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Linguistic Diversity in the Classroom, Student Achievement, and Social Integration

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Julia Bredtmann, Sebastian Otten, and Christina Vonnahme[1]

Linguistic Diversity in the Classroom, Student Achievement, and Social Integration

Abstract

In this article, we analyze whether non-native speakers in the classroom affect the educational achievement and social integration of migrant and native students. In contrast to previous studies, which mainly examine the effect of the share of immigrant pupils, we focus on language heterogeneity by using a novel measure of the degree of linguistic diversity in the classroom. Our analysis is based on a comprehensive survey of 4th-grade students in German primary schools, which contains detailed information on students' language and math scores, their social integration, as well as on sociodemographic and school characteristics. We find a negative association between the share of non-native speakers in the classroom and students' test scores and their social integration in the class. Conditional on the immigrant concentration in the class, the degree of linguistic diversity has no adverse effect on students' language and math skills, but worsens the social integration of immigrant students. We demonstrate the robustness of these findings in a variety of robustness checks.

JEL Classification: I21, I24, J15

Keywords: Linguistic diversity; educational performance; social integration; migrant peer effects

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[1] *Julia Bredtmann, RWI, IZA, and CReAM; Sebastian Otten, University College London, CReAM, and RWI; Christina Vonnahme, RWI and RUB.* *– This work was financially supported by the Mercator Foundation. The authors are grateful to Thomas Bauer and to participants of the 7th International Workshop on Applied Economics of Education, the 2017 annual meeting of the Leibniz Education Research Network (LERN), and the 2018 LERN Forum on Educational Policy for helpful comments and suggestions.* *– All correspondence to: Christina Vonnahme, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: christina.vonnahme@rwi-essen.de*

1 Introduction

Over the last decades, many Western countries experienced large inflows of immigrants. For instance, Germany witnessed a huge increase in immigration due to both rising immigrant populations from within the EU and a high number of refugees. In 2015, the net immigration of foreign people to Germany reached 1.24 million, which represents an 84 percent increase compared to 2014 and a record high in post-war history (BAMF 2015). The increase in immigration has drawn considerable attention to issues regarding the impact of immigrants on labor market outcomes of natives (e.g., Card 1990 & 2001; Borjas 2003; Dustmann *et al.* 2013 & 2017; Foged and Peri 2016) and the fiscal effects of immigration (e.g., Auerbach and Oreopoulos 1999; Dustmann and Frattini 2014; Preston 2014). Due to the rising share of immigrant students in destination countries, similar debates about the integration of immigrant children have opened in recent years. As children of immigrants exhibit significant gaps in school performance relative to native children (Ammermueller 2007; Schnepf 2007; Colding *et al.* 2009), concerns about adverse effects of immigrant children on the educational outcomes of native children have been raised. These concerns might motivate native parents to choose schools with a low immigrant concentration, thus fostering ethnic segregation in schools.

Despite being a key part of the immigration debate, the literature on the role of immigrant children in schools is relative small and the evidence remains largely inconclusive. Previous research has mainly focused on analyzing the effects of immigrant concentration in classes or schools on the educational outcomes of both immigrant and native children. However, rising migration flows do not only increase the share of immigrant children in schools, but the fact that current immigrants to Europe increasingly come from more culturally and linguistically distant countries also changes the ethnic and linguistic composition of the class. Yet, relatively little evidence exists on how the degree of ethnic or linguistic diversity in the classroom affects student outcomes.

In this paper, we examine whether – in addition to the immigrant concentration in the class – the linguistic composition of the immigrant group matters for native and migrant

students' educational outcomes. In particular, we analyze whether the degree of linguistic diversity in the class has an impact on students' language and math test scores as well as on their social integration. Analyzing the role of linguistic diversity has important implications for the optimal allocation of immigrant students to classes and is thus of utmost interest for both policymakers and educators. To provide conclusive evidence on this issue, we rely on contributions from the macroeconomic and political science literature (e.g., Easterly and Levine 1997; Alesina *et al.* 2003; Montalvo and Reynal-Querol 2005) and construct a novel measure of the degree of linguistic diversity in the class, which takes into account both the size of the different immigrant groups and the linguistic distance between them. Our analysis is based on a comprehensive survey of about 27,000 4^{th}-grade students in 1,249 German primary schools. The dataset is unique in containing detailed information on students' and their parents' migration history, on children's mother tongue, family and school characteristics, as well as results of standardized tests in both German language and math. Information on students' social integration in the class further allows us to shed light on whether social cohesion is affected by the linguistic diversity in the class.

Previous literature has mainly assessed the effects of immigrant peers by analyzing how the share of migrants in the class or school affects the educational outcomes of native and non-native students. The results of these studies are mixed. While Gould *et al.* (2009) for Israel, Cho (2012) and Diette and Oyelere (2014 & 2017) for the US, and Tonello (2016) and Ballatore *et al.* (2018) for Italy find adverse effects of immigrant concentration on the school performance of native pupils, Geay *et al.* (2013) for England find no spillover effects of non-native speakers on native students. Focusing on internal migrants in China, Wang *et al.* (2018) find a positive effect on local students' test scores in Chinese, but no effects on their math and English test scores.

Other studies focus not only on native students but also investigate the educational outcomes of students with a migration background. For instance, Ohinata and van Ours (2013) for the Netherlands and Schneeweis (2015) for Austria find no adverse effects for native students but some negative effects on immigrant students' school performance.

Jensen and Rasmussen (2011) for Denmark find negative effects of a higher immigrant concentration for both native and immigrant students. Evidence for Germany is rare. An exception is the study by Stanat (2006), which finds a small negative correlation between the share of non-native speakers in the school and reading test scores for 15-year-old natives and migrants. In general, the effects found in the literature are relative small and stronger (or only present) for migrants, suggesting that rather the educational integration of migrants than the school outcomes of native children are affected by immigrant peers.[1]

While several studies analyze the consequences of immigrant concentration in schools for students' educational outcomes, much less is known about the effects of the composition of the immigrant group in a class. However, when investigating students' peer effects, it is reasonable to argue that it is not only the share of migrants or non-native speakers that matters for students' outcomes, but that the degree of diversity among them is also relevant. As language proficiency is a strong predictor of children's schooling success, especially the degree of linguistic diversity in the classroom should matter for students' outcomes. On the one hand, the grouping of children with a similar mother tongue may improve their self-consciousness through identity-building and thus foster their learning outcomes. On the other hand, the formation of a large group of children with a different mother tongue than the majority language may slow the learning of this language and negatively impact learning by dividing the class and impeding the children's sense of togetherness.

The few existing studies that analyze the effects of class- or school-level diversity on students' outcomes focus on ethnic diversity. In particular, these studies use variants of the Herfindahl-Hirschman index calculated based on students' ethnicity or their (parents') country of birth to measure ethnic diversity within the class or school. Using PISA data of 15-year-old students from 15 OECD countries, Dronkers and van der Velden (2013) find a negative association between the ethnic diversity in the school and the language performance of immigrant students. The language performance of native students is only

[1]For a cross-country comparative perspective, see, e.g., Dustmann *et al.* (2012) and Brunello and Rocco (2013).

negatively influenced in highly stratified educational systems. The study by Maestri (2017) uses data of Dutch primary school students and finds that ethnic diversity has no impact on native students' literacy scores, but does increase those of immigrant students. The results further suggest a negative effect of ethnic diversity on social integration. Frattini and Meschi (2017) use administrative data on the universe of students in Italian vocational training institutions. They find that the presence of immigrant students in the classroom has no effect on native students' literacy achievements but small effects on their math scores. Ethnic diversity, however, has no effect on students' performance.

Our work contributes to the literature on the externalities of non-native peers on students' educational outcomes in several dimensions. First, we add to the small literature that analyzes the effect of the composition of the immigrant group on native and non-native students' school performance. While previous studies focus on ethnic heterogeneity to measure diversity in the class, we instead use information on students' mother tongue, which is particularly relevant in the context of language acquisition and application at school. Moreover, we extend the previously used diversity measure, the Herfindahl-Hirschman index, by incorporating a component measuring the distance between the different language groups into the diversity measure. The resulting Greenberg index is a more precise measure of the degree of linguistic heterogeneity in the class. In the context of social interactions in education, this is the first time that a diversity measure takes into account both the size of the different immigrant groups and the distance between them.

Second, we extend the empirical literature on Germany. With the exception of the study by Stanat (2006), which does not analyze diversity effects, there exists no evidence on the peer effects of non-native speakers on student achievement in German schools. Germany presents an interesting case study, as it is a country with a long migration history where concerns against immigrants and the question of how to integrate them best in the educational systems have recently become highly topical given high absolute and relative numbers of immigrants, in particular the 400,000 school-age refugees (The Economist 2017; Spiegel Online 2017).

