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# Immigrant Concentration at School and Natives' Achievement: Does the Type of Migrants and Natives Matter? 

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#### Abstract

Using a rich dataset of primary school students in the Netherlands, this paper investigates the heterogeneous effects of immigrant concentration in the classroom on the academic achievement of natives. To identify the treatment effect, it takes advantage of some features of the Dutch primary school system and uses cohort-by-cohort deviations in immigrant concentration within schools. While we report an insignificant impact of the share of immigrant classmates overall, we show that effects are heterogeneous, both in the type of immigrant classmates, and in the type of native students that are affected. Only immigrants that have been living in the country for a short period of time are found to negatively impact natives' performance. This negative impact is stronger among natives with low parental education. We also report a negative effect of the concentration of migrants with low parental education, while migrants with high parental education are found to have no impact. The importance of taking into account heterogeneity could explain the mixed findings reported by previous literature on the topic.


Keywords: Immigration, education, peer effects
JEL classification: I21, J15

## 1. Introduction

Given the sharp increase in international labor mobility and a recent rise in refugee inflows, national economies are facing the issue of economic integration of migrants to an unprecedented degree. While the economic consequences of immigration on the labor market have been widely studied, immigration could also affect schooling and human capital acquisition. A growing body of literature, initiated by the seminal contribution of Lazear (2001), shows that classroom composition can impact individual school performance. Policy measures taken by some governments also suggest that the growing concentration of immigrant students in the classroom is of concern among policy makers. In 2010, the Italian Ministry of Education introduced a law that caps at thirty percent the share of foreign-born students in public school classrooms. Such

[^0]measures, however, are mostly motivated by anecdotal evidence of disruption rather than rigorous experimental or quasi-experimental methods. In addition, economic theory is inconclusive about whether immigrant concentration in the classroom produces positive or negative effects, if any, on the performance of natives. Immigrant students in most high-income countries are from families with lower socio-economic background compared to natives, and they may also face specific difficulties associated with assimilation and host-country language acquisition. ${ }^{1}$ While it is plausible that a diverse student body has positive effects due to complementarities in abilities and types, a very heterogeneous class also makes teaching as well as peer interactions harder. ${ }^{2}$

Evidence on the impact of migration on the school system and human capital acquisition is still relatively limited and reports mixed findings. Part of the literature finds no impact of immigrant concentration in the classroom on natives' achievement, while a comparable number of contributions report negative effects. Although variation in local contexts may play a role in producing mixed results, difficulties in identifying treatment effects, but also potential heterogeneity in treatment effects could be at play. In particular, previous work treats immigrant children as an homogeneous group, and few studies distinguish between the effect of immigrant classmates on different socio-economic categories of natives.

This paper contributes to the growing but still thin literature on the impact of immigrant peers on natives' scholastic achievement in several respects. First, it sheds light on the fact that the effect of immigrant concentration in the classroom depends on the type of both immigrant and native students. In particular, we look separately at the impact of immigrant classmates that recently arrived to the Netherlands, as opposed to those that have been in the country for a longer period. For that purpose, we exploit unique information on the length of stay in the Netherlands of immigrant students to shed light on this question. To the best of our knowledge, this is the first contribution that distinguishes between different types of migrants when estimating the effects of immigrant concentration. It is plausible that immigrant children that recently entered the country generate distinct spillovers on natives' learning because they may have a weaker command of the native language or had less time to assimilate.

Our dataset also allows to look separately at the effect of the concentration of immigrants with different socio-economic backgrounds. One may posit that immigrant students from more disadvantaged families produce different spillovers on natives compared to immigrants with

[^1]higher parental education. To the best of our knowledge, this hypothesis has not been tested by previous literature. In addition, as the peer effect literature suggests that weaker students might be more strongly affected by classroom composition, we investigate the heterogeneous effects of immigrant concentration on different socio-economic categories of natives.

Second, the paper takes advantage of some features of the Dutch primary school system and of the PRIMA dataset to identify the effect of immigrant peers on natives' scholastic achievement. Estimates based on classroom-level peer composition reported in the literature are likely to suffer from non-random allocation of students between classrooms. ${ }^{3}$ On the other hand, using grade-level peer composition is likely to underestimate peer effects, as most learning spillovers are likely to occur at the classroom level (see Carrell et al. (2009) or Brodaty (2010), among others). The Dutch primary school system presents an attractive feature to tackle those issues, as the large majority of Dutch primary schools only have one classroom per grade. Although we report our main results for the full sample, we assess the robustness of our estimates in the subsample of schools with a single classroom per grade. Our identification strategy relies on small changes in immigrant concentration across cohorts within the same school, controlling for school-specific time trends in immigrant concentration. We run several tests to assess the validity or our identification strategy, including balancing tests for selection on observables, but also placebo tests which suggest that our results are not driven by selection on unobservables.

Finally, this study adds to the thin literature that investigates the effects of immigrant concentration on natives' achievement at school in early ages, as our sample consists of primary school students from age five. This focus on early ages is relevant in the specific context of the question investigated as immigrant classmates, defined as foreign-born students, have spent less time in the host country at those ages than older students. One could therefore expect greater disparities with native children in those ages and potentially stronger learning spillovers. Studying this question for young children is also important as the literature highlights the key role played by the acquisition of basic skills such as reading and simple arithmetics in fostering further skills and shaping labor market outcomes. ${ }^{4}$

Our results suggest that the impact of immigrant concentration on natives' test scores is heterogeneous, both in the type of immigrants that are part of the treatment, but also in the type of natives that are affected. While immigrant classmates who have already been in the Netherlands for some years are not found to impact natives' achievement, we report a negative and significant impact of the concentration of migrants that have been in the country for a

[^2]short period. The effect size is however small in magnitude, and statistically significant only for scholastic achievement in Dutch language. In addition, immigrant classmates with low parental education negatively impact natives' test scores in language, while immigrant classmates with high parental education do not. Furthermore, native students from a high socio-economic background are found not to be affected by the concentration of immigrant classmates in their classroom, even if those are recent migrants. On the other hand, we report adverse effects of the share of recent migrant classmates on the scholastic achievement of natives with low parental education.

The paper is organized as follows. Section 2 reviews related literature on the topic. Section 3 provides background information on immigration and primary education in the Netherlands. Section 4 presents our data. Section 5 describes our identification strategy and provides supporting evidence for its validity. Section 6 presents our main results while Section 7 performs some placebo tests and robustness checks. Section 8 concludes.

## 2. Related Literature

This paper first relates to the broader literature of peer effects at school. The hypothesis that the behavior and outcomes of students are affected by their peers is formalized in the seminal contribution of Lazear (2001). The classroom is viewed as a public good in which classroom disruption by some students produces negative externalities on the entire class. As students are heterogeneous in their propensity to disrupt the class, changes in classmates composition affect instruction and individual achievement. From an empirical point of view, a large body of literature using both experimental and non-experimental methods has attempted to estimate the effects of classroom composition on individual school performance. ${ }^{5}$

Evidence on the impact of immigrant classmates on scholastic achievement is more scarce. In the US, a related literature studies the effect of ethnic segregation on academic achievement. Using data from Texas public schools, Hoxby (2000) and Hanushek et al. (2004) use variation in ethnic composition of adjacent cohorts in a given school to identify the effect of ethnic composition on student outcomes. Both studies find that the test scores of African-american students are negatively affected by the share of African-american classmates, while white students' test scores are unaffected by the percentage of black classmates. Using quasi-experimental evidence from the Metropolitan Council for Education Opportunity (Metco) in Boston, Angrist and Lang (2004) exploit the fact that students from disadvantaged neighborhoods were transferred

[^3]by Metco to receiving schools to identify the effect of an increase in the share of minority classmates. They find no significant impact of an increase in the share of minority peers of the achievement of white students in math, reading, and language scores for 3rd, 5th, and 7th graders.

