Learning and Instruction 102 (2026) 102303

Contents lists available at ScienceDirect

Learning and Instruction

journal homepage: www.elsevier.com/locate/learninstruc

Teachers' immigration attitudes and students' performance

Anatolia Batruch *, Nicolas Sommet, Eva G.T. Green

Université de Lausanne, Switzerland

ARTICLE INFO

Keywords:
School climates
Teacher prejudice
Immigrant students
Achievement gap

ABSTRACT

Background: To ensure harmonious intergroup relations, schools must foster the academic integration of immigrant students. School diversity climates play a central role in shaping immigrant students' performance; however, most studies rely on students' perceptions of these climates. Because such perceptions are shaped by subjective experiences, they limit our understanding of how institutions can nurture inclusion. Measuring school diversity climates with an exogenous indicator, teachers' immigration attitudes in a school, offers a rigorous test of how those relate to students' academic achievement.
Aim: This study investigates whether school diversity climates, measured through teachers' immigration attitudes, are associated with immigrant students' academic performance.
Sample: We analyzed the 2018 PISA data from OECD countries that administered the teacher questionnaire. Our analytical sample included 46,740 students from 1544 schools and 35,452 teachers across seven countries.
Methods: We estimated country fixed-effects regression models with standard errors clustered at the school level to examine the interaction between students' migration status and school-aggregated teachers' explicit immigration attitudes on students' performance in science, mathematics, and reading.
Results: Across subjects, the achievement gap between native-born and first-generation immigrant students was smaller in schools where teachers expressed more inclusionary immigration attitudes.
Conclusion: Inclusionary school diversity climates, reflected in teachers' pro-immigration attitudes, appear to promote the academic integration of first-generation immigrant students, helping to narrow achievement disparities between immigrant and non-immigrant students. The difference in performance for first-generation students between more exclusionary and inclusionary school diversity climates corresponds on average to one year schooling.

Societies worldwide are becoming increasingly diverse in culture, ethnicity, race, and religion with rising immigration. In 2020, over 280 million people lived outside their home country—nearly double the figure 30 years earlier (McAuliffe & Oucho, 2024). By 2022, 15–35 % of 15-year-olds in Western Europe had an immigrant background, above the OECD average of 13 % (OECD, 2023). As climate change, conflict, globalization, and demographic decline likely amplify this trend, effective integration is critical to economic sustainability and long-term social welfare and cohesion. Schools play a pivotal role in this integration (De Paolo & Brunello, 2016). Despite rising immigration, anti-immigration attitudes have not diminished and continue to fuel divisive debates and unrest (Schmidt, 2021; Shehaj et al., 2021). Consequently, immigrants and their descendants face exclusion, prejudice, discrimination, and systemic inequalities (Esses, 2021; European Commission, 2019), which harm well-being, mental health, and academic achievement (Benner et al., 2018; Coll et al., 1996; Dimitrova et al., 2016). How schools respond to diversity can strongly shape intergroup relations, students' success, and broader social and economic outcomes (De Paolo & Brunello, 2016; Kende et al., 2022). This study examines whether teachers' immigration attitudes—aggregated at the school level—are associated with immigrant students' academic performance.

1. Determinants of immigrant achievement gaps

Immigrant students remain at heightened risk of underperforming on standardized tests relative to second-generation and non-immigrant peers (Dimitrova et al., 2016; Duong et al., 2016). They earn lower grades, are less likely to complete secondary school, and more often pursue shorter, less demanding tracks (Heath & Brinbaum, 2014). These gaps are commonly linked to differences in socioeconomic status, parental income, cultural capital (e.g., books at home), and speaking a

* Corresponding author. LIVES Centre, ISS-SSP-Géopolis, University of Lausanne, 1015, Lausanne, Switzerland.
E-mail address: anatolia.batruch@unil.ch (A. Batruch).

https://doi.org/10.1016/j.learninstruc.2025.102303
Received 13 June 2025; Received in revised form 12 December 2025; Accepted 16 December 2025
Available online 22 December 2025
0959-4752/

non-national language at home. Yet, even after accounting for these factors, a smaller but persistent achievement gap remains (European Commission, 2019; Porcu et al., 2023). This phenomenon has spurred research on structural contributors, showing that gap magnitudes vary markedly by context (Alieva et al., 2024; Sprong & Skopek, 2022). It varies across and within countries by immigrant group, host context, and subject (Dustmann et al., 2012). It is smaller in countries with higher human development (e.g., life expectancy, schooling, income; Arikan et al., 2020) and varies by discipline—typically small-to-moderate in math and reading but larger in science (Andon et al., 2014). Gaps are more pronounced where early tracking sorts students into selective pathways (e.g., at age 10 in Austria/Germany vs. 16 in Scandinavia) and, more broadly, under any form of segregation by neighborhood or academic ability (Entorf, 2015).

2. How school contributes to achievement gaps: school diversity climates

The achievement gap is also shaped by institutional (e.g., policies) and cultural (e.g., inclusivity norms) factors and their intersection—often termed the school cultural diversity climate. Cultural diversity climates encompass the practices, policies, norms, and overall atmosphere that structure interactions among students and between students and staff (Bardach et al., 2024; Phalet & Baysu, 2020). In a meta-analysis of 79 studies, Bardach et al. (2024) found that all climate types were positively related to academic outcomes—except colorblind climates, suggesting that when schools acknowledge cultural differences, immigrant students tend to perform better. Notably, most studies (73 out of 79) assessed climate via students' perceptions.

Studying students' perceptions avoids potential social desirability in school/teacher reports, but it has key limits. First, causal claims are hard when all focal variables are endogenous and numerous unmeasured traits (e.g., political orientation, rejection sensitivity, neuroticism, conscientiousness) could shape both climate perceptions and achievement. Second, focusing solely on perceptions obscures institutional/structural contributors: if the climate itself (not just perceptions) does not impact students, the relevance of school-level policy recommendations becomes questionable. In the meta-analysis, the teacher (vs. student) perspective was not a significant moderator of the effect of multicultural diversity. However, the effect of teacher-reported diversity climates—measured through self-reported multicultural efforts in classrooms—on student performance was nonsignificant and indistinguishable from zero (Bardach et al., 2024). This result is not necessarily surprising, given how difficult it is to demonstrate the direct detrimental effects of teachers' prejudice or stereotypes (Batruch et al., 2023).

