg_rooms	Average number of rooms per house	

Coeteris paribus, non-native students score significantly lower than their native peers and the gap is more pronounced in language skills (-15.9% in Language and -13.9% in Maths); females have lower scores in Maths (-1.08%) and higher in Language (+1.01%) with respect to males; students who enrolled earlier than natural age (i.e. students 'in advance') show a positive differential in test scores results (+6.67% Language, +7.83% Maths). Finally, being 'retained' induces a strong and negative effect on test scores. The effects are however different with respect to the Italian and non-native students: *coeteris paribus*, Italian students held back show results between 20% and 23% lower than Italian regular students, while non-native held back students show results that are between 6% and 13% lower than their non-native regular mates. This descriptive result is probably due to the allocation of non-native students to the initial grade. Non-native students are allocated to a given grade on the basis of their Language skills and not on the basis of a simple 'age-rule' (see Appendix A for details). This seems to be confirmed by the fact that non-native held back students show greater gaps in Language skills with respects to Math, while Italian held back students do not show relevant differences between Language and Math skills.

Table B2. Descriptive OLS: individual charactersitics determinants of Invalsi IC test scores.

	Dep. Var.: Log Individual Language Test Score			*Dep. Var.: Log Individual Math Test Score*		
	2008	*2009*	*2010*	*2008*	*2009*	*2010*
Non-native	-0.1455***	-0.1161***	-0.0933***	-0.1693***	-0.1009***	-0.0852***
	(0.0034)	(0.0054)	(0.0050)	(0.0045)	(0.0057)	(0.0054)
Female	0.0383***	0.0281***	-0.0358***	-0.0501***	-0.0356***	0.0497***
	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0011)	(0.0012)
Native 'retained'	-0.1833***	-0.2176***	-0.1969***	-0.3022***	-0.2262***	-0.2028***
	(0.0024)	(0.0031)	(0.0028)	(0.0038)	(0.0033)	(0.0030)
Non-native 'retained'	-0.1260***	-0.1207***	-0.1244***	-0.0593***	-0.0563***	-0.0778***
	(0.0047)	(0.0051)	(0.0047)	(0.0056)	(0.0044)	(0.0046)
In Advance	0.0563***	0.0669***	0.0864***	0.0952***	0.0607***	0.0869***
	(0.0025)	(0.0028)	(0.0039)	(0.0040)	(0.0029)	(0.0051)
Always stayed in Italy	.	0.0568***	0.0421***	.	0.0213***	0.0256***
		(0.0048)	(0.0042)		(0.0052)	(0.0044)
Mother Born in Italy	.	0.0054**	0.0084***	.	0.0033	0.0044
		(0.0026)	(0.0024)		(0.0027)	(0.0028)
Father Born in Italy	.	0.0186***	0.0260***	.	0.0111***	0.0130***
		(0.0030)	(0.0029)		(0.0032)	(0.0030)
State School	-0.0153***	-0.0170***	-0.0322***	0.0014	0.0251***	-0.0220***
	(0.0044)	(0.0042)	(0.0040)	(0.0078)	(0.0061)	(0.0064)
K8 School Type	-0.0167***	-0.0136***	-0.0157***	-0.0319***	-0.0226***	-0.0191***
	(0.0026)	(0.0027)	(0.0028)	(0.0042)	(0.0033)	(0.0041)
Additional controls:						
Cheating Dummy	X	X	X	X	X	X
Region FE	X	X	X	X	X	X
R sq.	0.084	0.104	0.127	0.082	0.080	0.102
Adj.R sq.	0.084	0.104	0.127	0.082	0.080	0.102
Clusters	5684	5688	5624	5684	5688	5625
N	484,372	433,902	418,197	484,286	433,940	418,197

(Robust std. errors in parenthesis, clustered at the school level), sig. level: * p<0.1, ** p<0.05, *** p<0.01

Appendix C. Analytical proofs

Recall the EPF with 'integration mechanism' (y^I) and its first derivative of EDP with integration with respect to non-native school share ($\theta \in [0; 0.5]$ as non-native students are the 'minority' type in the school):

$$y^I = p_N^{(1-\theta)} \left[p_F(\theta) \right]^{\theta}$$

$$\frac{\partial y^I}{\partial \theta} = y^I \left\{ \ln\left[\frac{p_F(\theta)}{p_N} \right] + \frac{\theta}{p_F(\theta)} p_F^{'}(\theta) \right\} \leq 0$$