Despite the importance of immigration issues for European countries, the literature on the effect of immigrant peers on natives' achievement is still thin and reports mixed findings. This question was studied in the European context by Jensen and Rasmussen (2011), Brunello and Rocco (2013), Ohinata and van Ours (2013), Geay et al. (2013), Ballatore et al. (2015), Schneeweis (2015), and Tornello (2016). ${ }^{6}$ While Ohinata and van Ours (2013), Geay et al. (2013) and Schneeweis (2015) report no effect on natives, other studies find statistically significant negative impacts.

Jensen and Rasmussen (2011) examine this issue in the Danish context. They use test score data from the Project for International Student Assessment (PISA) at age 15, combined with Danish administrative data on neighborhood composition to estimate the treatment effect. To address the non-random selection of immigrants between schools, they instrument the share of immigrants in the school by immigrant concentration within a larger geographical area. They report a negative effect of immigrant concentration on the school performance of natives in both mathematics and reading, although estimated effects are small in magnitude. An increase in immigrant concentration by 10 percentage points reduces natives' test scores by 0.03 and 0.09 standard deviations in mathematics and reading, respectively.

Brunello and Rocco (2013) rely on cross-country differences in immigrant concentration among 27 European countries to estimate the effect of immigrant students on natives' achievement. They use test scores at age 15 from the Program for International Student Assessment (PISA) in 2000, 2003, 2006 and 2009 to measure the school performance of natives. Their identification strategy relies on variations in immigrant concentration over time within countries, by aggregating PISA micro-level data on natives' test scores and immigrant concentration to the country-level. Their results show a negative but small effect of immigrant concentration on the school performance of natives. The precision of the estimation however suffers from a small sample size due to the data aggregation.

Ohinata and van Ours (2013) use data from the 2001 and 2006 Progress in International Reading Literacy Study (PIRLS), and the 1995 and 2007 Trends in International Mathematics and Science Study (TIMMS) in the Netherlands. They use variation in immigrant concentration across classrooms within the same school to identify the effect of having immigrant classmates

[^4]on natives' test scores, and find no significant impact. Geay et al. (2013) use data on students at the end of primary school in England from 2003 and 2009. They rely on the influx of Eastern European migrants to the UK after 2005 to instrument the effects of immigrant concentration. They find virtually no effect of immigrant concentration in the classroom on English native speakers. Ballatore et al. (2015) use classroom formation rules in Italy as an exogenous source of variation in the share of immigrant classmates, in a sample of Italian primary schools. They find an adverse effect of the concentration of immigrant students in the classroom on natives' test scores in both language and mathematcs. Schneeweis (2015), using Austrian primary school data, uses cohort-by-cohort variation in immigrant concentration within the same school to identify the treatment effect. She reports adverse effects of the share of immigrant classmates on the achievement of migrant students, but finds no impact on natives.

## 3. Background and Institutional Setting

### 3.1. Immigrants in the Netherlands

In 2011, the Netherlands were populated by a population of 1.77 million immigrants, representing around 11 percent of the country population. As in most European countries, the majority of immigrants residing in the Netherlands come from lower-income countries. In 2011, the main groups of non-western origin populating the country were Turks (21\%), Surinamese (19\%) Moroccans (17\%) and Antilleans (7\%). Between 40 and $50 \%$ of these groups are second-generation immigrants. Almost one third of the Dutch immigrant population originates from former colonies, mainly Indonesia, Surinam and the Dutch Antilles. These immigrants had mostly a good command of the Dutch language when they entered the country, and were comparatively well-educated within school systems modeled on the Netherlands. A second immigration wave, consisting mostly of Turkish and Moroccans, entered the Netherlands in the 1960s. This second immigration wave was largely driven by an increased demand for low-skilled labor. Turkish and Moroccan immigrants came first as workers, and later for family formation and reunification. As a result, the large majority of Turkish and Moroccan immigrants populating the Netherlands are from families with low educational backgrounds compared to native Dutch. In addition to these traditional groups, the Netherlands also hosts smaller immigrant groups from Iraq, Afghanistan or Iran.

The immigrant population is unevenly distributed across and within areas in the Netherlands. Non-western immigrants are considerably over-represented in the four major cities in the West of the country: Amsterdam, Rotterdam, The Hague and Utrecht. Approximately 50 percent of Surinamese and Moroccan immigrants live in one of the four major cities. Among
the four major cities, Amsterdam and Rotterdam have the highest share of non-western immigrants with about 35 percent. Non-western migrants are also unevenly distributed within cities. In some districts of Amsterdam, 75 percent or more of young people are from a non-Western origin, while relatively few immigrants reside in city centers.

The uneven distribution of immigrants across cities and neighborhoods is reflected in the primary school system. In Amsterdam for example, 127 of the 201 elementary schools have more than 50 percent of children with a migration background, and 102 schools have a concentration of more than 70 percent. In contrast, in the nine suburban municipalities within a short distance from one of the most segregated districts of Amsterdam, only one school hosts more than 50 percent of children of non-western parents with low parental education.

### 3.2. The Dutch primary school system

From age five, all children residing in the Netherlands are legally required to attend school. Dutch primary schooling consists of eight grades covering age groups from four to twelve. Contrary to most European countries, school choice is free in the Netherlands. Parents are not restricted to send their children to a school in a particular district, and are legally entitled to choose a school for their children, regardless of the neighborhood they live in. The primary school system consists of both public-authority and private schools that are both funded by the state. Both types of school receive, on top of their regular budget and based on the overall number of students, additional funding from the Ministry of Education on the basis of the percentage of immigrant students in their school population. The amount of additional funding is based on the total sum of weights assigned to students from different socio-economic categories enrolled in the school. The majority of students, children of Dutch middle class parents, receive a weight of 1 . Children of Dutch parents with low levels of education are allocated a weight of 1.25. Bargee's children are weighted 1.4 and children of itinerant parents 1.7. Finally, children of immigrant parents with low education receive the highest weight of 1.9. Schools have a great amount of freedom in deploying the extra staffing hours, for instance by reducing class size, offering remedial teaching or appointing classroom assistants. The additional funding can also be used to introduce more specific measures, such as school-wide language policies or reception facilities for newcomers.