3. Teachers' biases and school diversity climates

Despite being viewed as egalitarian, teachers are not immune to bias. Meta-analytic and large-scale studies indicate that teachers exhibit implicit and explicit biases toward ethnic minority students at levels comparable to, or only slightly lower than, those found in the general population, which can influence their expectations and interactions with students (Cate et al., 2019; Quinn, 2017; Starck et al., 2020; Turetsky et al., 2021). Indirect evidence of stereotypes and prejudice are also sometimes deduced from research on teachers' discriminatory behavior. Experimental studies indicate that minority students and socioeconomically disadvantaged students are graded less favorably and are more likely to be recommended for lower academic tracks (Batruch et al., 2017; Doyle, Harris, & Easterbrook, 2024). Observational studies also reveal disparities even after controlling for students' behavior and prior academic performance, often more pronounced by socioeconomic status than by ethnicity (Barg, 2013; Batruch et al., 2023; Timmermans et al., 2018). Yet, few studies are sufficiently powered to establish that teachers' stereotypes directly cause discriminatory behavior or minority underperformance.[1]

Focusing solely on individual teacher–student relationships is perhaps insufficient to explain immigrant students' underperformance, as both actors are embedded in broader institutional contexts. In secondary school, students interact with multiple teachers whose beliefs and practices are shaped by institutional norms and expectations. Supporting this view, Autin and colleagues (2019) found that teachers' discriminatory behavior emerged primarily when institutional structures encouraged differentiation (see also Batruch et al., 2017, 2019). Building on this reasoning, aggregating teachers' attitudes at the institutional level could be more informative than focusing on single teacher-student relationships because it captures not only the prevalence of teachers' biases within schools but also the broader institutional norms that foster or legitimize them.

Aggregating explicit immigration attitudes or implicit bias measures at the level of region or institution to capture context-dependent inclusionary or exclusionary cultural environments is referred to, depending on the field, as "systemic or structural bias" or as "normative climates" (Charlesworth et al., 2023; Green & Staerklé, 2023; Payne et al., 2017). In social psychology, explicit immigration attitudes are aggregated to capture exclusionary versus inclusionary "normative climates" within regions (Christ et al., 2014; Fasel et al., 2013; Van Assche et., 2017; Visintin et al., 2020). They serve as social environmental cues of socioecological inclusion (Greenaway & Turetsky, 2020). Exclusionary climates are associated with increased prejudice expression, over and above individuals' political orientations and socio-demographic characteristics, suggesting that exclusionary climates translate into harsher environments for minorities. Previous education research has captured "systemic or structural bias" in schools by aggregating teachers' implicit bias, but findings are mixed and frequently underpowered (e.g., Chin et al., 2020; Del Toro & Wang, 2023), and implicit measures face reliability and interpretive challenges relative to explicit self-reports (Corneille & Gawronski, 2024). These limitations highlight the need for alternative indicators, such as teachers' explicit immigration attitudes, to capture exclusionary versus inclusionary "normative climates" or "systemic bias" in schools more robustly.

There are several reasons to expect school-level teachers' immigration attitudes to relate to first-generation students' achievement. When teachers collectively endorse inclusionary views, they signal a multicultural school climate that values diversity and acceptance. Such climates could shape day-to-day teachers' practice—equitable expectations, culturally responsive instruction, respectful interactions, thereby strengthening first-generation students' belonging, motivation, engagement, and performance (Celeste, Baysu, Phalet, Meeussen, & Kende, 2019; Bardach et al., 2024). They can also shift peer norms toward greater respect and inclusion. Conversely, exclusionary attitudes may legitimize lower expectations and hierarchy-enhancing or discriminatory practices (Batruch et al., 2019), fostering environments where immigrant students are and/or feel devalued. Consistent with this logic, perceived teacher discrimination or peer bullying predicts lower achievement (Baysu et al., 2023; Civitillo et al., 2024; Martin et al., 2024). These collective signals are likely especially consequential for first-generation students, who face stronger linguistic and cultural barriers (Karakus et al., 2023) and rely more on institutional cues to gauge belonging within the school community.

4. Hypotheses

We address limitations in the school-climate literature by

[1] A notable exception is the study by Carlana (2019), which found a direct effect of teachers' implicit bias on the gender achievement gap.

aggregating teachers' explicit immigration attitudes at the school level leveraging PISA's large-scale, high-powered, multi-country dataset. This approach enables us to effectively assess the relationship between systemic explicit bias and immigrant students' academic performance across three distinct domains: science, mathematics, and reading. We hypothesize that a more inclusionary school diversity climate will be associated with higher performance from first-generation students (i.e., students born in another country) and a smaller performance gap between non-immigrant and first-generation immigrant students. Consistent with prior work, we expect second-generation students (native-born to immigrant parents) to perform closer to non-immigrants than to first-generation peers at baseline (Karakus et al., 2023). Whether exclusionary school climates affect them is unclear: effects are likely smaller than for first-generation students and may be null given that their performance is near that of non-immigrants. We also do not anticipate domain differences in the climate effect: although baseline gaps are slightly larger in science than in math or reading (Andon et al., 2014), the three domains are strongly correlated (OECD, 2019) and there is no evidence of domain-specific stereotypes toward immigrant students.

5. Method

5.1. Sample

Initial Sample. We merged data from students, teachers and schools in PISA 2018, resulting in an initial sample of 158,658 students and 107,367 teachers from 5563 schools across 19 countries.

Inclusion Criteria. We restricted the final sample to OECD countries (i.e., seven out of 19 countries) and public schools (3,964 schools of the total 5,563). We chose these two exclusion criteria because the current research focuses on identifying the school factors that contribute to the integration of immigrant students in contexts where immigration presents a societal challenge.

Criteria #1. Focusing on OECD Countries. We restricted to OECD countries because first-generation immigrant populations differ, particularly in their level of education, between non-OECD and OECD countries (d'Aiglepierre et al., 2020). To verify whether this was the case in our sample, we tested the interaction between student immigrant status (non-immigrant, first-generation, second-generation) and type of country (OECD vs. non-OECD) on parental level of education (measured using PISA's reporting of highest level of education of either parent, coded from 0 to 6). The interaction was significant, $F(2, 149{,}591) = 1175.21$, $p < .001$. In particular, parents of first-generation immigrant students had a higher level of education ($M = 5.16$, $SD = 1.36$) than parents of non-immigrant students ($M = 4.26$, $SD = 1.66$) in non-OECD countries, whereas we find the opposite pattern in OECD countries ($M = 4.32$, $SD = 1.85$, for parents of first-generation immigrants; $M = 4.84$, $SD = 1.5$ for parents of non-immigrants).