In contrast to the existing literature that focuses mainly on students in high schools

and above, we further contribute to the literature by analyzing the spill-over effects among primary school children. This allows us to evaluate the effects on native and non-native students at a young age. Knowledge about the effects at a young age is particular important as the foundation for success in school and later at work is already laid in the first years of schooling. The benefits of a high quality early childhood education are especially high for disadvantaged and immigrant children (Arnold and Doctoroff 2003; Heckman 2006). Moreover, the existing evidence on high school students is likely to reflect the accumulated impact from the exposure to immigrant students during many years of schooling. Studying young students has the advantage of reducing the extent of such an accumulated exposure effect.

Lastly, we contribute to the literature by analyzing whether the concentration and the composition of the non-native speakers in the class affect the social integration of migrant and native students. This is an important question as good student-student relationships are a key factor in creating a positive classroom climate (Kyriakides and Creemers 2008), which itself can be an important determinant of children's school success. Furthermore, the integration of immigrants and their children in the society of their destination country is one of the major challenges immigration countries face. Schools can provide the ideal environment to improve integration and reduce the difficulties faced by immigrant children. Providing evidence on the effects of class composition on migrants' social integration is therefore of particular interest for both policymakers and educators.

Overall, we find a negative association between the share of non-native speakers in the class and students' test scores and their social integration. Conditional on the immigrant concentration in the class, the degree of linguistic diversity has no impact on students' language and math test scores. This reveals that an increase in the number of students from more culturally or linguistically distant countries has no additional negative impact on students' educational outcomes. We find, however, that a higher linguistic diversity in the class hampers the social integration of non-native speakers. In particular, non-native students in classes with a high linguistic diversity are more likely to have arguments with their classmates and have less friends in class. This suggests that the social integration of

migrants could be improved by reducing linguistic diversity and allocating more students with the same linguistic background to the same class.

The remainder of the paper is as follows. Section 2 describes the data used and the construction of the linguistic diversity measure. In Section 3, we outline the empirical framework. Results and sensitivity analyses are discussed in Section 4. Section 5 provides concluding remarks.

2 Data and diversity measure

We analyze how linguistic diversity in the classroom affects the educational success of schoolchildren in Germany, a country with a high share of children with migration background that has been rising steadily in the past years.[2] For this purpose, we use data from the "Ländervergleich 2011" (which literally means "comparison of [federal] states"), an education study that was conducted among 27,081 4th grade students in 1,249 primary schools in all German federal states. The main aim of the survey was to systematically compare the achievements in German and math of children at the end of primary school, when they are typically between 9 and 10 years old. The sampling procedure first randomly selected primary schools in each federal state, and one class within each school. The dataset is particularly suitable for our research question as the sample size is large compared to other datasets. Moreover, it is unique in containing detailed information on the students' and their parents' and grandparents' migration history, on children's mother tongue, socioeconomic and school characteristics, and results of standardized tests in both German language (reading and listening) and math (five different learning fields: numbers and operations; space and form; patterns and structures; quantities and measures; data, frequencies and probabilities). The tests and surveys were the same for all students, and all students per class were included. The surveys covered the students, their parents, teachers and schoolmasters.[3]

[2]According to the German Microcensus, 28 percent of children under the age of 15 years had a migration background in 2011. This share has been rising up to 36 percent in 2017.

[3]A detailed description of the dataset is provided by Stanat *et al.* 2012 & 2014 and Richter *et al.* 2014.

Our sample includes 15,686 school children, containing 14,717 children whose mother tongue is German ("native speakers" or "natives") and 969 children whose mother tongue is a language other than German ("non-native speakers" or "migrants").[4]

The information on children's mother tongue, which is provided by the children's parents, is key to construct the two samples and to compute the measure of linguistic diversity. As this information is restricted to the ten most prevalent languages in the data, we impute further languages using information on the countries of birth of the children as well as of their parents and grandparents. The resulting distribution of 17 mother tongues is depicted in Figure 1. Turkish is the language spoken by most migrant children with a share of almost 50 percent. Further important languages include Russian, Polish and Kurdish with shares of more than 5 percent each.

Based on the information on children's mother tongue, we calculate our two main variables of interest, the share of non-native speakers and the linguistic diversity in the class. To construct the latter, we rely on contributions from the macroeconomic and political science literature, where different diversity measures have been refined and applied to analyze the impact of ethnolinguistic diversity on economic growth, redistribution, and measures of political stability (e.g., Easterly and Levine 1997; Alesina *et al.* 2003; Montalvo and Reynal-Querol 2005). Among the different measures, which can be summarized after Desmet *et al.* (2009) as measures of "social effective antagonism", the so-called Greenberg index (Greenberg 1956) stands out to suitably measure differential effects of linguistic diversity in the classroom on student performance. It is defined as

$$GI = \sum_{j=1}^{N} \sum_{k=1}^{N} s_j \, s_k \, \delta_{jk} \tag{1}$$

and increases in the number of (language) groups, N, and the similarity of the relative size of the different groups j, s_j. δ_{jk} measures the (linguistic) distance between each pair of groups j and k. By incorporating the distance between the groups, the diversity measure accounts for the heterogeneity between the groups leading to higher index values for a

[4]The sample is conditional on non-missing information on language and further individual, family and school characteristics as described below.

more diverse set of groups. With δ_{jk} and the group shares s_j scaled between zero and one, the Greenberg index ranges between zero and one where larger values indicate higher diversity. It is closely related to the simple measure of (ethno-linguistic) fractionalization, given as

$$ELF = 1 - \sum_{j=1}^{N} s_j^2 \,, \tag{2}$$

which is the reverse of the commonly used Herfindahl-Hirschman index:

$$HHI = \sum_{j=1}^{N} s_j^2 \,. \tag{3}$$

In contrast to these measures without distance, the Greenberg index is not "color-blind", i.e., it not only takes into account the number and size of different groups, but also one further characteristic, which is the linguistic distance to other groups. The color-blindness is described as a deficit of the Herfindahl-Hirschman index amongst others by Dronkers and van der Velden (2013), who use this measure in their analysis.

Desmet *et al.* (2005) show that for the effect of diversity on redistribution, the linguistic distance between the languages is highly important. We therefore incorporate linguistic distance into our analysis using a new measure of linguistic distance developed by linguists (see Bakker *et al.* 2009), which has recently been applied to the economic context by Isphording and Otten (2013 & 2014). The so-called "Levenshtein distance" is computed by comparing the phonetic similarity of each word of a given word list for each pair of languages. The "Swadesh word list" (Swadesh 1952) includes 40 standard words with translations in all languages. The average distance in the phonetic transcription between two languages is scaled between zero (no linguistic distance) and 100 (maximum linguistic distance). We rescale it to range between zero and one to include it in our measure for linguistic diversity.

As the share of Germans is already captured by our second variable of interest, the percentage of non-native speakers in the class, we calculate linguistic diversity within the group of non-native speakers in the class. The mean of the resulting measure of linguistic diversity is 0.33 for the sample of non-native speakers and 0.09 for the sample

of native German speakers, as shown in Table A1. It is, by definition, zero for classes without non-native speakers, which we explicitly capture by including a respective indicator variable for these classes.

The share of non-native speakers in the class is 0.28 for the migrant and 0.06 for the native subsample. This already points to a certain concentration of migrants in schools, or more in general to a segregation of natives and migrants. 50 percent of the children in the native subsample are in classes in which none of the children has a mother tongue other than German. The distribution of the share of non-native speakers for natives and migrants is displayed in Figure A1.

To measure students' performance in school, we rely on the results of the standardized tests in German language and math that have been conducted as part of the survey. The standardized test scores are scaled to a mean of 500 and a standard deviation of 100 in the gross sample, as is common for several education datasets including the PISA data. In our sample, children whose native language is German on average achieve test scores of 522 and 521 points in language and math, respectively. In the migrant sample, the scores are substantially lower with 450 points in language and 456 points in math. The standard deviation is slightly higher in the migrant sample. To analyze if linguistic diversity has an impact on children's cohesion, i.e. beyond individual performance, we use a measure of social integration as a further dependent variable. The social integration index is calculated as an average of four questions on children's relations with classmates. The children indicated whether they agreed: (1) not, (2) rather not, (3) rather or (4) completely that they have (i) friendly classmates, (ii) caring classmates, (iii) many friends in class and (iv) no arguments with classmates. In general, most answers indicate a high social integration. On average, migrants agreed slightly less with the questions asked (see Table A1).[5]

Figure 2 shows the correlation between the three outcome variables and the linguistic diversity in the classroom, as measured by the Greenberg index. It reveals that linguistic

[5]The distribution of the three dependent variables for the sample of native and non-native speakers is depicted in Figure A2.

diversity is negatively correlated with test scores with correlations of around -0.24, but less so with the index of social integration where correlations range at around 0.1. Classes without any non-native speakers or with only one non-German language group have, by definition, a diversity of zero.