## 4. Data and Descriptive Statistics

### 4.1. The PRIMA data set

We constructed our panel of primary schools from six successive waves of the PRIMA longitudinal survey in the Netherlands. The survey was carried out every two years from 1994
to 2004 to follow the development of cognitive and non-cognitive skills of students throughout primary school. Participating schools were chosen to be representative of the entire population of Dutch primary schools. ${ }^{7}$ As we have multiple observations per school, we pooled all grades and years to exploit within school variation in the proportion of immigrant students. We linked the successive waves of PRIMA to build a panel of Dutch primary schools, observed in grade two, four, six and eight every two years from 1994 to 2004 . We obtain a panel of about 600 schools with 12,053 cohort-level observations. ${ }^{8}$

The data collected in PRIMA is based on answers to detailed questionnaires filled by teachers, parents, and school principals. As a result, the dataset contains rich information at the student, classroom and school levels. In particular, it contains detailed information on students' socio-economic and migration background. It allows to know whether the student is foreign born, the length of stay in the Netherlands, as well as the country of origin of the parents. We categorize as immigrants students for which the answer to the question "How long has the child been living in the Netherlands" is not "always". Our definition of immigrants is therefore restricted to first-generation migrants that are foreign born, and does not include second generation migrants, as it is usually the case in the literature. Student performance is measured by tests administered by the Dutch National Institute for Educational Measurement in Dutch language and mathematics. These tests were developed by the Dutch government testing agency to measure students' readiness in the two topics. We standardize individual raw test scores in the dataset so that the mean is 50 and the standard deviation is 10 . Within each classroom, all students are sampled as long as they are present the day of the test. Contrary to many educational datasets used for peer effect estimation, an attractive feature of the PRIMA dataset is that very few values are missing for the variables of interest. This allows to significantly alleviate the issue of non-random missing values in classroom peer data outlined by Sojourner (2013).

### 4.2. Descriptive Statistics

Table 1 and Table 2 report student-level and cohort-level summary statistics of our sample, respectively. Table 1 shows that immigrant students have lower parental education compared to native students, as it is the case in most European countries. More than 43 percent of immigrant children have a father that did not study beyond primary school, as opposed to only 15 percent of native Dutch students. The proportion of immigrant students whose father

[^5]achieved low levels of education is particularly high among Turkish and Moroccan immigrants, which account for around one fourth of the total number of immigrants in our sample. 67 percent of Moroccan and Turkish students have a father that did not study beyond primary school, while this proportion is only 29 percent for immigrants from other countries. Table 1 shows that immigrant children in the sample perform on average significantly worse than native Dutch students, both in arithmetic and Dutch language tests. In addition, the achievement gap between native and immigrant students remains once we condition for parental education. This gap shows at all levels of parental education, and is larger in the subsample of Moroccan and Turkish immigrants.

Table 1: Background characteristics and outcomes of immigrant and native students

|  | Native Dutch | Immigrants |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | All | Turkish/ Moroccan | Former colonies | Other immigrants |
| \% of students by parental education |  |  |  |  |  |
| Primary | 15.23 | 43.88 | 67.41 | 25.06 | 32.23 |
| Lower secondary | 38.41 | 25.79 | 18.17 | 47.29 | 26.61 |
| Upper secondary | 28.37 | 16.66 | 10.96 | 20.34 | 20.96 |
| University | 17.99 | 13.67 | 3.45 | 7.29 | 20.09 |
| Total | 100 | 100 | 100 | 100 | 100 |
| Average test score - Dutch language |  |  |  |  |  |
| Father's education: primary | 43.53 | 41.21 | 40.18 | 42.55 | 42.04 |
| Father's education: lower secondary | 49.51 | 44.52 | 41.09 | 44.18 | 44.35 |
| Father's education: upper secondary | 52.66 | 46.89 | 42.96 | 45.36 | 45.97 |
| Father's education: university | 55.10 | 48.84 | 46.07 | 48.99 | 47.20 |
| All students | 50.46 | 44.94 | 40.85 | 44.23 | 43.05 |
| Average test score - mathematics |  |  |  |  |  |
| Father's education: primary | 45.74 | 44.70 | 44.34 | 43.43 | 45.26 |
| Father's education: lower secondary | 49.12 | 46.26 | 45.21 | 44.11 | 46.65 |
| Father's education: upper secondary | 52.05 | 48.35 | 47.41 | 45.34 | 47.96 |
| Father's education: university | 54.34 | 50.50 | 50.05 | 47.69 | 49.71 |
| All students | 50.29 | 46.69 | 45.01 | 44.21 | 46.89 |
| Number of students | 347,875 | 22,450 | 5,917 | 1,678 | 14,855 |
| Note. Individual raw test scores were standardized to have a mean of 50 and a standard deviation of 10. The upper panel reports the distribution of students by parental education, for each subgroup. Figures in the top panel read: $3.45 \%$ of Turkish/Moroccan immigrant students have a father that completed higher education. The middle and bottom panels show the average test scores for each subgroup, by level of parental education. Figures in the middle and bottom panels read: Dutch students whose father has primary education have an average verbal test score of 42.74 . |  |  |  |  |  |

Table 2 reports student characteristics and outcomes aggregated at the cohort level, by level of immigrant concentration. We refer to cohort-level observation as the set of students in grade $g$ of school $s$, in year $y$. We observe significant selection of native students between cohorts with different levels of immigrant concentration. As expected, natives from more disadvantaged families tend to concentrate in cohorts where the fraction of immigrant students is high. The share of native students with a father that did not study beyond primary school ranges from 11 percent in cohorts with no immigrant to more than 37 percent in grades with more than 50 percent of immigrant students. The academic achievement of natives is also lower in cohorts
with a high fraction of immigrant students. On the other hand, there is no clear pattern regarding the average achievement of immigrant students in school cohorts with different immigrant concentrations.

Table 2: Summary statistics - aggregate statistics at the school cohort level

|  | All | Percentage of immigrants in the school cohort |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | No immigrant | 0-10 | 10-20 | 20-50 | 50+ |
| Cohort characteristics |  |  |  |  |  |  |
| Number of students in the cohort | 26.34 | 22.03 | 29.79 | 23.11 | 21.96 | 29.24 |
|  | (13.02) | (12.36) | (14.11) | (11.23) | (11.49) | (15.82) |
| Fraction of immigrant students | 0.063 | - | 0.053 | 0.137 | 0.279 | 0.820 |
|  | (0.133) | - | (0.021) | (0.027) | (0.072) | (0.180) |
| Share of natives with low parental education | 0.162 | 0.111 | 0.164 | 0.261 | 0.343 | 0.378 |
|  | (0.23) | (0.19) | (0.21) | (0.26) | (0.28) | (0.36) |
| Average test score in Dutch language |  |  |  |  |  |  |
| All students | 49.89 | 51.13 | 49.77 | 47.37 | 45.72 | 45.93 |
|  | (5.37) | (5.01) | (4.91) | (5.46) | (5.41) | (5.65) |
| Immigrant students |  | (5.01) | $45.73$ |  |  |  |
|  | (9.13) | - | $(10.12)$ | (8.21) | (6.86) | (6.09) |
| Native students |  |  |  |  |  | 44.87 |
|  | (5.42) | (5.04) | (4.97) | (5.71) | (5.79) | (8.15) |
| Average test score in mathematics |  |  |  |  |  |  |
| All students | 49.88 | 50.76 | 49.76 | 48.08 | 46.99 | 47.41 |
|  | (4.94) | (4.82) | (4.58) | (4.95) | (5.12) | (4.76) |
| Immigrant students |  | - | $47.30$ |  |  |  |
|  | (9.03) | - | $(10.05)$ | (8.10) | $(7.10)$ | (5.07) |
| Natives | 50.00 | 50.81 | 49.89 | 48.35 | 47.34 | 46.99 |
|  | (5.04) | (4.87) | (4.68) | (5.16) | (5.33) | (6.75) |
| Number of school cohorts | 12,053 | 6,522 | 3,403 | 1,322 | 686 | 120 |

Note. Reported statistics were aggregated to the school cohort level. Immigrants with a father that did not complete upper secondary education are categorized as having low parental education. Standard deviations at the cohort level are reported in parentheses. Natives with low parental education are defined as having a father that did not complete upper secondary education.