Criteria #2. Focusing on Public Schools. We restricted to public schools because first-generation immigrant populations also differ, particularly in parental level of education, between private and public schools. To verify whether this was the case in our sample, we tested the interaction effect between student immigrant status (non-immigrant, first-generation, second-generation) and type of school (public vs. private) on parental level of education. The interaction was significant, $F(2, 139{,}990) = 69.91$, $p < .001$. Parents of first-generation immigrant students had a higher level of education ($M = 5.18$, $SD = 1.35$) than parents of non-immigrant students ($M = 5.02$, $SD = 1.33$) in private schools. In contrast, there was no difference in parental level of education between these groups in public schools ($M = 4.35$, $SD = 1.83$, for parents of first-generation immigrants; $M = 4.31$, $SD = 1.69$, for parents of non-immigrants).

Final Sample. After applying our two exclusion criteria, the final sample comprised 46,740 students ($M_{\text{age}} = 15.81$, $SD = 0.29$), including 23,088 girls (49.4 %) and 23,652 boys, and 35,452 teachers nested in 1544 schools from 7 countries (Chile, Germany, Spain, Great Britain, South Korea, Portugal, United States). Table 1 presents descriptive statistics of the sample.

5.2. Variables

Performance in Science, Mathematics, and Reading (Outcome). We used PISA plausible values for science, mathematics, and reading. To increase the accuracy of the measurement, PISA provides ten plausible values for each of these domains, rather than one single value. These plausible values serve as multiple imputations of students' latent performance in the PISA standardized science, mathematics and reading tests, thereby representing a range of possible performance scores for each student. Plausible values are scaled to M = 500, SD = 100. According to the PISA 2018 Technical Report (OECD, 2019, ch. 12), median reliability across countries exceeds 0.80 for all domains, indicating high measurement precision.

Immigrant Status (Predictor). Students' immigrant status was coded: 1 = Non-immigrant student (87.43 %), 2 = Second-generation student (6.42 %), and 3 = First-generation student (6.15 %).

School Diversity Climate (Predictor). Teachers were asked to report their attitudes toward immigration. We created a school-level score by averaging, within each school, teachers' responses to four items on a scale from 1 "Strongly disagree" to 4 "Strongly agree": "Immigrant children should have the same opportunities for education that other children in the country have"; "Immigrants who live in a country for several years should have the opportunity to vote in elections"; "Immigrants should have the opportunity to continue their own customs and lifestyle"; "Immigrants should have all the same rights that everyone else in the country has" ($\alpha = .84$, $M = 3.29$, $SD = 0.60$). The score theoretically ranges from 1, indicating a school where all teachers have very negative immigration attitudes (exclusionary school diversity climate), to 4, indicating a school where all teachers have very positive immigration attitudes (inclusionary school diversity climate). To justify aggregating teachers' immigration attitudes to the school level, we estimated ICC(1) and ICC(2) from teacher-level data using Bliese's (2000) formulas. Thirty percent of the variance in teachers' attitudes was between schools (ICC(1) = 0.30), and the reliability of school mean scores was high (ICC(2) = 0.91), supporting aggregation to the school level.

5.3. Analytical strategy

School-Cluster Robust Standard Errors and Country Fixed-Effects Models. Our main model accounts for three challenges in the data: (1) PISA performance measures are reported as plausible values, (2) observations are not independent because students are nested within schools, and (3) there are substantial differences between countries, making within-country analyses essential. To address the first issue, we estimated linear regression models in which plausible values for each performance score were regressed on immigrant status, school diversity

Table 1
Description of the PISA 2018 sample and variables.

Variable	M ± SD or %
Mean age	15.81 ± 0.29
Percent of schoolgirls	49.40 %
Percent of non-immigrant students	87.43 %
Percent of native speakers	87.33 %
Student–teacher ratio	11.91 ± 5.21
School % of non-native speakers (as estimated by school principals)	17.05 ± 24.34
School % of low-SES students (as estimated by school principals)	24.14 ± 24.13
School truancy (as reported by school principals)	2.34 ± 0.79
Lack of respect for teachers (as reported by school principals)	2.23 ± 0.70
School drug problem (as reported by school principals)	1.85 ± 0.70
Teachers' education (PROAT5AB)	0.76 ± 0.36

climate, and their interaction. Regarding the second issue, the mean intraclass correlation coefficients across plausible values were $\overline{\text{ICC}} = 0.19$, 0.20, and 0.21 for science, mathematics, and reading performance, respectively. This indicates that about 20 % of the variance in performance is attributable to between-school differences within countries. We used school-clustered robust standard errors to account for this heterogeneity (McNeish et al., 2017). Regarding the third issue, we included country fixed effects to control for all observed and unobserved country-related differences (Allison, 2009), allowing us to estimate pooled within-country effects of school diversity climate on non-immigrant and immigrant students' performance (Sommet & Lipps, 2025). This approach ensures that students are compared only within the same country, eliminating time-constant cross-national confounders—a crucial step given the wide variation in national multicultural policies and immigrant populations.

Plausible Values. We followed OECD (2009) and Jerrim, Lopez-Agudo, et al. (2017)'s protocol to pool estimates across the ten plausible values. For each outcome, we ran the model separately for each plausible value and combined results with Rubin's rules: (a) average the 10 coefficients per predictor; (b) average the corresponding squared standard errors to obtain the within-imputation variance; (c) compute between-imputation variance and combine it with the within-imputation variance to obtain the total variance, from which is derived the pooled standard error. These pooled estimates were then used to build confidence intervals and compute *p*-values for statistical inferences. We implemented this procedure using the 'PV' Stata module (Macdonald, 2023).