In the empirical analysis, we control for several individual and family characteristics to isolate the association between linguistic diversity and student outcomes. As individual characteristics, we include gender and a linear and quadratic measure of age, measured with monthly precision, to account for non-linear effects. To capture the pure age effect, we also include a dummy variable for students who repeated at least one of the four grades in primary school.

For non-native speakers, we further take the linguistic distance between their mother tongue and German into account. In addition, we include an indicator variable for whether these children are first-generation immigrants. As our samples are defined based on children's mother tongue and not on their ancestry, native speakers may be born abroad or have foreign ancestry as well. We capture potential differences between these children and children without foreign ancestry by a dummy variable that equals one for first- or second-generation immigrants. For non-native speakers, we further add indicators for their region of origin, which capture the main so-called guest worker countries (Greece, Italy, Turkey), former Yugoslavia, Eastern European countries and the remaining countries.

Family characteristics cover the education level of the mother and the father in three categories (high, medium and low, based on the ISCED classification) as well as their employment status, distinguishing between white-collar workers, blue-collar workers and others. For mothers, we further control for whether they are full-time employed, part-time employed or not employed.

The school characteristics capture differences between cities of different size by a linear variable for the number of inhabitants at the school location and indicator variables for private vs. public and all-day vs. half-day schooling.

3 Empirical framework

To analyze the role of linguistic diversity in student performance, we estimate the following regression equation:

$$y_{ic} = \alpha + \beta\, migshare_c + \gamma\, diversity_c + X'_{ic}\,\delta + S'_c\,\theta + \rho_s + \epsilon_{ic}\,, \tag{4}$$

where y_{ic} denotes the test score or social integration index of student i in class c. $migshare_c$ is the share of students with a non-German mother tongue in class c and $diversity_c$ is the linguistic diversity of non-native speakers in the class. X_{ic} are individual and family characteristics and S_c are school characteristics as described in Section 2. ρ_s denotes fixed effects for the 16 German federal states, which capture regional differences in population structures and student outcomes between the states. ϵ_{ic} depicts the error term. All analyses are conducted separately for native and non-native speakers.[6] Combined student, class, and school weights are used in all analyses and standard errors are clustered at the class level.

The main coefficient of interest is $\hat{\gamma}$, the estimated effect of the linguistic diversity in the classroom on students' test scores and social integration. For $\hat{\gamma}$ to represent a causal estimate, we would have to assume that there are no unobserved characteristics that are both correlated with linguistic diversity and students' outcomes. In the absence of panel data or a (quasi-)random allocation of students to schools and classes, this assumption is at risk of being violated. Nevertheless, we argue that by conditioning on the share of immigrants in the classroom as well as on an extensive set of background characteristics of students, their family, and their school, the linguistic diversity in each class should no longer be correlated with the error term ϵ_{ic}. While the share of non-native speakers may still be correlated with the error term, there is no reason to believe that, conditional on the migrant share, the linguistic composition of the immigrant group is correlated with any unobserved factors that influence students' outcomes.

[6] Note that for native speakers, Equation 4 includes an indicator variable for classes without non-native speakers as a further class characteristic.

Though we are not able to test the exogeneity assumption directly, we perform two indirect tests to check the validity of our identification assumption. Table 1 provides results from a balancing test, which analyses whether observable characteristics that potentially influence student outcomes are correlated with linguistic diversity. Columns (1) and (3) contain the estimated coefficients from separate regressions for each control variable, i.e., they measure the pure correlation between linguistic diversity and each observable characteristic.[7] Columns (2) and (4) show the results from similar regressions, but each of them conditioning on all other control variables, including the share of non-native speakers in the class. After including all other controls, the estimated coefficients should go to zero if variation in linguistic diversity is truly random. The results reveal that in the unconditional case, some of the background characteristics are correlated with linguistic diversity. However, they also show that including additional controls does a good job of removing the association between each specific control and linguistic diversity. Except for the share of non-native speakers in the class, which is – by definition – to some extent correlated with the diversity measure, hardly any of the other control variables are significantly correlated with linguistic diversity. In addition, the point estimates are very small in magnitude and the signs of the coefficients point in no clear direction. We thus conclude that, once we control for other observable characteristics, linguistic diversity is not systematically related to school and family background characteristics.

Nevertheless, to assess if the lack of complete balancedness might potentially skew results in a certain direction, we further perform an omnibus test. The test exploits the fact that, in order to bias our results, covariates would need to be systematically correlated with both linguistic diversity and students' outcomes. In the first stage (results not shown), we use the full set of control variables, except for linguistic diversity, to predict our outcome variables, i.e., students' language and math scores and their social integration. In the second stage, we then regress the predicted outcome variables on linguistic diversity. As Panel A of Table 2 shows, linguistic diversity is significantly negatively correlated with the three predicted outcome variables. However, this correlation accrues from the fact

[7]For categorical variables, we include the indicator variables for all categories in one regression.

that in our setting, the share of non-native speakers is by definition positively correlated with linguistic diversity (and negatively correlated with the outcome variables). Once the share of non-native speakers is conditioned on (Panel B of Table 2), linguistic diversity is not significantly correlated with the predicted outcome variables. We are thus confident that observed (and unobserved) correlates of the linguistic composition of school classes are unlikely to confound our regression results.

4 Results

4.1 Share of non-native speakers

Our analysis on the effect of linguistic diversity on student performance is based on the role of the share of non-native speakers in the class. To shed light on the importance of the share of non-native speakers in the class, we therefore start our analysis by estimating Equation 4 without the measure of linguistic diversity. Accordingly, Tables 3 and 4 show the results from ordinary least square regressions that explain student performance by the share of non-native-speakers in the class (columns (1), (3), and (5)) as well as individual, family, and school characteristics (columns (2), (4), and (6)). For ease of interpretation, all coefficient estimates for social integration (columns (5) and (6)) are multiplied by 100.

For the native subsample (Table 3), the share of non-native speakers in the class is significantly negatively associated with both students' test scores and their social integration. Adding individual, family, and school characteristics reduces the negative link between the share of non-native speakers and students' test scores, while the effect on social integration remains unchanged. A 10 percentage points increase in the share of non-native speakers in the class (which corresponds to an increase by approximately 1 standard deviation) lowers the language (math) test score of native speakers by around 8.7 (7.8) points, which corresponds to reductions in test scores of about 0.11 (0.09) standard deviations. The effects on language and math are therefore comparable in magnitude. A similar increase in the share of non-native speakers reduces social integration by 0.29

points or 0.05 standard deviations.

For non-native speakers (Table 4), there is also a negative link between the share of non-native speakers in the class and schooling outcomes. The estimated coefficients are smaller than for the native sample, however, and not statistically significant for social integration. The inclusion of individual, family, and school characteristics slightly weakens this relationship, which provides some evidence for segregation of immigrants along observable characteristics. A 10 percentage points (1 standard deviation) increase in the migrant share is associated with a 4-point (0.1 standard deviations) reduction in the language test score and an 8-point (0.16 standard deviations) reduction in the math test score. In terms of standard deviations, the effect on language is therefore of comparable size to that for the native sample, while the effect on math is larger in the migrant sample.

Overall, the results show that the link between the share of non-native speakers in the class and individual student performance is highly significant, but moderate in size. A 1 standard deviation increase in the share of non-native speakers reduces test scores by at most 0.16 standard deviations. This is in line with previous literature on the effect of the class share of immigrants on student performance. In particular, our results are of similar size as those of Stanat (2006), who uses PISA data to analyse students' performance in German secondary schools. However, studies that use instrumental variable or fixed effects regression to address the potential endogeneity of the migrant share in the class usually find smaller effects (e.g., Ohinata and van Ours 2013; Diette and Oyelere 2014). As we are not able to fully address the problem of a selection of disadvantaged students into classes with many migrants, our estimates represent upper bounds of the true effects of the share of non-native speakers on students' outcomes. Our results further reveal that the association between the migrant share and student's test scores is larger for non-native than for native speakers (at least in math). This is in line with most of the previous literature, which typically finds more adverse effects for migrants than for natives, but contradicts the results of Jensen and Rasmussen (2011), who find opposite effects. Lastly, our finding of a weaker social integration of native students in classes with many non-native speakers is consistent with Ohinata and van Ours (2013), who observe more bullying in

classes with higher immigrant shares.