## 5. Empirical Strategy

### 5.1. The Identification Problem

In the standard experimental terminology, we are interested in estimating the effect of the treatment $I_{i}$ received by native student $i$ on outcome $Y_{i}$, where $I_{i}$ denotes immigrant concentration in the school cohort of native student $i$. For simplicity in the exposure, we consider the case in which $I_{i}$ is binary and takes the value 1 if immigrant concentration in the school cohort is above a certain threshold, and 0 otherwise. $Y_{i}$ denotes the outcome of interest, which is the standardized test score obtained by native student $i$. In an experimental setting where the treatment $I$ is allocated randomly to individuals, the causal effect $\beta$ of $I$ on $Y$ is estimated consistently by the expected difference between outcomes of the treated and the non-treated:

$$
\begin{equation*}
E\left\{\beta_{i}\right\}=E\left[Y_{i}\left(I_{i}=0\right)\right]-E\left[Y_{i}\left(I_{i}=1\right)\right] \tag{1}
\end{equation*}
$$

In a non-experimental setting like ours, however, the treatment $I$ is non-randomly allocated to native students, and is likely to be correlated with observables and unobservables that also affect $Y$. This non-random selection into treatment generates a bias in the estimate $E\left\{\beta_{i}\right\}$. In this context, the estimated treatment effect can be expressed as:

$$
\begin{equation*}
\hat{\beta}=E\left\{\beta_{i}\right\}+E\left[Y_{i}(0) \mid I_{i}=1\right]-E\left[Y_{i}(0) \mid I_{i}=0\right] \tag{2}
\end{equation*}
$$

Where $Y_{i}(0)$ denotes the potential outcome $Y$ of native student $i$ without treatment $I$. The second term $E\left[Y_{i}(0) \mid I_{i}=1\right]-E\left[Y_{i}(0) \mid I_{i}=0\right]$ corresponds to the estimation bias resulting from the difference in potential outcomes of the treated and non-treated, in the counterfactual situation of no treatment. This is the fundamental problem of selection into peer groups evidenced in the seminal contributions of Manski (1993) or Sacerdote (2001), which can contaminate peer effect estimates. In our context, we would expect $E\left[Y_{i}(0) \mid I_{i}=1\right]-E\left[Y_{i}(0) \mid I_{i}=0\right]<0$. Students selected into treatment $I_{i}=1$, i.e. who have a high share of immigrant children in their classroom, are more likely to be from families with low socio-economic status and would have lower test scores than non-treated students, even in the absence of treatment.

The most obvious component of selection occurs between schools. Schools draw students from different neighborhoods and family backgrounds, leading to a concentration of students with similar characteristics in the same school. It is therefore crucial to use within-school variation to identify the causal effect of immigrant concentration in the classroom on the achievement of natives.

A second type of selection of native and immigrant students into classrooms occurs within schools. Once school-fixed effects are accounted for, estimation of the effect of immigrant concentration might still be inconsistent if the allocation of students to classrooms within the same school is not random. School directors, teachers, or parents may indeed allocate students to classrooms in a non-random fashion, according to student characteristics that may not be observed by the researcher. Contrary to selection between schools, this second type of selection has received little attention in the literature, and is also more difficult to address. One notable exception is Ballatore et al. (2015) who attempt to account for the endogeneity of classroom composition according to migrant status using rules of classroom formation in Italy.

Carrell et al. (2009) also show that estimates for peer effects greatly differ depending on the accuracy with which econometricians identify the set of relevant peers. Estimating peer effects at the classroom level typically yields larger estimates, but one can doubt of the exogeneity of classroom formation outside the experimental setting. It seems natural, however, to expect that a significant fraction of peer effects in learning arises at the classroom level, since classes
are the basic unit where learning takes place. Therefore, using a grade-level measure of $I_{i}$ may generate a downward bias in the estimation of $\beta$ due to measurement error, as outlined by Brodaty (2010).

### 5.2. Identification of Immigrant peer effects

We are able to exploit one desirable feature of the Dutch context to tackle these issues. Dutch primary schools are on average of small size, and the large majority of schools only have one classroom per grade-level. In 2010, the average number of students enrolled by Dutch primary schools was 220 according to the Dutch Ministry of Education, which represents approximately 27.5 students per grade level. This figure is slightly lower in our sample of schools where the average number of students per grade is 26.3 (Table 2 ). In about 70 percent of the grade-level observations in our sample, students enrolled in the same grade are in the same classroom. While we conduct our baseline estimation on the full sample of schools, we also report our results for schools with a single classroom per grade, to assess the robustness of the estimates.

To address the potential endogeneity of students allocation to classrooms, we measure $I_{i}$ by the fraction of immigrant students in the grade, instead of using classroom-level peer measures. Our identification strategy therefore follows the spirit of Hoxby (2000), or Lavy and Schlosser (2011). We use the fact that several cohorts of students are observed within the same school, and rely on variation in immigrant concentration across cohorts to identify $\beta$. In other words, we examine whether the outcomes of native students across grades within the same school and year change systematically with the proportion of immigrant students in the same cohort.

The inclusion of school fixed effects accounts for the most obvious source of student sorting between schools. This selection is likely to be particularly acute in the Netherlands, where a free school choice policy applies. In addition, there might also be some school-specific time varying factors that affects both students' outcomes and immigrant concentration. For example, school administration might change from one year to another and affect both immigrant concentration as well as test scores. To account for this possibility, we use a full set of school-year fixed effects $\gamma_{s y}$.

Since the test scores of students within the same school cohort are likely to be correlated and may therefore deflate standards errors, we follow the approach of Angrist and Lavy (1999) by using grade-level aggregates for estimation instead of individual data. We collapse individual observations to grade level averages and estimate the effect of the share of immigrants in the grade on the average test score of native students. Using our panel of schools observed in four different grades over several years, we estimate the following reduced-form equation:

$$
\begin{equation*}
\bar{Y}_{s g y}=\alpha_{g}+\gamma_{s y}+\beta I_{s g y}+\rho \bar{X}_{s g y}+\varepsilon_{s g y} \tag{3}
\end{equation*}
$$

Where $s$ denotes the school, $y$ denotes the year, and $g$ the grade. $\bar{Y}_{s g y}$ denotes the average test score of native students in a given school cohort. $\alpha_{g}$ is a grade effect, and $\gamma_{s y}$ is a school-byyear effect. $\bar{X}_{s g y}$ is a vector of cohort characteristics that is not necessary for the estimation if cohort-by-cohort changes in immigrant concentration is exogeneous, but it is added to the specification as a robustness check. $I_{s g y}$ is the proportion of immigrant students in the cohort in grade $g$ of school $s$ in year $y$. We are interested in estimating consistently $\beta$, which captures the effect of immigrant concentration in the school cohort on the average test score of native students.