Control Variables. All analyses included the same sets of student-level and school-level control variables. Most variables were selected based on Ferri et al.'s (2023) analysis of the most important predictors of national-immigrant achievement gaps. We included five student-level: age, gender (1 = girls; 2 = boys), track level (1 = general; 2 = pre-vocational; 3 = vocational; 4 = modular), home language (1 = native language; 2 = other), and SES (PISA standardized index of economic, social and cultural status); and eight potential school-level confounders: school area (1 = village; 2 = small town; 3 = town; 4 = city; 5 = large city), school admission policies based on performance (1 = never; 2 = sometimes; 3 = always), student-teacher ratio, percentage of non-native speakers (as estimated by school principals), percentage of low-SES students (as estimated by school principals) and the proportion of teachers with a Bachelor degree. We also included three additional control variables: the extent to which students' truancy, lack of respect for teachers, and alcohol or drug use affect learning in the school (as reported by school principals; 1 = *Not at all* to 4 = *A lot*), because these indicators capture potential behavioral consequences or confounder of low achievement. Controlling for them reduces the likelihood of a reverse causal explanation: lower student achievement could lead to more disruptive behavior, which may foster negative attitudes toward immigrants among teachers. In the supplementary material, Table S1 reports the correlations among outcomes, predictors, and student-level control variables, while Table S2 reports the correlations among outcomes, predictors, and school-level control variables.

Regression Equation. Below is the cluster-robust fixed-effects regression equation used in the main analysis:

$$\begin{aligned} Performance^{p}_{ij} = {} & B_1 \times Immigrant^{d1}_{ij} + B_2 \times Immigrant^{d2}_{ij} + B_3 \times Climate_{ij} \\ & + B_4 \times Immigrant^{d1}_{ij} \times Climate_{ij} + B_5 \times Immigrant^{d2}_{ij} \times Climate_{ij} + B_{ij} \\ & \times Control_{ij} + \alpha_j + e_{wit} \end{aligned} \tag{1}$$

… where $i = 1, 2, \ldots, N$ students, $j = 1, 2, \ldots, 7$ countries,

… where $Performance^{p}_{ij}$ represents the plausible value p for performance in a given domain, $Immigrant^{dn}_{ij}$ represents a dummy variable n contrasting two of the three student immigrant status groups, $Control_{ij}$ represents a vector of control variables, α_j represents the country fixed effect, and e_{wij} represents the within-country residual. Residuals are assumed to be normally distributed ($e_{wij} \sim \mathcal{N}(0, \sigma^2)$), homoscedastic ($\mathrm{Var}(e_{wij} \mid X_{ij}) = \sigma^2$), and independent beyond school (as standard errors are clustered at the school level) and country (as country fixed effects are included).

Note (2): Following Giesselmann and Schmidt-Catran (2022), we conducted Hausman tests to assess whether the interaction terms required double-demeaning. None were significant ($ps > 0.05$), indicating that the model was correctly specified.

6. Results

6.1. Main analyses

We hypothesized that an inclusionary school diversity climate would be associated with smaller gaps in school performance between non-immigrant and first-generation immigrant students. Table 2 presents the estimate from the school-cluster robust standard errors and country fixed-effects models testing the interaction effect between school diversity climate and students' immigrant status for each of the three dependent variables (i.e., plausible values of student performance in science, mathematics, and reading). All continuous predictors were standardized (at the individual or school-level, depending on the variable).

As seen in Table 3 (line 1), the omnibus tests of the inclusionary school diversity climate × immigration status were significant for all dependent variables. As seen in Tables 2 and 4, upon decomposing the interactions, we found a similar simple slope pattern across the dependent variables: there is a significant gap between each of the groups (i.e., non-immigrant, second-generation and first-generation students). The effect of school diversity climate on performance is not significant for the non-immigrant students nor for second-generation students. However, as predicted, the effect of school diversity climate on performance is positive and significant for first-generation students. Specifically, as shown in Table 2, a one–standard-deviation increase in school-level teachers' immigration attitudes is associated with an average performance increase of 6 points in mathematics, 10 in science and 12 in reading. In sum, first-generation immigrant students have better science, mathematics, and reading performances in schools where teachers have more inclusionary immigration attitudes as compared to schools where teachers have more exclusionary immigration attitudes.

As for the differences in performance gap between students as a function of school diversity climate, Fig. 1[2] shows, as expected, that the gap in science performance was smaller in schools where teachers' immigration attitudes are more inclusionary (First-generation: M = 479.18; SE = 3.45; Second-generation: M = 481.52; SE = 4.09; Non-immigrant: M = 496.20; SE = 1.72) than in schools where teachers' immigration attitudes are more exclusionary (First-generation: M = 453.90; SE = 4.04; Second-generation: M = 479.74; SE = 3.83; Non-immigrant: M = 492.01; SE = 1.71). We find the same pattern for math performance whereby students' performance gap was smaller in schools where teachers' immigration attitudes are more inclusionary (First-generation: M = 468.33; SE = 3.07; Second-generation: M = 478.84; SE = 3.77; Non-immigrant: M = 495.01; SE = 1.63) than in schools where teachers' immigration attitudes are more exclusionary (First-generation: M = 451.40; SE = 3.70; Second-generation: M = 479.89; SE = 3.63; Non-immigrant: M = 491.75; SE = 1.63). The pattern is again replicated for the reading performance whereby students' performance gap was smaller in schools where teachers' immigration

[2] Because marginal means and graphs cannot be recovered with Stata PV module (i.e., imputing the outcome) for science, mathematics and reading performance, we conducted the same analyses replacing the imputed plausible values of performance with the mean performance values (Table 3, line 6; see Baysu et al., 2023).

Table 2
Estimates from the Fixed-Effects Model Testing the Interaction Between School Diversity Climate and Students' Immigrant Status (non-immigrant, Second generation, First generation).