The coefficients of the control variables are mostly in line with theoretical expectations and in accordance with previous research. Most individual characteristics are highly significant determinants of school success. Girls achieve higher language test scores than boys, but perform worse in math. Concerning social integration, they tend to get along better with their classmates than do boys. For non-native speakers, the differences are statistically insignificant for language test scores and social integration, but even stronger for math. Age has a non-linear effect on schooling outcomes: Young and very old native children show worse outcomes compared to medium-aged students, even though this effect is not driven by children who repeated a class, who perform worse than non-repeaters. For children with a non-German mother tongue, the age effects are similar for language test scores, weaker and insignificant for social integration, and even reverse (but insignificant) for math. Concerning students' migration background, the results reveal that German-speaking children who have foreign ancestry have lower test scores and a weaker social integration than children without foreign-born parents or grandparents. Similarly, children with a non-German mother tongue who were born abroad show worse outcomes than second- or third-generation immigrants. The differences are statistically insignificant, however. Non-native speakers from Eastern Europe perform better in language and math than children from the main so-called guest worker countries, but are not as well socially integrated.

With respect to the family characteristics, the number of books at home and parents' education are significant positive determinants of test scores for both native and non-native children, though the effects are less pronounced for the latter. For natives, also large differences by parents' employment status are observed, in particular with regard to the occupation of fathers. In addition, native children with part-time instead of full-time employed mothers show slightly better math scores and social integration. Beyond that, the labour force status of the mother is not very decisive for students' test scores or social integration.

The school characteristics do not explain much of the variation in test scores and social

integration, conditional on the individual and family characteristics described. Outcomes slightly increase with the number of inhabitants at the school location, even more for non-native speakers. In addition, native students at private schools perform significantly worse at math. School characteristics also include fixed effects for the federal state where the school is located. As educational systems differ by federal state in Germany, they are important additional control variables.

In general, the fact that the coefficient estimates for non-native speakers are less statistically significant could be due to the small sample size, which is much smaller for non-natives than for natives. However, while standard errors are often slightly higher in the migrant sample, the main difference between the two samples is in the size of the estimated coefficients, which are smaller in the migrant sample. This is also evident from the regressions R^2, which are of similar size or even larger for the sample of non-native speakers.

4.2 Diversity

In what follows, we extend the basic analysis and add our measure for the linguistic diversity in the class, namely the Greenberg index, to the regression to investigate whether the linguistic composition of the group of non-native speakers matters for students' outcomes, given a certain share of migrants in the class. Table 5 shows the main results of estimating Equation 4 for the samples of native and non-native speakers. Columns (1) and (3) replicate the coefficient estimates for the migrant share from columns (2), (4) and (6) of Tables 2 and 3. Columns (2) and (4) then extend the respective regression by adding linguistic diversity.

The results reveal that, given the share of non-native speakers in the class, the extent of linguistic diversity has no significant effect on students' test scores. For native speakers, the coefficient estimates are close to zero. For non-native speakers, the coefficients are somewhat larger, especially for the language test score. Here, the inclusion of the diversity index reduces the coefficient estimate for the migrant share by about half. Therefore, both

the share of non-native speakers and the degree of linguistic diversity among them have a non-negligible negative, but insignificant impact on the language proficiency of non-native speakers.

With respect to social integration, linguistic diversity has no impact on native speakers, but significantly worsens the social integration of non-native speakers. Here, an increase in linguistic diversity by 10 percentage points (1 standard deviation) lowers the integration index by 0.25 (0.11 standard deviations). Hence, our results reveal that the extent of linguistic diversity among the non-native speakers in a class is more important than the size of this group in determining the social integration of migrants.

Table 6 further disentangles the diversity effect on migrants by distinguishing between different components of the social integration index (columns (2) through (5)). The results reveal that a higher linguistic diversity increases the probability to have arguments with classmates and decreases the probability to have many friends in class. This suggests that higher diversity might hamper communication among non-native speakers and could lead some students to feel isolated within the class. Whether classmates are friendly or caring in general, on the other hand, is less affected by the extent of linguistic diversity among classmates.

Our findings suggests that the degree of linguistic diversity neither helps nor hinders student performance as measured by test scores, but might challenge the social integration of non-native speakers in the class. The result that linguistic diversity is unrelated to students' test scores is in line with Frattini and Meschi (2017), who, focusing on vocational training students, find no effect of ethnic diversity on natives' test scores in math and literacy. It is, however, in contrast to the findings of Dronkers and van der Velden (2013), who find that ethnic diversity hampers the language skills of migrants (and of natives in highly stratified school systems). Maestri (2017), however, finds a positive effect of ethnic diversity on students' test scores, in particular for language performance. Our small or null findings, and the different results in general, might be explained by two opposing effects working against each other: One the one hand, having many children with a similar mother tongue in the class may improve students' self-consciousness through identity-building and

foster communication and interaction among students with the same mother tongue. On the other hand, the formation of a large group of children with a different mother tongue than the native language may also slow the learning of this language and negatively impact learning by dividing the class and impeding the children's sense of togetherness.

4.3 Robustness checks

We perform several robustness checks in order to test whether the use of alternative measures of linguistic diversity and the inclusion of additional control variables affect our results. The respective regression results are summarized in Table 7.

We start by using a measure of linguistic polarization instead of linguistic diversity to explain students' outcomes. The so-called Esteban-Ray index (Esteban and Ray 1994) is calculated as

$$ER = \sum_{j=1}^{N} \sum_{k=1}^{N} s_j^{1+\alpha} \, s_k \, \delta_{jk} \, , \tag{5}$$

where again, N is the number of language groups with group shares s_j and δ_{jk} is the linguistic distance between each pair of groups j and k. As compared to the Greenberg index, our primary measure of linguistic diversity, the sensitivity factor α lets the index peak for two groups of the same size and maximum linguistic distance.[8] In contrast to the Greenberg index, which monotonously increases in the number of different groups, the polarization index thus captures non-linear effects of a clustering of students along their native languages. The respective regression results using the polarization index are shown in Panel A of Table 7. Replacing linguistic diversity by linguistic polarization leaves the results for native speakers largely unaffected. For non-native speakers, the estimated effect of the linguistic composition in the classroom on language test scores slightly increases in magnitude (in relative terms) and turns significant at a 10-percent level. A 10-percentage point (1 standard deviation) increase in linguistic polarization reduces the language test scores of non-native speakers by 1.8 points (0.08 standard deviations). The respective effect of the migrant share remains insignificant. This result supports our conclusion

[8]Following previous literature (Montalvo and Reynal-Querol 2005), we set α to one and normalize the index to take on values between zero and one.

that, for non-native speakers, the linguistic composition of the class is more important in explaining their outcomes than the actual size of the migrant group. For math and social integration, the results remain largely unchanged.

In Panel B, we apply the Herfindahl-Hirschman index (Equation 3) as an alternative measure for linguistic diversity, which has been used by previous studies that take linguistic or ethnic diversity in the class into account (Dronkers and van der Velden 2013; Frattini and Meschi 2017; Maestri 2017). As described in Section 2, the Herfindahl-Hirschman index is calculated as the sum of all squared language shares in a class. It thus differs from the Greenberg index in that the linguistic distance between each two groups is not considered. Moreover, the scale is reversed, i.e., the Herfindahl-Hirschman index decreases rather than increases in the number of different groups. The results show that for both natives and migrants, the results are qualitatively and quantitatively robust to using this alternative measure of linguistic diversity[9], which reveals that the inclusion of linguistic distance does not drive our estimation results.

Next, we test whether instead of the degree of linguistic diversity in general, the (relative) size of the own language group matters for schooling outcomes of migrants. The results (Panel C), however, show that the share of students from the own language group has no explanatory power for the test scores or the social integration of non-native speakers.

Finally, we go back to our original model including linguistic diversity and add two further control variables. Panel D shows the results of including a measure of students' cognitive skills in the model, which is obtained from a test containing deductive reasoning problems that all students had to solve as part of the survey. We do not include the results of this cognitive skill test in our main regressions, as they are closely correlated to test scores (here as well, the questions at hand have to be read and understood). The results reveal that cognitive skills are a strong predictor of students' test scores, and that adding them to the model to some extent reduces the adverse impact of the share of non-native

[9]Note that due to the reverse scale of the Herfindahl-Hirschman index as compared to the Greenberg index, the signs of the coefficients are reversed.

speakers in the class. The coefficient estimates for linguistic diversity, however, are merely affected by controlling for students' cognitive skills.

Panel E shows the results when adding the migrant share at the school level as an additional control variable. Controlling for this more aggregate share might capture neighbourhood segregation above and beyond the share of non-native speakers in the class. The inclusion of this control variable reduces the coefficients for the share of non-native speakers in the class, which is due to the two variables being closely correlated. The results for the role of linguistic diversity in children's schooling outcomes, however, remain unaltered.