Even after controlling for school-by-year fixed effects, one might still be concerned that variation in immigrant concentration across grades within schools is correlated with unobservable time-varying factors. In particular, changes in immigrant concentration across cohorts within schools may reflect endogenous changes in neighborhood population, or students' mobility. To alleviate this concern, we first follow Hoxby (2000) and add to our baseline equation a full set of school-specific linear trends. For each school-year cell, we estimate a school-specific linear trend $\sigma_{s}$ by regressing the fraction of immigrants in each grade of the school observed in a given year on a time variable, and a constant. Our reduced-form equation to estimate the effect of immigrant concentration in the cohort therefore becomes:

$$
\begin{equation*}
\bar{Y}_{s g y}=\alpha_{g}+\gamma_{s y}+\sigma_{s} \text { cohort }+\beta I_{s g y}+\rho \bar{X}_{s g y}+\varepsilon_{s g y} \tag{4}
\end{equation*}
$$

$\beta$ is therefore identified from the deviations in the proportion of immigrant students in the cohort from its linear school trend. The identifying assumption is that, once we allow for linear trends in immigrant concentration, remaining changes in the share of immigrant students by cohort are driven by factors that are exogenous to natives' test scores, such as the distribution of immigrants' birth year in the neighborhood. In other words, while the proportion of immigrant students in a school is relatively stable over time, there exists cohort-by-cohort variations that are purely driven by demographics.

One potential threat to the identification strategy is the fact that families might react to changes in immigration concentration within the same school by moving away their children from the school. However, while parents may know the average immigrant composition of a given school, it is very difficult to predict the exact composition of a particular cohort. In particular, the exact fraction of immigrant students enrolled in a particular school cohort is unknown to parents before the beginning of the school year, and school departures are typically not allowed once the school year has already started.

### 5.3. Evidence on the Validity of the Identifying Assumption

To investigate potential non-random variation in immigrant concentration across cohorts, we regressed our treatment variable, i.e. the fraction of immigrant students, on the characteristics of native students in the same cohort and other cohort characteristics. Table 3 reports the results of these balancing tests, where the fraction of immigrants in the cohort is regressed on each of the measures of native students' socio-economic background and other cohort characteristics, in separate regressions. Column 1 presents the results of a naïve benchmark OLS regression controlling for year and grade effects. The naïve estimates show a large and significant association between natives' observable characteristics, in particular parental education, and the percentage of immigrants in the cohort. Correlations between immigrant concentration and natives' parental education are large in magnitude, and significant at the one percent level. As evidenced earlier, natives with low parental education tend to concentrate in schools with a high fraction of immigrant students.

Column 2 shows that the inclusion of school fixed effects reduces dramatically the magnitude of those correlations. All estimates become statistically insignificant, with the exception of natives whose parents have primary education as highest degree. Using within-school variation in immigrant concentration therefore significantly alleviates issues of selection. Once school fixed effects are accounted for, there is little remaining association between immigrant concentration and cohort characteristics.

Column 3 shows the association between the share of immigrants in the grade and natives' characteristics when school-by-year fixed effects are controlled for. This specification further controls for school-specific year effects to account for idiosyncratic shocks that could affect a school in a given year, and may be correlated with immigrant concentration. Controlling for school-specific year effects further decreases the magnitude of the correlations, which become virtually zero and insignificant for all cohort characteristics included in the test.

Finally, Column 4 shows the association between cohort characteristics and the fraction of immigrants resulting from our identification strategy, controlling for school linear time trend in immigrant concentration. The magnitude of all correlations are virtually zero and very similar to the school-by-year fixed effect estimates, but the addition of school-specific trends eliminates the remaining association between enrollment in the grade and immigrant concentration. This indicates that the variation in immigrant concentration resulting from our identification strategy is uncorrelated with changes in observables relevant for achievement.

Our identification strategy requires the fraction of immigrants in the cohort to be uncorrelated to both observable and unobservable cohort characteristics. As emphasized by Gould et al. (2009), this type of balancing test does not provide a proof for random assignment. How-
ever, the lack of association between treatment and other correlates of academic achievement resulting from our identification strategy suggests that unobservables are also unlikely to be correlated with the treatment, especially if those unobservables are correlated with observables. Overall, the sharp contrast between the naïve estimates and those resulting from our identification strategy shows the extent to which it eliminates the bias stemming from selection. To further alleviate concerns of remaining spurious correlations between immigrant concentration in the cohort and unobservables, we also conduct in Section 8 placebo treatment tests suggesting that this is not the case.

Table 3: Balancing tests for the validity of the identification strategy

| Dependent variable: \% of immigrants in the cohort | Ordinary Least Squares <br> (1) | School fixed effects <br> (2) | School-by-year fixed effects <br> (3) | School-by-year fixed effects + linear trend <br> (4) |
| :---: | :---: | :---: | :---: | :---: |
| \% of natives whose father has primary education | $\begin{gathered} 0.147^{* * *} \\ (0.013) \end{gathered}$ | $\begin{gathered} -0.010 \\ (0.007) \end{gathered}$ | $\begin{aligned} & -0.001 \\ & (0.006) \end{aligned}$ | $\begin{aligned} & -0.004 \\ & (0.005) \end{aligned}$ |
| \% of natives whose father has lower secondary education | $\begin{gathered} -0.012 \\ (0.0122) \end{gathered}$ | $\begin{gathered} 0.002 \\ (0.005) \end{gathered}$ | $\begin{gathered} 0.001 \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.002 \\ (0.004) \end{gathered}$ |
| \% of natives whose father has upper secondary education | $\begin{gathered} -0.132^{* * *} \\ (0.013) \end{gathered}$ | $\begin{aligned} & -0.012^{*} \\ & (0.006) \end{aligned}$ | $\begin{gathered} -0.001 \\ (0.006) \end{gathered}$ | $\begin{gathered} -0.001 \\ (0.004) \end{gathered}$ |
| \% of natives whose father has university education | $\begin{gathered} -0.092^{* * *} \\ (0.012) \end{gathered}$ | $\begin{gathered} 0.014 \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.004 \\ (0.006) \end{gathered}$ | $\begin{gathered} 0.001 \\ (0.005) \end{gathered}$ |
| Fraction of female students | $\begin{aligned} & 0.04^{* *} \\ & (0.014) \end{aligned}$ | $\begin{gathered} 0.014 \\ (0.009) \end{gathered}$ | $\begin{aligned} & -0.002 \\ & (0.005) \end{aligned}$ | $\begin{gathered} 0.003 \\ (0.005) \end{gathered}$ |
| Fraction of natives from disadvantaged families | $\begin{gathered} 0.105^{* * *} \\ (0.010) \end{gathered}$ | $\begin{gathered} 0.010 \\ (0.008) \end{gathered}$ | $\begin{gathered} 0.006 \\ (0.006) \end{gathered}$ | $\begin{gathered} 0.002 \\ (0.004) \end{gathered}$ |
| Average class size | $\begin{gathered} -0.092^{* * *} \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.007 \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.010 \\ (0.010) \end{gathered}$ | $\begin{gathered} -0.002 \\ (0.008) \end{gathered}$ |
| Enrollment in the grade | $\begin{gathered} 0.038^{* * *} \\ (0.009) \end{gathered}$ | $\begin{gathered} -0.018^{* *} \\ (0.008) \end{gathered}$ | $\begin{aligned} & -0.013 \\ & (0.017) \end{aligned}$ | $\begin{gathered} -0.002 \\ (0.007) \end{gathered}$ |
| Number of school cohorts | 12,053 | 12,053 | 12,053 | 12,053 |
| Notes. ${ }^{* * *}$ : significant at the $1 \%$ level, ${ }^{* *}$ : significant at estimates from separate regressions of the percentage of explanatory variable. Robust standard errors clustered include grade dummies. | e $5 \%$ leve migrant the school | *: significant dents in the evel are repo | the $10 \%$ level hool cohort on d in parenthes | ch row reports corresponding All regressions |

## 6. Results

### 6.1. Linear Effects of Immigrant Concentration

Our first set of results report the linear effects of the share of immigrants in the cohort on the test score of natives, shown in Table 4. According to the baseline estimates, immigrant concentration in the grade has a negative impact on natives' test scores in language and mathematics, but both estimates are statistically insignificant. In addition, the estimated effect size is very low in magnitude: an increase by 10 percentage points in the share of immigrant classmates in the cohort reduces the average verbal test score of natives by less than 0.10 , compared
to a standard deviation of 5.4 in natives' average language test score. The estimated effect is smaller for mathematics test scores and very close to zero. The inclusion of the full set of cohort average characteristics as controls has little impact on the effect size, as expected in a quasi-experimental setting.