	Science B (SE)	Math B (SE)	Reading B (SE)
School diversity climate (SDC)	2.07 (1.41)	1.51 (1.41)	2.35 (1.46)
Non-immigrant vs. 2G student	−13.17*** (3.53)	−13.99*** (3.78)	−7.21* (3.17)
Non-immigrant vs. 1G student	−27.42*** (3.95)	−33.36*** (3.38)	−28.27*** (2.96)
SDC × 2G student (ref: non-immigrant)	−0.98 (3.07)	−2.20 (2.91)	−3.13 (2.82)
SDC × 1G student (ref: non-immigrant)	10.08** (3.07)	6.29* (2.85)	11.74*** (3.13)
Other language (ref: native language)	−12.87*** (2.98)	−8.50** (2.94)	−15.21*** (3.00)
Male (ref: female)	7.62*** (1.65)	12.45*** (1.45)	−19.62*** (1.37)
Socioeconomic status (ESCS)	21.82*** (0.96)	23.37*** (0.84)	21.52*** (0.76)
Pre-vocational (ref: general track)	−79.59*** (7.46)	−81.94*** (8.82)	−81.92*** (7.22)
Vocational (ref: general track)	−49.18*** (6.81)	−42.76*** (6.58)	−45.63*** (7.11)
Partly based on performance (ref: open)	0.90 (3.28)	0.12 (3.24)	−2.95 (3.74)
Based on performance (ref: open)	1.87 (5.19)	2.63 (5.10)	−0.16 (5.40)
Small town (ref: village)	4.26 (5.16)	6.22 (5.36)	8.43 (5.92)
Town (ref: village)	8.64 (5.33)	10.16 (5.46)	17.02** (5.99)
City (ref: village)	13.81* (5.64)	15.62** (5.76)	24.41*** (6.14)
Large city (ref: village)	20.09** (7.39)	24.59** (7.52)	32.49*** (8.00)
Student–teacher ratio	1.56 (1.35)	0.90 (1.51)	2.23 (1.43)
School % of low-SES students	−13.12*** (1.67)	−12.20*** (1.60)	−13.42*** (1.69)
School % of non-native speakers	−0.28 (1.34)	−0.10 (1.36)	−0.31 (1.42)
School truancy	−3.49* (1.41)	−4.27** (1.40)	−3.07* (1.43)
School drug problems	−6.95*** (1.48)	−6.55*** (1.43)	−7.46*** (1.48)
Lack of respect for teachers	2.89* (1.24)	2.52* (1.18)	2.68* (1.30)
Teachers' education (PROAT5AB)	−0.57 (1.44)	−0.31 (1.40)	−0.57 (1.53)
Country fixed effects	Yes	Yes	Yes
N schools	846	846	846
N teachers	19,786	19,786	19,786
N students	24,178	24,178	24,178
R^2	0.15	0.17	0.16

Note: The model controls for student's age, gender, track level, home language, SES, school area, school admission policies, student–teacher ratio, percentage of non-native speakers, percentage of low-SES students, student truancy, lack of respect for teachers, students' alcohol and drug use, and the proportion of teachers with a bachelor's degree.
***p < .001, **p < .01, *p < .05.

attitudes are more inclusionary (First-generation: $M = 476.23$; $SE = 3.73$; Second-generation: $M = 481.36$; $SE = 4.25$; Non-immigrant: $M = 492.09$; $SD = 1.81$) than in schools where teachers' immigration attitudes are more exclusionary (First-generation: $M = 447.05$; $SE = 4.46$; Second-generation: $M = 483.02$; $SD = 3.81$; Non-immigrant: $M = 487.21$; $SE = 1.88$). The difference in performance for first-generation immigrant students (when comparing school diversity climates at ± 1SD) is 25.27 points in science, 16.93 points in mathematics and 29.18 points in reading. Given that the standard deviation for performance is 100 in PISA, the difference (inclusionary vs. exclusionary climates) is between 1/6 to 1/3 standard deviation.

6.2. Robustness analysis: alternative specification

In a second step, we conducted similar analyses with alternative specifications to ensure that the results were robust (see omnibus interaction effects in Table 3).

Table 3
Omnibus Tests for Interaction Between School Diversity Climate and Students' Immigrant Status on performance in Main and Alternative Models.

	Science	Math	Reading
Main Model			
Fixed-effects model with controls (plausible values)	$F(2, 845) =$ 11.83**	$F(2, 845) =$ 6.55*	$F(2, 845) =$ 18.37***
Fixed-effects model without controls (plausible values)	$F(2, 1543) =$ 24.37***	$F(2, 1543) =$ 17.96***	$F(2, 1543) =$ 26.38***
Sampling Weights			
Fixed-effects model with weights with controls (plausible values)	$F(2, 845) =$ 8.79*	$F(2, 845) =$ 4.61†	$F(2, 845) =$ 13.45**
Fixed-effects model with weights without controls (plausible values)	$F(2, 1543) =$ 17.27***	$F(2, 1543) =$ 8.25*	$F(2, 1543) =$ 21.89***
Alternative Models			
Multilevel model with controls (mean values)	$F(2, 845) =$ 11.35**	$F(2, 845) =$ 7.76*	$F(2, 845) =$ 13.03***
Double-demeaned fixed-effects model with controls (mean values)	$F(2, 845) =$ 5.84**	$F(2, 845) =$ 4.07*	$F(2, 845) =$ 6.01*
Stratified analyses with controls (mean values)	$F(2, 845) =$ 8.82*	$F(2, 845) =$ 8.92*	$F(2, 845) =$ 11.94**
Fixed-effects model with controls (mean values)	$F(2, 845) =$ 8.01***	$F(2, 845) =$ 4.69**	$F(2, 845) =$ 10.43***

† $p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$.

Table 4
Estimates from the interaction between school diversity climate and students' immigrant status in the fixed-effects model with imputed data for control variables.

	Science *B* (*SE*)	Math *B* (*SE*)	Reading *B* (*SE*)
School diversity climate × Immigration status (Reference category: Non-immigrant)			
School diversity climate × First-generation immigrant students	56.45[a] (13.47)	41.17[a] (12.37)	62.14[a] (13.84)
School diversity climate × Second-generation immigrant students	18.44 (15.33)	7.94 (13.91)	8.13 (15.03)

Note: The model controls for students' age, gender, track level, home language, SES, school area, school admission policies, student-teacher ratio, percentage of non-native speakers, percentage of low-SES, students' truancy, lack of respect for teachers and alcohol and drug use and the proportion of teachers with a bachelor's degree. Variables were not standardized for this analysis.
[a] $p < .001$.

Control Variables. We re-estimated the main fixed-effects analysis while excluding control variables. We replicated the hypothesized interaction between student immigrant status and school diversity climate on performance in 3 of 3 models.

Sampling Weights. We re-estimated the main fixed-effects analysis, with and without controls, using sampling weights to adjust for PISA's clustered design, oversampling in some countries, and school nonresponse. Following Jerrim, López-Agudo, et al. (2017), we combined respondent sampling weights with balanced-repeated-replication weights. Because our estimand is the pooled within-country effect, we used senate weights so that each country contributes equally. As in PISA (2009), we used Fay's method with a factor of 0.5. As the replicate-weight procedure cannot be combined with school-clustered standard errors, we removed clustering. We replicated the hypothesized interactions in 5 of 6 models (the *p*-value for mathematics in the model with controls was $p < .10$).