5 Conclusion

Rising immigration flows in many Western countries have led to an increase in the number of immigrant children in schools and changed the ethnic and linguistic composition of student populations. In this paper, we analyze the effect of immigrant peers in the classroom on the educational achievement and social integration of native and non-native speakers. While previous literature has mainly focused on investigating the effects of immigrant concentration in the class or school on student outcomes, we explicitly take the composition of the immigrant group into account. In doing so, we construct a novel measure of the degree of linguistic diversity in the class, which is based on contributions from the macroeconomic and political science literature (e.g., Easterly and Levine 1997; Alesina *et al.* 2003; Montalvo and Reynal-Querol 2005) and incorporates both the size of the different immigrant groups and the linguistic distance between them. Our analysis is based on a comprehensive survey of 4th-grade students in German primary schools, which contains detailed information on students' migration background, family and school characteristics, results of standardized tests in both German language and math, as well as information on students' social integration in the class. Germany represents an interesting case to analyze the effects of classroom diversity: As the assignment of children to primary schools is solely based on their residence, the share of immigrant students at a school is a

consequence of the locational choice of families and can thus hardly be influenced. School principals, however, can regulate the allocation of migrants within a grade of a given school, thereby influencing the degree of linguistic diversity among immigrant students in a class.

A major identification problem when establishing potential educational spill-over effects is related to student selection into schools. If schools with a relatively high linguistic diversity attract native and non-native children whose educational skills are different from those in schools with a relatively low linguistic diversity, we might erroneously conclude that diversity has spill-over effects in the class. We address this potential selectivity by exploring the variation in linguistic diversity across schools with similar levels of immigrant concentration. Within the group of classes with the same level of immigrant concentration, there may still be a selectivity issue due to potential non-random allocation of students to classes or higher allocation of teaching resource to classes with a higher linguistic diversity. However, we find no evidence to support these concerns.

Our results reveal a negative association between the share of non-native speakers in the class and students' test scores and their social integration. Conditional on the immigrant concentration in the class, the degree of linguistic diversity, however, has no impact on students' language and math test scores. This suggests that an increase in the number of students from more culturally or linguistically distant countries has no additional negative impact on students' educational outcomes. We find though that a higher linguistic diversity in the class hampers the social integration of non-native speakers. In particular, non-native students in classes with a high linguistic diversity are more likely to have arguments with their classmates and have less friends in class. Hence, while the outcomes of native students are unaffected by the degree of linguistic diversity, the social integration of migrants could be improved by reducing linguistic diversity and allocating more students with the same linguistic background to the same class.

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Figures

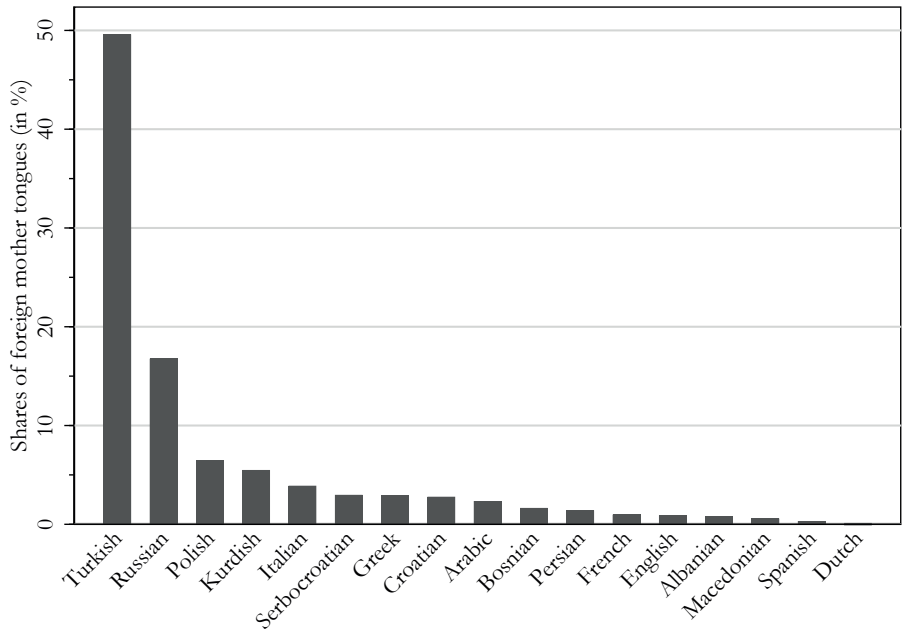

Figure 1: Distribution of Non-German Languages
Source: Own calculations based on IQB 2011 data.

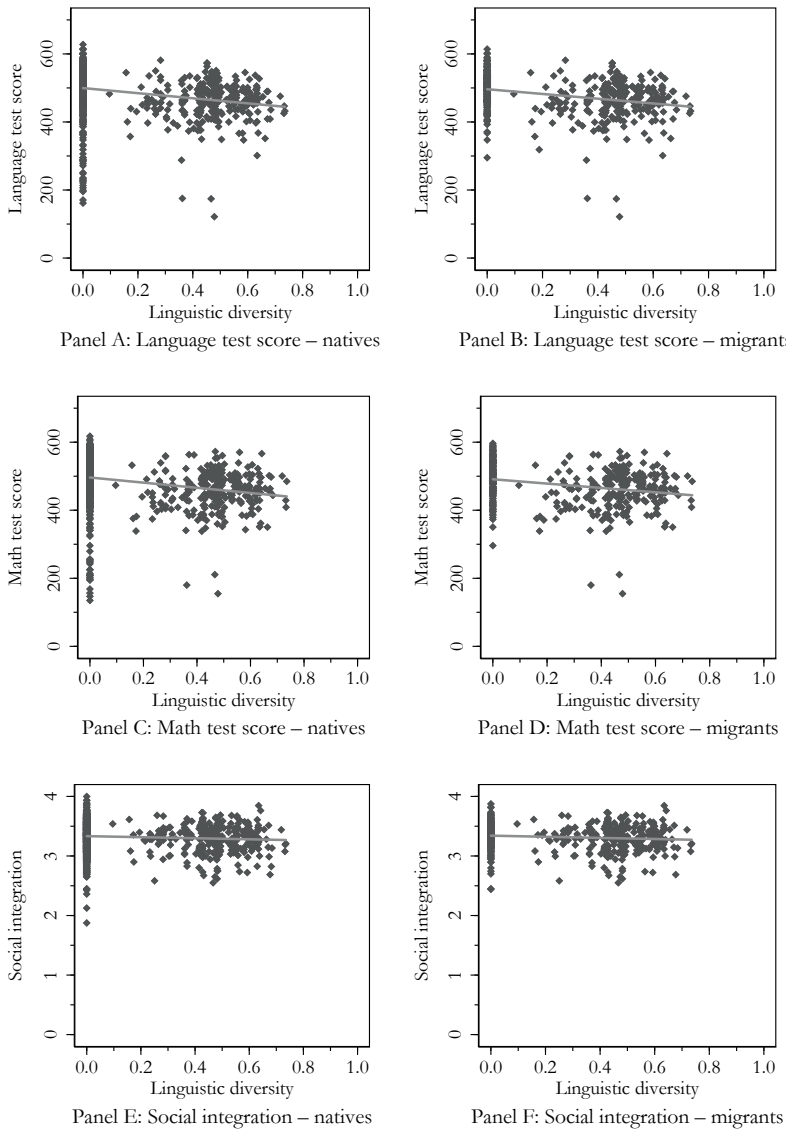

Figure 2: Correlation of Linguistic Diversity and Student Outcomes
Source: Own calculations based on IQB 2011 data.