Table 4: Baseline linear effect of the share of immigrant classmates

|  | Natives' <br> language score |  | $\begin{aligned} & \hline \hline \text { Natives' } \\ & \text { math score } \end{aligned}$ |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) |  | (3) | (4) |
| Share of immigrants in the cohort | $\begin{aligned} & \hline-0.776 \\ & (0.697) \end{aligned}$ | $\begin{aligned} & \hline-0.751 \\ & (0.769) \end{aligned}$ | $\begin{aligned} & \hline-0.185 \\ & (0.701) \end{aligned}$ | $\begin{aligned} & \hline-0.191 \\ & (0.706) \end{aligned}$ |
| Enrollment (2nd polyn.) |  | $\checkmark$ |  | $\checkmark$ |
| Cohort mean controls |  | $\checkmark$ |  | $\checkmark$ |
| Grade effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| School-by-year effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Number of cohorts | 12,053 | 12,053 | 12,053 | 12,053 |
| Notes. ${ }^{* * *}$ : significant at level, *: significant at the tered at the school level a cohort mean characteristic of parental education, the the share of disadvantaged ing system, the average c experience. | the $1 \%$ l $10 \%$ level e reporte include: share of students ass size | vel, **: s <br> Robust in paren the share male stu ccording the grad | icant at ard erro es. Con tudents s in the e Dutch acher's | he $5 \%$ <br> clus- <br> ols for <br> level <br> ohort, <br> eight- <br> ars of |

### 6.2. Heterogeneous Treatment Effects by Immigrant Type

Previous literature treats migrants as an homogenous group. However, immigrant classmates could generate different spillovers on natives depending on how long they have been in the host country, or on their socio-economic and educational background. To investigate this question, we estimate the effect of alternative treatments. First, we exploit valuable information on the length of stay of immigrant students in the Netherlands available in the data. One hypothesis is that the negative effect of the share of immigrants in the cohort, if any, is larger if migrants recently arrived to the country than if they have already been living in the host country for a longer period, and had more time to assimilate.

To investigate this possibility, we estimate the effect of two alternative treatments: the share of recent immigrants in the cohort (treatment 1), and the share of longer-term immigrants in the cohort (treatment 2). We classify as recent immigrants foreign-born students who have been living in the Netherlands for a maximum of three years, and long-term immigrants as foreign-born children who have been living in the country for more than three years. Table 5 reports the estimates for these two alternative treatment effects. Our estimates show that the share of recent immigrants in the grade has a negative and statistically significant effect on natives' verbal test scores. The estimated effect size is relatively small in magnitude. According
to our estimation, an increase of the share of recent immigrants by 10 percentage points reduces natives' average language test score by -0.30 , about 0.06 standard deviation. The estimated effect on natives' outcomes in mathematics is also negative, but the effect size is smaller and statistically insignificant. Estimates for the effect of the share of long-term immigrants in the grade show virtually no effect of the treatment on natives' test scores in both language and mathematics.

Table 5: Alternative treatments, based on immigrants' duration of stay in the Netherlands

|  | Natives' language score |  |  |  | Natives' math score |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment 1: Share of recent immigrants in cohort | $\begin{gathered} \hline-3.08^{* * *} \\ (0.981) \end{gathered}$ | $\begin{gathered} -2.88^{* * *} \\ (0.977) \end{gathered}$ |  |  | $\begin{gathered} \hline-1.55 \\ (0.913) \end{gathered}$ | $\begin{gathered} \hline-1.49 \\ (0.906) \end{gathered}$ |  |  |
| Treatment 2: Share of other immigrants in cohort |  |  | $\begin{gathered} 0.145 \\ (0.688) \end{gathered}$ | $\begin{gathered} 0.168 \\ (0.676) \end{gathered}$ |  |  | $\begin{gathered} 0.012 \\ (0.691) \end{gathered}$ | $\begin{gathered} -0.027 \\ (0.653) \end{gathered}$ |
| Enrollment (2nd polyn.) |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Cohort mean controls |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Grade effects | , | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| School-by-year effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Number of cohorts | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 |
| Notes. ${ }^{* * *}$ : significant at the $1 \%$ level, ${ }^{* *}$ : significant at the $5 \%$ level, ${ }^{*}$ : significant at the $10 \%$ level. Robust standard errors clustered at the school level are reported in parentheses. Controls for cohort mean characteristics include: the share of students by level of parental education, the share of female students in the cohort, the share of disadvantaged students according to the Dutch weighting system, the average class size in the grade, teacher's years of experience. Foreign-born students who have been living in the Netherlands for a maximum of three years are categorized as recent migrants. |  |  |  |  |  |  |  |  |

One potential mechanism behind those findings could be that it takes time for immigrant children to assimilate and acquire a stronger command of the local language. During this time, they may require additional teaching resources, which could leave fewer resources for native children studying in the same classroom. This effect is likely to be less pronounced when immigrant children have already spent substantial time in the country, acquired a stronger command of the host country language, and started to assimilate to the local context.

We also distinguish between the exposure to migrants from different socio-economic and educational backgrounds. As educational attainment is a key predictor of earnings and economic status, we classify immigrant children whose father achieved less than upper secondary education as being from families with low socio-economic background. Although most migrants to the Netherlands have low parental education, about $35 \%$ of migrant students in our sample have a father that completed upper secondary education or higher. Our results are reported in Table 6. They show a negative impact of migrants from a low socio-economic background on natives' test scores in language, while migrants with higher parental education have no statistically significant impact on natives. Once again, the negative impact is only statistically significant for
language test scores, and the effect size is relatively small compared to the standard deviation of natives' average test score.

Table 6: Alternative treatment effects, by immigrants' parental education

|  | Natives' language score |  |  |  | Natives' math score |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment 1: Share of immigrants with low parental educ. in cohort | $\begin{aligned} & -2.08^{* *} \\ & (0.905) \end{aligned}$ | $\begin{aligned} & -2.11^{* *} \\ & (0.977) \end{aligned}$ |  |  | $\begin{gathered} -1.32 \\ (0.987) \end{gathered}$ | $\begin{gathered} -1.28 \\ (0.999) \end{gathered}$ |  |  |
| Treatment 2: Share of immigrants with high parental educ. in cohort |  |  | $\begin{gathered} 0.783 \\ (1.102) \end{gathered}$ | $\begin{gathered} 0.541 \\ (1.205) \end{gathered}$ |  |  | $\begin{gathered} 0.076 \\ (0.668) \end{gathered}$ | $\begin{aligned} & -0.068 \\ & (0.662) \end{aligned}$ |
| Enrollment (2nd polyn.) |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Cohort mean controls |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Grade effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| School-by-year effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Number of cohorts | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 | 12,053 |
| Notes. ${ }^{* * *}$ : significant at the $1 \%$ errors clustered at the school level of students by level of parental edu according to the Dutch weighting with low parental education are de | vel, **: <br> e report ation, th stem, the ned as h | nificant in parent hare of average ng a fath | the $5 \%$ eses. Co male stud ass size that did | evel, *: trols for nts in the the gra not com | ficant at t mean ort, the eacher's upper se | e $10 \%$ l aracteris hare of d ars of ex ndary | el. Rob ics includ advanta erience. ucation. | standard the share students migrants |

### 6.3. Heterogeneous Effects by Natives' Types

We previously assumed that the effect of immigrant concentration was identical for all types of natives. However, the literature on classroom peer effects suggests that spillovers might be heterogeneous across students types. In particular, weak students are typically found to be more responsive to their peer composition than students from less disadvantaged backgrounds. Hanushek et al. (2003) find that the performance of students in the lower end of the ability distribution is more negatively impacted by the presence of repeaters in their grade. To investigate this possibility in our context, we look at the impact of immigrant concentration on two types of natives. We look separately at the impact on natives with low parental education and high parental education, as a proxy for family background and socio-economic status.