Alternative Models. We re-tested the interaction effects between student immigrant status and school diversity climate, in (1) multilevel models with control variables and the median performance, in (2) school-clustered robust standard errors and double-demeaned models

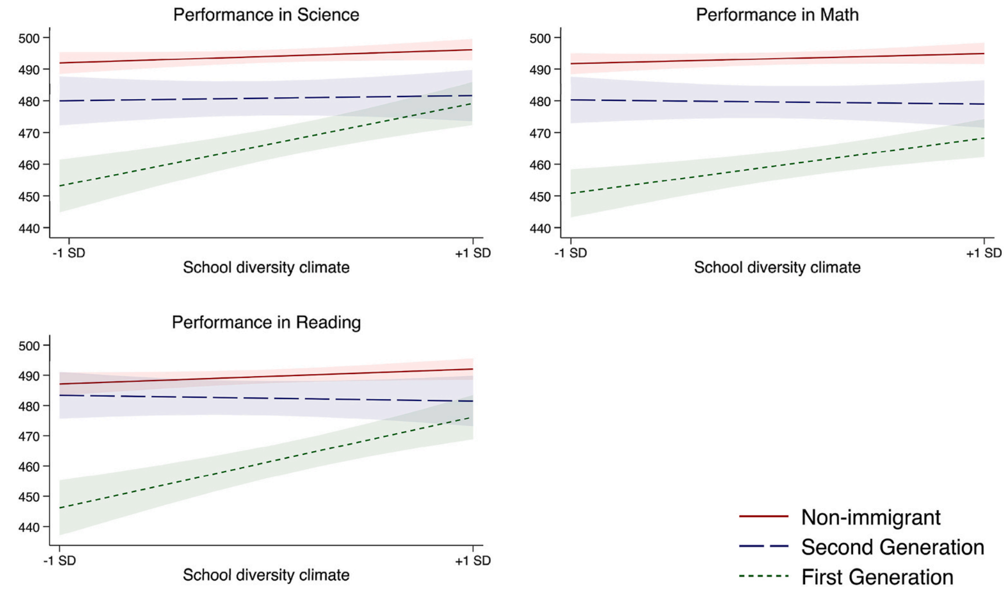

Fig. 1. Graphical Representation of the Effect of School Diversity Climate as a Function of Students' Immigrant Status.
Note: The regression lines were obtained from fixed-effect models with the mean performance values (see Table 3, line 6) and the following control variables: students' age, gender, track level, home language, SES, school area, school admission policies, student-teacher ratio, percentage of non-native speakers, percentage of low-SES, students' truancy, lack of respect for teachers and alcohol and drug use and the proportion of teachers with a bachelor's degree. Shaded areas represent 95 % confidence intervals.

with country-fixed effects and controls variables and median performance values and in (3) stratified analyses with control variables and median performance values. We replicated the hypothesized effect in 12 of 12 models.

6.3. Robustness analysis: multiple imputations

In a third step, we imputed all control variables to maximize sample size and test robustness. We used multiple imputation by chained equations (MICE), creating 20 level-1 datasets for student-level controls and 20 level-2 datasets for school-level controls. We then re-ran the same models (school-clustered standard errors with country fixed effects) to test the interaction between school diversity climate and immigrant status on science, mathematics, and reading. Because plausible values are themselves imputations, MICE could not be combined with the Stata PV module for the outcomes. We therefore manually derived, combined, and adjusted coefficients and standard errors for the three focal interactions across the 10×3 plausible values (90 estimates). Given the computational burden, we report only these focal estimates, without control-variable outputs or marginal-effects figures. Results were substantively unchanged (see Table 4): the school climate effect differed significantly for first-generation versus non-immigrant students in all three domains and remained non-significant for second-generation versus non-immigrant students.

7. Discussion

The study tested whether schools' diversity climates, measured with teachers' explicit immigration attitudes, are linked to first-generation immigrants' achievement. We predicted that more inclusionary climates would boost first-generation students' performance, narrowing gaps with non-immigrant and second-generation peers. The data support this: In schools where teachers collectively endorsed inclusionary immigration attitudes, first-generation students achieved significantly higher scores across all domains; by contrast, in more exclusionary school climates, gaps between first-generation and non-immigrant students were evident. The climate-related gain effectively reduced—and in science and reading, even closed—the achievement gaps. The improvement corresponds to over one year of schooling (Avvisati & Givord, 2023).

Another notable finding is the differential impact of school climate on first-versus second-generation immigrant students. Although first-generation students benefited from inclusionary climates, no comparable effect appeared for second-generation peers. Likely reasons include (1) second-generation students' greater language proficiency and system familiarity (Dimitrova et al., 2016), making them less sensitive to teachers' attitudes; (2) teachers' self-reported attitudes reflecting behaviors directed primarily toward first-generation students or (3) second-generation students not self-identifying as immigrants and thus feeling less affected by exclusionary climates.

To our knowledge, this is the first evidence that (1) teachers' explicit immigration attitudes constitute a key facet of school inclusionary climate and (2) such climates relate to immigrant students' performance in science, mathematics, and reading. This finding is especially important given the lack of sufficiently powered evidence directly linking teachers' explicit prejudice to achievement gaps. Using PISA's large-scale, multi-country dataset enabled robust analyses across diverse educational contexts which enhances the generalizability of its findings. The dataset included many schools ($N = 1{,}544$), providing substantial statistical power to detect meaningful institutional-level effects. We adjusted for numerous student- and school-level covariates and the results proved robust across various model specifications and multiple imputation procedures. This rigor reduces confounding concerns and strengthens the inference that teachers' explicit immigration attitudes help shape immigrant students' academic outcomes.