Tables

Table 1: Balancing Test

	Natives		Migrants	
	No controls Coeff./SE	Controls Coeff./SE	No controls Coeff./SE	Controls Coeff./SE
Main explanatory variable				
Share of non-native speakers in class	131.09***	130.91***	62.81***	68.81***
	(8.67)	(9.24)	(10.79)	(10.62)
Individual characteristics				
Female	−1.04**	−0.35	1.14	0.73
	(0.47)	(0.34)	(2.32)	(2.14)
Age	−25.68*	−1.86	43.09	45.73
	(13.64)	(9.63)	(57.35)	(44.15)
Age^2	1.20*	0.06	−1.97	−2.21
	(0.64)	(0.46)	(2.69)	(2.07)
Repeater	1.02	0.78	5.03	6.62*
	(1.14)	(0.91)	(3.93)	(3.78)
1^{st}- or 2^{nd}-generation migrant	7.23***	0.59	–	–
	(1.02)	(0.65)		
1^{st}-generation migrant	–	–	−1.24	−1.28
			(3.56)	(2.98)
Linguistic distance to German	–	–	−0.59**	−0.81***
			(0.28)	(0.24)
Region of origin (reference: main guest worker countries)				
Former Yugoslavia	–	–	7.36*	2.69
			(4.41)	(3.57)
Eastern Europe	–	–	0.64	3.47
			(3.59)	(3.34)
Remaining (Europe and other continents)	–	–	9.35**	8.92***
			(4.32)	(3.28)
Family characteristics				
Number of books at home	−0.00	0.01**	−0.04	−0.03**
	(0.00)	(0.00)	(0.02)	(0.01)
Fathers' education level (reference: low education)				
Medium	−0.09	−0.19	1.36	−1.59
	(1.04)	(0.65)	(4.20)	(3.38)
High	−0.30	0.77*	−1.04	−2.69
	(0.52)	(0.42)	(2.35)	(2.44)
Missing information	−0.27	−0.28	0.26	−5.05
	(0.96)	(0.83)	(3.64)	(3.18)
Mothers' education level (reference: low education)				
Medium	−0.08	−0.62	10.62***	7.77**
	(0.90)	(0.67)	(3.58)	(3.25)
High	−1.16**	−0.30	2.27	1.92
	(0.53)	(0.49)	(3.03)	(2.73)
Missing information	0.75	0.10	7.34	4.93
	(1.43)	(1.02)	(4.47)	(3.51)
Fathers' employment status (reference: white-collar)				
Blue-collar	−0.85	−1.13**	−1.75	0.33
	(0.78)	(0.51)	(3.89)	(2.80)
Other	−1.48***	−0.94**	3.03	4.46
	(0.56)	(0.43)	(3.91)	(3.04)
Missing information	0.44	−0.16	4.59	3.74
	(0.87)	(0.76)	(4.17)	(3.18)
Mothers' employment status (reference: white-collar)				
Blue-collar	1.63**	0.30	0.38	−1.16
	(0.80)	(0.49)	(3.09)	(2.45)
Other	−0.07	−0.32	−1.55	−5.63*
	(0.56)	(0.52)	(3.08)	(3.00)
Missing information	0.70	−1.03	−3.02	−3.81
	(0.94)	(0.76)	(3.49)	(3.23)
Mothers' labour force status (reference: full-time employed)				
Part-time	1.67**	0.25	−2.96	−1.07
	(0.68)	(0.46)	(3.22)	(3.14)
No employment	1.64**	−0.45	−4.16	−1.60
	(0.71)	(0.46)	(3.19)	(2.76)
Missing information	2.26	0.48	−6.16	−1.94
	(1.42)	(1.02)	(4.20)	(3.94)
School characteristics				
Number of inhabitants at school location (in 1,000)	0.03***	−0.00	0.02**	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Private school	−4.95**	−1.17	−21.49***	−29.69**
	(2.04)	(1.59)	(6.43)	(12.79)
All-day school	2.86*	0.09	−1.64	−1.38
	(1.58)	(1.08)	(4.69)	(3.11)
State fixed effects	No	Yes	No	Yes
Classes	1,187	1,187	460	460
Observations	14,717	14,717	969	969

Notes – OLS regression results with robust standard errors (clustered at class level) in parentheses. – Columns (1) and (3) show the results from separate regressions of linguistic diversity on each explanatory variable (and a constant). – Columns (2) and (4) show the results from a regression of linguistic diversity on all explanatory variables (and a constant). – Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Omnibus Test

	Natives			Migrants		
	Language test score Coeff./SE	Math test score Coeff./SE	Social integration Coeff./SE	Language test score Coeff./SE	Math test score Coeff./SE	Social integration Coeff./SE
Panel A: No controls						
Linguistic diversity	−36.19***	−34.55***	−9.76***	−12.08*	−33.32***	−10.27**
	(4.87)	(5.23)	(1.53)	(6.86)	(9.76)	(4.13)
Classes	1,187	1,187	1,187	460	460	460
Observations	14,717	14,717	14,717	969	969	969
Panel B: Conditional on migrant share						
Share of non-native speakers in class	−169.76***	−145.62***	−42.22***	−49.50***	−74.31***	−14.56**
	(10.83)	(12.74)	(3.47)	(11.31)	(15.58)	(7.05)
Linguistic diversity	7.36	2.82	1.55	4.60	−8.28	−5.37
	(4.82)	(6.19)	(1.58)	(7.52)	(9.87)	(4.34)
Classes	1,187	1,187	1,187	460	460	460
Observations	14,717	14,717	14,717	969	969	969

Notes – OLS regression results with robust standard errors (clustered at class level) in parentheses. – The panels show second-stage results of regressions of predicted outcomes on linguistic diversity with no controls (Panel A) and the share of non-native speakers in the class as control variable (B). For natives, a dummy variable for whether there are no non-native speakers in the class is further included in Panel B. – In the first stage, outcomes are predicted based on all explanatory variables except for linguistic diversity. – Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Share of Non-native Speakers and Student Outcomes – Native Sample

	Language test score		Math test score		Social integration	
	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE
Main explanatory variable						
Share of non-native speakers in class	−108.39***	−87.34***	−97.58***	−77.66***	−28.53***	−28.83***
	(15.89)	(15.21)	(15.66)	(15.47)	(9.69)	(10.10)
Individual characteristics						
Female	–	10.74***	–	−18.04***	–	12.48***
		(1.65)		(2.02)		(1.52)
Age	–	204.73***	–	148.83**	–	127.33**
		(55.53)		(61.24)		(51.71)
Age^2	–	−10.38***	–	−7.80***	–	−5.99**
		(2.68)		(2.96)		(2.49)
Repeater	–	−31.57***	–	−43.53***	–	−8.90*
		(5.19)		(6.04)		(5.25)
1^{st}- or 2^{nd}-generation migrant	–	−12.28***	–	−7.73**	–	−4.39*
		(2.66)		(3.17)		(2.40)
Family characteristics						
Number of books at home	–	0.27***	–	0.24***	–	0.06***
		(0.01)		(0.02)		(0.01)
Fathers' education level (reference: low education)						
Medium	–	27.10***	–	24.50***	–	3.11
		(3.85)		(4.26)		(3.08)
High	–	14.66***	–	14.07***	–	1.68
		(2.39)		(2.77)		(2.12)
Missing information	–	−6.67*	–	−5.99	–	−3.07
		(3.75)		(4.25)		(3.49)
Mothers' education level (reference: low education)						
Medium	–	26.75***	–	27.23***	–	7.25**
		(3.34)		(3.67)		(2.81)
High	–	15.03***	–	17.17***	–	0.12
		(2.32)		(2.73)		(2.00)
Missing information	–	15.87***	–	15.00**	–	−7.91
		(4.81)		(6.13)		(5.14)
Fathers' employment status (reference: white-collar)						
Blue-collar	–	−13.93***	–	−15.19***	–	−7.12***
		(2.70)		(3.08)		(2.21)
Other	–	−6.77***	–	−5.39*	–	0.18
		(2.22)		(2.75)		(1.95)
Missing information	–	−14.54***	–	−17.01***	–	−12.36***
		(3.57)		(3.99)		(3.27)
Mothers' employment status (reference: white-collar)						
Blue-collar	–	−15.50***	–	−13.65***	–	−1.65
		(2.83)		(3.32)		(2.73)
Other	–	−0.45	–	−3.22	–	1.90
		(2.58)		(3.02)		(2.39)
Missing information	–	−6.59*	–	−7.48*	–	−3.58
		(3.89)		(4.44)		(3.70)
Mothers' labour force status (reference: full-time employed)						
Part-time	–	3.24	–	9.71***	–	7.43***
		(2.27)		(2.56)		(1.76)
No employment	–	−2.73	–	1.20	–	−0.84
		(2.73)		(3.08)		(2.18)
Missing information	–	−9.17*	–	2.90	–	0.51
		(5.42)		(6.24)		(4.84)
School characteristics						
Number of inhabitants at school location (in 1,000)	–	0.02	–	0.02*	–	0.01
		(0.01)		(0.01)		(0.01)
Private school	–	−3.02	–	−33.08**	–	1.25
		(7.33)		(14.25)		(5.46)
All-day school	–	1.42	–	4.42	–	1.15
		(3.06)		(3.24)		(1.86)
Constant	528.56***	−528.65*	527.21***	−225.73	341.12***	−350.96
	(1.93)	(287.99)	(1.99)	(316.74)	(1.05)	(268.95)
State fixed effects	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.02	0.24	0.01	0.21	0.00	0.05
Classes	1,187	1,187	1,187	1,187	1,187	1,187
Observations	14,717	14,717	14,717	14,717	14,717	14,717

Notes – OLS regression results with robust standard errors (clustered at class level) in parentheses. – Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Share of Non-native Speakers and Student Outcomes – Migrant Sample