We run the same regressions as in Table 5 separately for these two groups. Results are presented in Table 7. Among natives with high parental education, the estimated treatment effects are approximately -1 for mathematics and language, and statistically insignificant. Among native students with low parental education, estimated effects on language and mathematics test scores are both negative, and larger in magnitude compared to natives with high parental education. The estimated treatment effect is approximately 3.35 for Dutch language test scores, and significant at the $5 \%$ level. For mathematics, estimates are statistically insignificant. This indicates heterogeneity in treatment effects, depending on the socio-economic background of native students receiving the treatment.

Table 7: Heterogeneous treatment effects by natives' parental education

|  | Natives with high parental education |  |  |  | Natives with low parental education |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Language score (1) <br> (2) |  | Math score <br> (3) <br> (4) |  | Language score (5) <br> (6) |  | Math score |  |
| Panel A: <br> Share of recent immigrants in cohort | $\begin{gathered} -1.131 \\ (1.291) \end{gathered}$ | $\begin{aligned} & -1.184 \\ & (1.223) \end{aligned}$ | $\begin{gathered} -0.935 \\ (1.178) \end{gathered}$ | $\begin{gathered} -0.620 \\ (1.171) \end{gathered}$ | $\begin{gathered} -3.34^{* *} \\ (1.457) \end{gathered}$ | $\begin{gathered} -3.35^{* *} \\ (0.446) \end{gathered}$ | $\begin{gathered} -1.13 \\ (1.402) \end{gathered}$ | $\begin{gathered} -1.12 \\ (1.379) \end{gathered}$ |
| Enrollment (2nd polyn.) <br> Cohort mean controls |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Grade effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| School-by-year effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Number of cohorts | 11,062 | 11,062 | 11,062 | 11,062 | 11,664 | 11,664 | 11,664 | 11,664 |
| Panel B: Share of other immigrants in cohort | $\begin{gathered} 0.202 \\ (1.425) \end{gathered}$ | $\begin{gathered} 0.156 \\ (1.375) \end{gathered}$ | $\begin{gathered} 0.090 \\ (1.502) \end{gathered}$ | $\begin{gathered} 0.118 \\ (1.563) \end{gathered}$ | $\begin{gathered} -1.503 \\ (1.657) \end{gathered}$ | $\begin{gathered} -1.462 \\ (1.276) \end{gathered}$ | $\begin{aligned} & -0.608 \\ & (1.643) \end{aligned}$ | $\begin{gathered} 0.587 \\ (1.576) \end{gathered}$ |
| Enrollment (2nd polyn.) |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Cohort mean controls |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Grade effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| School-by-year effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Number of cohorts | 11,062 | 11,062 | 11,062 | 11,062 | 11,664 | 11,664 | 11,664 | 11,664 |
| Notes. ${ }^{* * *}$ : significant at the $1 \%$ level, ${ }^{* *}$ : significant at the $5 \%$ level, ${ }^{*}$ : significant at the $10 \%$ level. Robust standard errors clustered at the school level are reported in parentheses. Controls for cohort mean characteristics include: the share of students by level of parental education, the share of female students in the cohort, the share of disadvantaged students according to the Dutch weighting system, the average class size in the grade, teacher's years of experience. Low parental education refers to having a father that did not complete upper secondary education while high levels of parental education are defined as having a father that completed upper secondary education or more. |  |  |  |  |  |  |  |  |

## 7. Robustness Checks

### 7.1. Falsification Tests

To further check whether our estimates do no capture a spurious correlation between immigrant concentration and other cohort-specific factors, we conduct falsification tests with placebo regressions. Instead of regressing native students' outcomes on the true presence of immigrants in their school cohort (actual treatment), we estimate regressions in which the treatment measure is replaced by a dummy for the presence of immigrants in the previous cohort, or in the next cohort (placebo treatments). If native students' outcomes are affected by cohort-specific unobservables correlated with immigrant concentration at the school level, then the placebo should also be significantly associated with outcomes. Finding a significant effect of the placebo on test scores would therefore cast doubt on the validity of the identification strategy.

Results reported in Table 8 show no association between the share of immigrants in the previous or next cohort and native students' test scores. Estimates of placebo effects are much smaller than for the actual treatment, statistically insignificant, and of inconsistent signs. For example, when using the presence of immigrants in the next cohort (placebo 1) instead of the actual presence of immigrants in the cohort, the estimated effect on natives' language
scores is -0.36 (standard error: 1.24), compared to -3.08 with the actual treatment. When the proportion of immigrants in the previous cohort is used as alternative placebo (placebo 2), the estimated coefficient is of the opposite sign, and also statistically insignificant. This can be viewed as further evidence that our estimates capture the true effect of immigrant concentration on students' outcomes, rather that the confounding influence of cohort-specific characteristics. In particular, if endogenous student mobility was driving our results, we would expect the share of immigrants in previous cohorts to be a significant predictor of current achievement. The results of our placebo regressions suggest that this is not the case.

Table 8: Falsification tests - placebo regressions

|  | Natives' <br> language score |  | Natives' math score |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | (2) | (3) | (4) |
| Treatment variable: |  |  |  |  |
| Actual treatment: Share of recent immigrants in cohort | $\begin{gathered} -3.08^{* * *} \\ (0.981) \end{gathered}$ | $\begin{gathered} -2.88^{* * *} \\ (0.977) \end{gathered}$ | $\begin{gathered} -1.55 \\ (0.913) \end{gathered}$ | $\begin{gathered} -1.49 \\ (0.906) \end{gathered}$ |
| Placebo 1: Share of recent immigrants in next cohort | $\begin{gathered} -0.361 \\ (1.241) \end{gathered}$ | $\begin{gathered} 0.120 \\ (0.112) \end{gathered}$ | $\begin{gathered} 0.038 \\ (1.201) \end{gathered}$ | $\begin{gathered} 0.179 \\ (1.192) \end{gathered}$ |
| Placebo 2: Share of recent immigrants in previous cohort | $\begin{gathered} 0.526 \\ (1.189) \end{gathered}$ | $\begin{gathered} 0.534 \\ (1.181) \end{gathered}$ | $\begin{gathered} -0.472 \\ (1.092) \end{gathered}$ | $\begin{gathered} -0.294 \\ (1.071) \end{gathered}$ |
| Enrollment (2nd polyn.) |  | $\checkmark$ |  | $\checkmark$ |
| Cohort mean controls |  | $\checkmark$ |  | $\checkmark$ |
| Grade effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| School-by-year effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| N. of Observations | 12,053 | 12,053 | 12,053 | 12,053 |
| Robust standard errors clustered at the school level are reported in parentheses. Each row reports estimates from separate regressions with the corresponding treatment variable. Controls for cohort mean characteristics include: the share of students by level of parental education, the share of female students in the cohort, the share of disadvantaged students according to the Dutch weighting system, the average class size in the grade, teacher's years of experience. |  |  |  |  |

### 7.2. Restricting the Sample to Schools with One Classroom per Grade

Our baseline estimates use grade-level peer composition to identify the causal effect of immigrant students in the classroom on the achievement of natives. As detailed earlier, the potential bias associated with using grade-level measures as opposed to classroom-level measures is greatly attenuated in our context as most primary schools in the Netherlands only have one classroom per grade. We however assess the robustness of our findings in the subsample of schools with a single classroom per grade, which represent approximately $70 \%$ of our sample of schools.