This study also advances our understanding of cultural diversity climates by showing that aggregated teacher attitudes have measurable implications for student outcomes. While past studies often relied on students' perceptions, which limit causal interpretations due to endogeneity concerns (Bardach et al., 2024), our use of teachers' explicit attitudes helps mitigate these issues: aggregating explicit views likely reduces social-desirability error, and prejudice may exert stronger effects at the institutional level by capturing the broader school environment. In sum, by proposing a new measure of school climates, we identified an important *structural* contributor to academic disparities. These findings also contribute to theories on how normative climates shape institutional dynamics (Kende et al., 2024; Phalet & Baysu, 2020). Prior work shows that regional anti-immigration norms foster exclusionary attitudes (Christ et al., 2014; Visintin et al., 2020). Our results suggest the same dynamics operate within schools, aligning with accounts of structural bias (Charlesworth & Banaji, 2021; Payne et al., 2017). In short, biases are not only individual; they are embedded in institutional climates that shape outcomes for marginalized students (Batruch et al., 2019; Green & Staerklé, 2023).

7.1. Limitations

As with any study, several limitations apply. First, although aggregating teacher attitudes offers a more exogenous climate indicator than student perceptions, self-reports may still reflect social desirability. Second, the cross-sectional design limits causal inference; longitudinal or quasi-experimental work is needed. Third, the mechanisms remain untested: inclusionary schools may prompt more responsive pedagogy that boosts engagement and belonging (Celeste et al., 2019) and/or foster peer norms that reduce discrimination (Baysu et al., 2023). Future research could trace these pathways directly. Finally, our focus on public schools in OECD countries constrains generalizability to other educational contexts.

7.2. Policy and practical implications

These findings carry clear implications for education policy and practice. As migration rises, institutions need strategies to support diverse student populations (European Commission, 2019). Given the observed effect sizes, fostering inclusionary school climates may meaningfully improve first-generation students' achievement. Interventions can target students (individual solution), teachers (individuals or structural solution), or structural features like leadership and policy. Our results point especially to teacher-focused efforts—e.g., professional development that reduces prejudice and builds multicultural competencies (Starck et al., 2020). However, interventions that target only individual bias awareness rarely yield lasting change (Forscher et al., 2019; Paluck et al., 2021). Our results point to structural, school-level approaches: address teachers' explicit attitudes toward immigrant rights and opportunities (Charlesworth & Banaji, 2021) by providing structured opportunities to collectively reflect on their beliefs, learn about cultural differences, and adopt inclusive strategies. Other approaches may be identifying influential actors within the school (e.g., influential teachers) to lead school climate discussions (Paluck et al., 2016) or implementing structural policies that limit opportunities for bias—such as anonymized testing or cross-grading of exams (Autin et al., 2019; Batruch et al., 2023).

8. Conclusion

To our knowledge, this is the first large-scale, multi-country study showing that aggregated teacher explicit attitudes—rather than student perceptions—capture a meaningful facet of school diversity climate with measurable impact to achievement. By using a rigorous design and a well-powered international dataset, we answer calls to examine institutional drivers of educational inequality and provide theoretically and practically relevant evidence of structural contributors to immigrant students' outcomes. As immigration rises globally, shaping institutional climates will be essential for educational equity, social cohesion, and societal well-being.

CRediT authorship contribution statement

Anatolia Batruch: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Nicolas Sommet:** Writing – review & editing, Visualization, Validation, Software, Methodology, Formal analysis. **Eva G.T. Green:** Writing – review & editing, Conceptualization.

Code availability

The script is available on the OSF page for the project: https://osf.io/xfdjm.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used CHAT GPT 4.0 in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Funding

This study was supported by an Ambizione fellowship by the Swiss National Science Foundation (SNSF) to Dr. Anatolia Batruch (PZ00P1_216024).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2025.102303.

References

Alieva, A., Hildebrand, V. A., & Van Kerm, P. (2024). The progression of achievement gap between immigrant and native-born students from primary to secondary education. *Research in Social Stratification and Mobility, 92*, Article 100961. https://doi.org/10.1016/j.rssm.2024.100961

Allison, P. D. (2009). *Fixed effects regression models*. SAGE publications.

Andon, A., Thompson, C. G., & Becker, B. J. (2014). A quantitative synthesis of the immigrant achievement gap across OECD countries. *Large-scale assessments in education, 2*, 1–20. https://doi.org/10.1186/s40536-014-0007-2

Arikan, S., van de Vijver, F. J., & Yagmur, K. (2020). Mainstream and immigrant students' primary school mathematics achievement differences in European countries. *European Journal of Psychology of Education, 35*(4), 819–837. https://doi.org/10.1007/s10212-019-00456-2

Autin, F., Batruch, A., & Butera, F. (2019). The function of selection of assessment leads evaluators to artificially create the social class achievement gap. *Journal of Educational Psychology, 111*(4), 717–735. https://doi.org/10.1037/edu0000307

Avvisati, F., & Givord, P. (2023). The learning gain over one school year among 15-year-olds: An international comparison based on PISA. *Labour Economics, 84*, Article 102365. https://doi.org/10.1016/j.labeco.2023.102365Getrightsandcontent

Bardach, L., Röhl, S., Oczlon, S., Schumacher, A., Lüftenegger, M., Lavelle-Hill, R., … Zitzmann, S. (2024). Cultural diversity climate in school: A meta-analytic review of its relationships with intergroup, academic, and socioemotional outcomes. *Psychological Bulletin, 150*(12), 1397–1439. https://doi.org/10.1037/bul0000454

Barg, K. (2013). The influence of students' social background and parental involvement on teachers' school track choices: Reasons and consequences. *European Sociological Review, 29*(3), 565–579. https://doi.org/10.1093/esr/jcr104

Batruch, A., Autin, F., Bataillard, F., & Butera, F. (2019). School selection and the social class divide: How tracking contributes to the reproduction of inequalities. *Personality and Social Psychology Bulletin, 45*, 470–477. https://doi.org/10.1177/0146167218791804

Batruch, A., Autin, F., & Butera, F. (2017). Re-Establishing the social-class order: Restorative reactions against high-achieving, Low-SES pupils. *Journal of Social Issues, 73*, 42–60. https://doi.org/10.1111/josi.12203

Batruch, A., Geven, S., Kessenich, E., & Van de Werfhorst, H. (2023). Inequality in teacher track recommendations: A review study. *Teaching and Teacher Education, 123*, Article 103985. https://doi.org/10.1016/j.tate.2022.103985

Baysu, G., Agirdag, O., & De Leersnyder, J. (2023). The association between perceived discriminatory climate in school and student performance in math and reading: A cross-national analysis using PISA 2018. *Journal of Youth and Adolescence, 52*(3), 619–636. https://doi.org/10.1007/s10964-022-01712-3

Benner, A. D., Wang, Y., Shen, Y., Boyle, A. E., Polk, R., & Cheng, Y. P. (2018). Racial/ethnic discrimination and well-being during adolescence: A meta-analytic review. *American Psychologist, 73*(7), 855–883. https://doi.org/10.1037/amp0000204

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein, & S. W. J. Kozlowski (Eds.), *Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions* (pp. 349–381). Jossey-Bass/Wiley.