	Language test score		Math test score		Social integration	
	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE
Main explanatory variable						
Share of non-native speakers in class	−46.61**	−41.25**	−79.51***	−75.51***	−17.93	−20.20
	(20.79)	(20.07)	(23.18)	(21.56)	(13.56)	(16.98)
Individual characteristics						
Female	–	2.94	–	−31.97***	–	7.68
		(7.56)		(7.08)		(4.83)
Age	–	232.59*	–	−158.63	–	70.07
		(137.30)		(166.97)		(119.80)
Age^2	–	−12.18*	–	6.11	–	−3.43
		(6.58)		(7.84)		(5.67)
Repeater	–	−20.32	–	−46.36***	–	−9.06
		(14.42)		(15.43)		(10.51)
1^{st}-generation migrant	–	−14.06	–	−10.21	–	−6.07
		(10.38)		(10.59)		(8.57)
Linguistic distance to German	–	−0.69	–	−0.51	–	0.34
		(0.66)		(0.84)		(0.68)
Region of origin (reference: main guest worker countries)						
Former Yugoslavia	–	7.95	–	4.90	–	−7.81
		(13.55)		(15.53)		(9.75)
Eastern Europe	–	31.37***	–	32.03***	–	−14.19*
		(8.81)		(9.70)		(8.39)
Remaining (Europe and other continents)	–	22.24**	–	−9.98	–	−1.26
		(10.87)		(12.61)		(12.03)
Family characteristics						
Number of books at home	–	0.20***	–	0.21***	–	0.02
		(0.06)		(0.07)		(0.05)
Fathers' education level (reference: low education)						
Medium	–	1.84	–	4.67	–	−1.98
		(13.21)		(14.51)		(12.45)
High	–	14.82*	–	29.27***	–	6.14
		(8.59)		(9.17)		(6.17)
Missing information	–	19.45	–	28.21**	–	10.22
		(11.94)		(12.52)		(6.88)
Mothers' education level (reference: low education)						
Medium	–	4.19	–	26.27	–	7.91
		(15.09)		(19.95)		(13.69)
High	–	21.63**	–	26.64***	–	−10.32
		(9.25)		(9.11)		(8.54)
Missing information	–	−13.01	–	−26.85*	–	2.94
		(15.93)		(15.81)		(8.99)
Fathers' employment status (reference: white-collar)						
Blue-collar	–	−2.42	–	−6.36	–	8.34
		(8.13)		(9.65)		(7.25)
Other	–	11.76	–	3.23	–	9.69
		(10.14)		(10.68)		(8.46)
Missing information	–	−12.92	–	−22.19	–	−2.96
		(11.20)		(14.27)		(10.18)
Mothers' employment status (reference: white-collar)						
Blue-collar	–	7.75	–	7.95	–	−8.39
		(9.51)		(12.02)		(8.93)
Other	–	−5.72	–	−6.00	–	−12.10
		(10.76)		(11.79)		(10.05)
Missing information	–	−22.17**	–	−11.33	–	6.54
		(10.95)		(12.52)		(9.28)
Mothers' labour force status (reference: full-time employed)						
Part-time	–	4.75	–	−9.48	–	−12.51
		(9.23)		(11.21)		(7.93)
No employment	–	7.97	–	−1.12	–	−16.86*
		(9.20)		(10.42)		(8.96)
Missing information	–	21.92*	–	21.14	–	−8.86
		(12.66)		(13.95)		(10.12)
School characteristics						
Number of inhabitants at school location (in 1,000)	–	0.04*	–	0.06***	–	0.00
		(0.02)		(0.02)		(0.02)
Private school	–	−6.99	–	−6.31	–	−7.99
		(18.18)		(34.20)		(23.38)
All-day school	–	−13.32	–	−9.97	–	6.14
		(10.15)		(10.56)		(6.23)
Constant	463.46***	−607.69	478.47***	1489.26*	335.85***	−39.21
	(6.85)	(722.17)	(7.84)	(901.07)	(4.80)	(629.98)
State fixed effects	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.01	0.23	0.02	0.31	0.00	0.05
Classes	460	460	460	460	460	460
Observations	969	969	969	969	969	969

Notes – OLS regression results with robust standard errors (clustered at class level) in parentheses. – Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Linguistic Diversity and Student Outcomes

	Natives		Migrants	
	Coeff./SE	Coeff./SE	Coeff./SE	Coeff./SE
Panel A: Language test score				
Share of non-native speakers in class	−87.34***	−106.07***	−41.25**	−26.92
	(15.21)	(23.38)	(20.07)	(22.60)
Linguistic diversity	–	−6.17	–	−20.83
		(10.61)		(16.39)
Adjusted R^2	0.24	0.25	0.23	0.24
Panel B: Math test score				
Share of non-native speakers in class	−77.66***	−93.63***	−75.51***	−81.75***
	(15.47)	(22.39)	(21.56)	(22.42)
Linguistic diversity	–	−6.02	–	9.07
		(10.32)		(14.77)
Adjusted R^2	0.21	0.21	0.31	0.31
Panel C: Social integration				
Share of non-native speakers in class	−28.83***	−38.08**	−20.20	−2.77
	(10.10)	(15.06)	(16.98)	(18.89)
Linguistic diversity	–	6.85	–	−25.32**
		(6.70)		(12.06)
Adjusted R^2	0.05	0.05	0.05	0.05
Classes	1,187	1,187	460	460
Observations	14,717	14,717	969	969

Notes – OLS regression results with robust standard errors (clustered at class level) in parentheses. – The results in columns (1) and (3) correspond to those in columns (2), (4) and (6) of Tables 3 and 4. – Columns (2) and (4) show results from regressions that include the linguistic diversity in the classroom as an additional explanatory variable. For the native sample, a dummy variable for whether there are no non-native speakers in the class is further included. – Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Linguistic Diversity and Social Integration of Migrants

	Social integration Coeff./SE	Friendly classmates Coeff./SE	Caring classmates Coeff./SE	Many friends in class Coeff./SE	No arguments with classmates Coeff./SE
Share of non-native speakers in class	−2.77	−17.60	13.35	16.02	−26.47
	(18.89)	(24.75)	(23.20)	(27.41)	(25.24)
Linguistic diversity	−25.32**	−20.15	2.77	−33.28*	−45.59**
	(12.06)	(15.82)	(14.90)	(17.85)	(17.86)
Adjusted R^2	0.05	0.05	0.07	0.08	0.06
Classes	460	460	456	458	457
Observations	969	962	954	956	958

Notes – OLS regression results with robust standard errors (clustered at class level) in parentheses. – The results in column (1) correspond to those in column (6) of Table 4. – Columns (2) through (5) include results from corresponding regressions on each of the four categories the social integration index is built of. – Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robustness Checks

	Natives			Migrants		
	Language test score Coeff./SE	Math test score Coeff./SE	Social integration Coeff./SE	Language test score Coeff./SE	Math test score Coeff./SE	Social integration Coeff./SE
Panel A: Linguistic polarization						
Share of non-native speakers in class	−104.96***	−97.27***	−35.71**	−31.22	−79.87***	−11.67
	(21.05)	(21.00)	(14.02)	(19.93)	(21.53)	(18.38)
Linguistic polarization	−4.91	−2.24	3.50	−17.82*	7.74	−15.14*
	(5.95)	(5.31)	(3.77)	(10.58)	(9.77)	(8.63)
Adjusted R^2	0.25	0.21	0.05	0.24	0.31	0.05
Classes	1,187	1,187	1,187	460	460	460
Observations	14,717	14,717	14,717	969	969	969
Panel B: Herfindahl-Hirschman index						
Share of non-native speakers in class	−109.35***	−96.33***	−38.54**	−29.85	−83.00***	−3.86
	(23.12)	(22.34)	(15.02)	(22.68)	(22.30)	(18.64)
Herfindahl-Hirschman index	3.33	3.61	−6.60	15.38	−10.10	22.04**
	(9.45)	(9.22)	(6.00)	(14.90)	(13.69)	(10.86)
Adjusted R^2	0.25	0.21	0.05	0.24	0.31	0.05
Classes	1,187	1,187	1,187	460	460	460
Observations	14,717	14,717	14,717	969	969	969
Panel C: Share of own language group						
Share of non-native speakers in class	–	–	–	−32.82	−63.23**	−29.55
				(22.29)	(24.84)	(19.26)
Share of own language group in class	–	–	–	−23.40	−34.09	25.97
				(43.21)	(31.72)	(28.92)
Adjusted R^2	–	–	–	0.23	0.31	0.05
Classes	–	–	–	460	460	460
Observations	–	–	–	969	969	969
Panel D: Cognitive skills						
Share of non-native speakers in class	−74.27***	−48.31***	−35.99**	−9.38	−61.29***	−0.49
	(21.38)	(18.00)	(15.14)	(20.86)	(20.37)	(18.76)
Linguistic diversity	−9.39	−10.95	6.64	−25.22	3.96	−25.25**
	(9.32)	(8.19)	(6.66)	(15.71)	(13.44)	(11.92)
Cognitive skills	5.02***	6.51***	0.35***	4.65***	5.29***	0.35
	(0.13)	(0.15)	(0.12)	(0.41)	(0.42)	(0.39)
Adjusted R^2	0.40	0.42	0.05	0.37	0.45	0.05
Classes	1,183	1,183	1,183	458	458	458
Observations	14,629	14,629	14,629	962	962	962
Panel E: Migrant share at school						
Share of non-native speakers in class	−95.80***	−84.42***	−46.58***	−1.19	−72.69**	−1.28
	(24.51)	(23.02)	(15.51)	(29.75)	(28.14)	(23.81)
Linguistic diversity	−5.23	−5.18	6.07	−19.38	9.58	−25.24**
	(10.36)	(10.30)	(6.68)	(15.88)	(14.69)	(12.09)
Migrant share at school	−12.89	−11.57	10.66**	−34.53	−12.15	−2.00
	(9.38)	(7.17)	(5.42)	(21.00)	(18.43)	(16.20)
Adjusted R^2	0.25	0.21	0.05	0.24	0.31	0.05
Classes	1,187	1,187	1,187	460	460	460
Observations	14,717	14,717	14,717	969	969	969