Estimated effects of the concentration of recent migrants in the two samples are displayed in Table 9. The estimated effect of the concentration of recent immigrants in the cohort on
natives' language test scores is negative and significant at the $1 \%$ level in both subsamples. The effect size is also very similar, although estimates are slightly larger in the restricted sample for language, and very similar for mathematics. The slightly smaller effect size in language could result from a residual downward bias in the estimation of spillovers in schools that have more than one classroom per grade. Alternatively, it could also originate from migrant spillovers being actually larger in smaller schools because, for example, they might be lacking adequate structures to accommodate recent migrants.

Table 9: Linear treatment effect in full sample and restricted sample

|  | Full sample |  |  |  | Schools with a single class per grade |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Natives' language score <br> (1) <br> (2) |  | Natives' math score |  | Natives' <br> language score |  | Natives' math score |  |
|  |  |  | (3) | (4) | (5) | (6) | (7) | (8) |
| Share of recent migrants in cohort | $\begin{gathered} \hline-3.08^{* * *} \\ (0.981) \end{gathered}$ | $\begin{gathered} \hline-2.88^{* * *} \\ (0.977) \end{gathered}$ | $\begin{gathered} -1.55 \\ (0.913) \end{gathered}$ | $\begin{gathered} -1.49 \\ (0.906) \end{gathered}$ | $\begin{gathered} -3.60^{* * *} \\ (1.28) \end{gathered}$ | $\begin{gathered} \hline-2.98^{* * *} \\ (1.38) \end{gathered}$ | $\begin{gathered} \hline-1.48 \\ (1.27) \end{gathered}$ | $\begin{gathered} \hline-0.980 \\ (1.19) \end{gathered}$ |
| Enrollment (2nd polyn.) |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Cohort mean controls |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |  | $\checkmark$ |
| Grade effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| School-by-year effects | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Number of cohorts | 12,053 | 12,053 | 12,053 | 12,053 | 8,188 | 8,188 | 8,188 | 8,188 |
| Notes. ${ }^{* * *}$ : significant a errors clustered at the sch of students by level of pa according to the Dutch w | the $1 \%$ leve ol level a ntal educ ghting sy | l, ${ }^{* *}$ : sig reported ion, the m, the | nt at th enthese of femal class s | $5 \%$ leve Control students in the | ignificant cohort me e cohort, teacher' | the $10 \%$ charact e share of ears of ex | . Rob <br> inclu dvanta nce. | tand he sh stude |

## 8. Conclusion

Our findings contribute to the literature on immigrant peer effects in the classroom by showing that spillovers vary depending on the duration of stay of first-generation immigrant classmates in the country, but also on the socio-economic background of both immigrant and native students. This new evidence could partly explain why previous contributions estimating the effect of immigrant concentration on natives' educational attainment report mixed results. Our findings in the Dutch context suggest that only immigrant students that have been living in the country for a short period negatively impact natives' performance in language. On the other hand, the share of immigrant classmates who have already been living in the country for longer periods of time is found to have no effect on natives' achievement.

Although the exact mechanisms behind these results would need to be further investigated, our findings suggest that assimilation and host country language acquisition may play a role in generating immigrant peer effects in the classroom. If heterogeneity among classmates drives learning spillovers as suggested by Lazear (2001), and if immigrant students progressively assimilate and acquire a greater command of the host language over time, it is plausible to observe
learning spillovers decline with the duration of stay of immigrants in the host country. The fact that adverse effects are only statistically significant for language test scores also points towards host country language proficiency as a potential channel.

The adverse effects of recent migrants on natives are relatively small in magnitude. An increase by 10 percentage points in the share of recent migrants in the classroom is estimated to reduce natives' language test scores by about 0.06 standard deviation. The specificities of the Dutch primary school system and the features of our dataset provide comfort on the precision of our estimates. The predominance of schools with a single classroom per grade in the Netherlands allows to circumvent the issue of non-random allocation of students to classroom by using grade-level measures of peer composition, while alleviating concerns about attenuation biases resulting from measuring peer composition at the grade level. The robustness of our baseline findings in the subsample of schools with a single classroom per grade further alleviate concerns. In addition, our balancing and falsification tests suggest that our estimates are not contaminated by selection.

We also find that native students with low parental education are mostly impacted by immigrant concentration, both because they appear more vulnerable to the presence of recent immigrants in the classroom, but also because they are exposed to immigrant peers with lower parental education. The fact that adverse effects are stronger among natives from more disadvantaged families is consistent with the peer effect literature showing that the academic performance of weaker students tend to suffer more from the presence of low achievers in the classroom. One potential explanation for this finding is that natives from disadvantaged families are lacking resources at home to substitute for classroom instruction, which is affected by the presence of recent immigrants. Overall, our results suggest that policies putting in place integration programs for recently arrived migrant students could be useful to mitigate those effects, particularly in schools where native and immigrant children disproportionally come from disadvantaged families. Because of the similarities shared by the migration context in the Netherlands with other countries, particularly the predominance of migrants from low socio-economic backgrounds, we believe our findings are of relevance beyond the Dutch context.

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[^1]:    ${ }^{1}$ The scholastic achievement of immigrant students has been shown to be poor compared to native children in most high-income countries. According to the OECD Program for International Student Assessment (PISA), the performance gap between first generation immigrants and natives amounts to around half a standard deviation in math, reading, and science (OECD, 2012).
    ${ }^{2}$ See Lazear (2001) for theoretical insights on the topic and Duflo et al. (2011), among others, for an empirical application.

[^2]:    ${ }^{3}$ One recent exception is Ballatore et al. (2015) which attempt to account for the endogeneity of classroom formation to identify the effect of immigrant classmates.
    ${ }^{4}$ See Cunha and Heckman (2007), among others.

[^3]:    ${ }^{5}$ Epple and Romano (2011) or Brodaty (2010) provide a literature review of applied work estimating peer effects in the classroom.

[^4]:    ${ }^{6}$ Outside Europe, Gould et al. (2009) have also investigated the long-term impact of immigrant concentration in the classroom on the matriculation rates of natives in Israel.

[^5]:    ${ }^{7}$ The full PRIMA dataset consists of a representative sample of about 420 schools and also includes an additional sample of about 180 schools with children from a low socio-economic background.
    ${ }^{8}$ We refer to a cohort observation as a grade of a given school observed in a given year. For example, grade 2 of school 1 observed in 1994 is a cohort observation.