Recall properties and definitions concerning $p_F(\theta)$ function and complete them with the properties of the second derivative:

$$p_F(\theta) = \begin{cases} p_N \text{ if } \theta = 0 \\ \overline{p}_F < p_F(\theta) < p_N \text{ if } \theta \in (0; 0.5) \\ \overline{p}_F < p_N \text{ if } \theta = 0.5 \end{cases}$$

$$p_F^{'}(\theta) = \frac{\partial p_F(\theta)}{\partial \theta} = \begin{cases} 0 \text{ if } \theta = 0 \\ \overline{p}_F < p_F^{'}(\theta) < 0 \text{ if } \theta \in (0; 0.5) \\ \overline{p}_F^{'} < 0 \text{ if } \theta = 0.5 \end{cases}$$

$$p_F^{"}(\theta) = \frac{\partial^2 p_F(\theta)}{\partial \theta^2} = \begin{cases} 0 \text{ if } \theta = 0 \\ < 0 \text{ if } \theta \in (0; 0.5) \\ \overline{p}_F^{"} < 0 \text{ if } \theta = 0.5 \end{cases}$$

Then, the second derivative of y^I with respect to θ takes the following form:

$$\begin{aligned} \frac{\partial^2 y^I}{\partial \theta^2} &= \frac{\partial y^I}{\partial \theta} \left\{ \ln\left[\frac{p_F(\theta)}{p_N} \right] + \frac{\theta}{p_F(\theta)} p_F^{'}(\theta) \right\} + \\ &+ y^I \left\{ \frac{p_F^{'}(\theta)}{p_F(\theta)} + \frac{p_F^{'}(\theta)}{p_F(\theta)} + \theta \frac{p_F(\theta) p_F^{"}(\theta) - p_F^{'}(\theta) p_F^{'}(\theta)}{\left[p_F(\theta) \right]^2} \right\} = \\ &= \frac{\partial y^I}{\partial \theta} \left\{ \ln\left[\frac{p_F(\theta)}{p_N} \right] + \theta \frac{p_F^{'}(\theta)}{p_F(\theta)} \right\} + \frac{y^I}{p_F(\theta)} \left\{ 2 p_F^{'}(\theta) + \theta p_F^{"}(\theta) - \theta \frac{\left[p_F^{'}(\theta) \right]^2}{p_F(\theta)} \right\} = \\ &= \mathrm{A}(\theta) + \mathrm{B}(\theta) \end{aligned}$$

Then, for $\theta\to 0^+$:

$$\lim_{\theta\to 0^+}\frac{\partial^2 y^I}{\partial\theta^2}=\frac{\partial y^I}{\partial\theta}\left\{\ln\left[\frac{p_F(\theta)}{p_N}\right]+\theta\frac{p_F^{'}(\theta)}{p_F(\theta)}\right\}+\frac{y^I}{p_F(\theta)}\left\{2p_F^{'}(\theta)+\theta p_F^{''}(\theta)-\theta\frac{\left[p_F^{'}(\theta)\right]^2}{p_F(\theta)}\right\}=0^-$$

In fact, notice that $A(\theta)\to 0$ and $B(\theta)\to 0$ as $\theta\to 0^+$.
While for $\theta\to 0.5^-$ the sign is different from zero, but undetermined as it depends on the values $\overline{p}_F, \overline{p}_F^{'}, \overline{p}_F^{''}$:

$$\lim_{\theta\to 0.5^-}\frac{\partial^2 y^I}{\partial\theta^2}=(p_N\overline{p}_F)^{1/2}\left[\ln\frac{\overline{p}_F}{p_N}+\frac{1}{2}\frac{\overline{p}_F^{'}}{\overline{p}_F}\right]^2+\left[2\overline{p}_F^{'}+\frac{1}{2}\overline{p}_F^{''}-\frac{1}{2}\frac{(\overline{p}_F^{''})^2}{\overline{p}_F}\right]\neq 0$$

The sign of the second derivative depends on $p_F(\theta)$ function. However, it is possible to derive its sign for $\theta\to 0^+$ that together with the information on first derivative (under general regularity conditions and holding the properties of $p_F(\theta)$) this is sufficient[56] for an horizontal inflection point to exist in a neighbourhood of $\theta=0^+$. These results allow to draw the qualitative graph in Figure 4, which shows the decreasing slope, an horizontal inflection point in a neighbourhood of $\theta=0^+$, but possible undetermined concavity or convexity for $\theta>0$.

[56] Assuming $p_F^{'''}(\theta)\big|_{\theta=0}\neq 0$

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