Notes – OLS regression results with robust standard errors (clustered at class level) in parentheses. – Panel A shows results similar to Table 5 where linguistic diversity is replaced by a measure for linguistic polarization, the Esteban-Ray polarization index (see Equation 5). – Panel B shows results similar to Table 5 where linguistic diversity is replaced by the Herfindahl-Hirschman index (see Equation 3). – Panel C shows results similar to Table 5 where linguistic diversity is replaced by the share of the own language group in the class. – Panel D shows results similar to Table 5 where a measure for students' cognitive skills is added as a further control variable. – Panel E shows results similar to Table 5 where the migrant share at the school is added as control variable. – Asterisks indicate p-values according to: *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1: Descriptive Statistics

	Natives		Migrants	
	Mean	SD	Mean	SD
Dependent variables				
Language test score	521.54	79.30	450.36	80.68
Math test score	520.88	89.69	456.11	92.60
Social integration	3.39	0.61	3.31	0.60
Friendly classmates	3.43	0.72	3.28	0.77
Caring classmates	3.16	0.88	3.21	0.84
Many friends in class	3.43	0.91	3.34	0.93
No arguments with classmates	3.56	0.79	3.41	0.89
Class composition				
Linguistic diversity	0.09	0.19	0.33	0.25
Share of non-native speakers in class	0.06	0.10	0.28	0.19
No non-native speakers in class	0.50	0.50	–	–
Individual characteristics				
Female	0.50	0.50	0.52	0.50
Age	10.41	0.46	10.53	0.54
Repeater	0.06	0.23	0.10	0.30
Linguistic distance to German	0.00	0.00	96.17	4.82
1^{st}- or 2^{nd}-generation migrant	0.13	0.34	–	–
1^{st}-generation migrant	–	–	0.16	0.37
Region of origin				
Main guest worker countries	–	–	0.58	0.49
Former Yugoslavia	–	–	0.09	0.28
Eastern Europe	–	–	0.24	0.43
Remaining (Europe and other continents)	–	–	0.09	0.29
Family characteristics				
Number of books at home	103.51	68.32	57.01	56.93
Education level of father				
Low	0.30	0.46	0.45	0.50
Medium	0.06	0.24	0.06	0.24
High	0.57	0.49	0.38	0.49
Missing information	0.07	0.25	0.11	0.31
Education level of mother				
Low	0.35	0.48	0.60	0.49
Medium	0.09	0.28	0.05	0.21
High	0.53	0.50	0.28	0.45
Missing information	0.03	0.16	0.07	0.26
Employment status of father				
White-collar	0.55	0.50	0.26	0.44
Blue-collar	0.18	0.39	0.40	0.49
Other	0.18	0.39	0.17	0.37
Missing information	0.08	0.28	0.17	0.38
Employment status of mother				
White-collar	0.67	0.47	0.24	0.43
Blue-collar	0.11	0.32	0.26	0.44
Other	0.14	0.35	0.26	0.44
Missing information	0.07	0.25	0.23	0.42
Labour force status of mother				
Full-time	0.19	0.39	0.17	0.38
Part-time	0.54	0.50	0.29	0.45
No employment	0.24	0.43	0.37	0.48
Missing information	0.03	0.17	0.17	0.37
School characteristics				
Number of inhabitants at school location (in 1,000)	83.71	146.05	186.79	191.60
Private school	0.03	0.17	0.01	0.12
All-day school	0.42	0.49	0.56	0.50
Additional explanatory variables				
Linguistic polarization	0.15	0.32	0.49	0.36
Herfindahl-Hirschman index	0.90	0.21	0.64	0.28
Share of own language group in class	0.94	0.10	0.16	0.13
Cognitive skills	17.70	6.51	15.23	6.90
Migrant share at school	0.17	0.20	0.39	0.25
Observations	14,717		969	

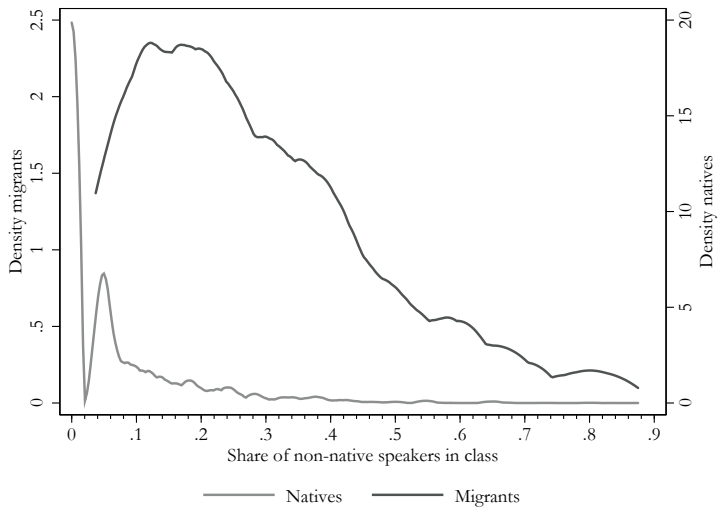

Figure A1: Distribution of Migrant Share for Natives and Migrants
Source: Own calculations based on IQB 2011 data.

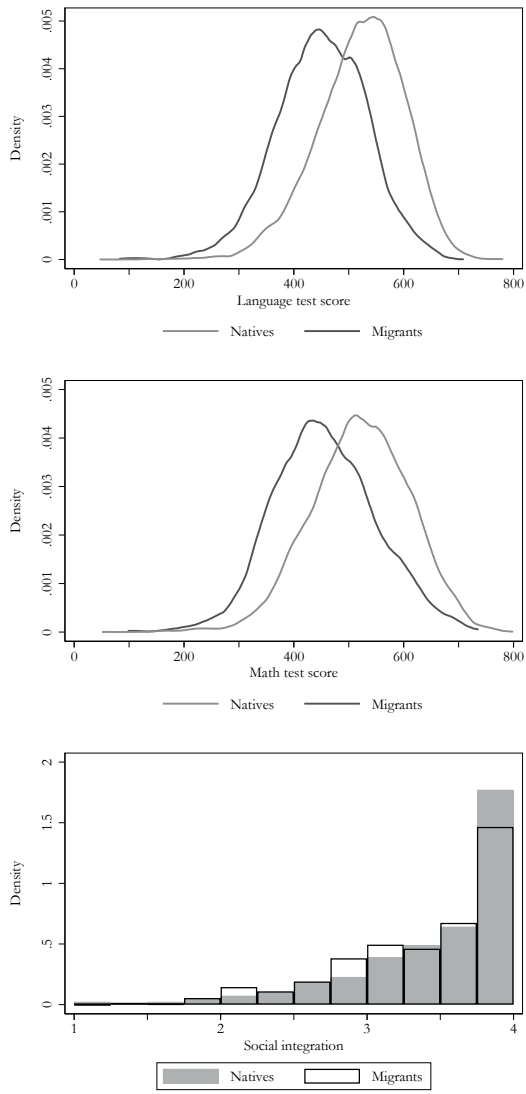

Figure A2: Distribution of Outcome Variables for Natives and Migrants
Source: Own calculations based on IQB 2011 data.