Carlana, M. (2019). Implicit stereotypes: Evidence from teachers' gender bias. *Quarterly Journal of Economics, 134*(3), 1163–1224. https://doi.org/10.1093/qje/qjz008

Celeste, L., Baysu, G., Phalet, K., Meeussen, L., & Kende, J. (2019). Can school diversity policies reduce belonging and achievement gaps between minority and majority youth? Multiculturalism, colorblindness, and assimilationism assessed. *Personality and Social Psychology Bulletin, 45*(11), 1603–1618. https://doi.org/10.1177/0146167219838

Charlesworth, T. E., & Banaji, M. R. (2021). Patterns of implicit and explicit attitudes II. Long-term change and stability, regardless of group membership. *American Psychologist, 76*(6), 851. https://doi.org/10.1037/amp0000810

Charlesworth, T. E., Navon, M., Rabinovich, Y., Lofaro, N., & Kurdi, B. (2023). The project implicit international dataset: Measuring implicit and explicit social group attitudes and stereotypes across 34 countries (2009–2019). *Behavior Research Methods, 55*(3), 1413–1440. https://doi.org/10.3758/s13428-022-01851-2

Chin, M. J., Quinn, D. M., Dhaliwal, T. K., & Lovison, V. S. (2020). Bias in the air: A nationwide exploration of teachers' implicit racial attitudes, aggregate bias, and student outcomes. *Educational Researcher, 49*(8), 566–578. https://doi.org/10.3102/0013189X20937240

Christ, O., Schmid, K., Lolliot, S., Swart, H., Stolle, D., Tausch, N., … Hewstone, M. (2014). Contextual effect of positive intergroup contact on outgroup prejudice. *Proceedings of the National Academy of Sciences, 111*(11), 3996–4000. https://doi.org/10.1073/pnas.1320901111

Civitillo, S., Mayer, A. M., & Jugert, P. (2024). A systematic review and meta-analysis of the associations between perceived teacher-based racial–ethnic discrimination and student well-being and academic outcomes. *Journal of Educational Psychology, 116*(5), 719. https://doi.org/10.1111/desc.13380

Coll, C. G., Crnic, K., Lamberty, G., Wasik, B. H., Jenkins, R., Garcia, H. V., & McAdoo, H. P. (1996). An integrative model for the study of developmental competencies in minority children. *Child Development, 67*(5), 1891–1914. https://doi.org/10.1111/j.1467-8624.1996.tb01834.x

Corneille, O., & Gawronski, B. (2024). Self-reports are better measurement instruments than implicit measures. *Nature Reviews Psychology*, 1–12. https://doi.org/10.1038/s44159-024-00376-z

d'Aiglepierre, R., David, A., Levionnois, C., Spielvogel, G., Tuccio, M., & Vickstrom, E. (2020). A global profile of emigrants to OECD countries: Younger and more skilled migrants from more diverse countries. *OECD social, employment and migration working* (p. 239). Paris: OECD Publishing. https://doi.org/10.1787/0cb305d3-en

De Paolo, M., & Brunello, G. (2016). *Education as a tool for the economic integration of migrants*. Institute for the Study of Labor. http://ftp.iza.org/dp9836.pdf.

Del Toro, J., & Wang, M. T. (2023). Stereotypes in the classroom's air: Classroom racial stereotype endorsement, classroom engagement, and STEM achievement among Black and White American adolescents. *Developmental Science, 26*(6), Article e13380. https://doi.org/10.1016/j.learninstruc.2020.101437

Dimitrova, R., Chasiotis, A., & Van de Vijver, F. (2016). Adjustment outcomes of immigrant children and youth in Europe. *European Psychologist, 21*(2). https://doi.org/10.1027/1016-9040/a000246

Doyle, L., Harris, P. R., & Easterbrook, M. J. (2024). Quality and quantity: How contexts influence the emergence of teacher bias. *Social Psychology of Education, 27*(4), 1855–1882. https://doi.org/10.1007/s11218-023-09882-z

Duong, M. T., Badaly, D., Liu, F. F., Schwartz, D., & McCarty, C. A. (2016). Generational differences in academic achievement among immigrant youths: A meta-analytic review. *Review of Educational Research, 86*(1), 3–41. https://doi.org/10.3102/0034654315577680

Dustmann, C., Frattini, T., & Lanzara, G. (2012). Educational achievement of second-generation immigrants: An international comparison. *Economic Policy, 27*(69), 143–185. https://doi.org/10.1111/j.1468-0327.2011.00275.x

Entorf, H. (2015). *Migrants and educational achievement gaps*. IZA World of Labor. https://doi.org/10.15185/izawol.146

Esses, V. M. (2021). Prejudice and discrimination toward immigrants. *Annual Review of Psychology, 72*(1), 503–531. https://doi.org/10.1146/annurev-psych-080520-102803

European Commission. (2019). *PISA 2018 and the EU: Striving for social fairness through education*. Publications Office of the European Union. https://doi.org/10.2766/964797

Fasel, N., Green, E. G. T., & Sarrasin, O. (2013). Facing cultural diversity: Anti-immigrant attitudes in Europe. *European Psychologist, 18*(4), 253–262. https://doi.org/10.1027/1016-9040/a000157

Ferri, V., Di Castro, G., & Marsiglia, S. (2023). Does the immigrant background affect student achievement? cross-country comparisons of PISA scores. *Rivista Italiana di Economia, Demografia e Statistica*, 91–102.

Forscher, P. S., Lai, C. K., Axt, J. R., Ebersole, C. R., Herman, M., Devine, P. G., & Nosek, B. A. (2019). A meta-analysis of procedures to change implicit measures. *Journal of Personality and Social Psychology, 117*(3), 522–559. https://doi.org/10.1037/pspa0000160

Giesselmann, M., & Schmidt-Catran, A. W. (2022). Interactions in fixed effects regression models. *Sociological Methods & Research, 51*(3), 1100–1127. https://doi.org/10.1177/0049124120914934

Green, E. G. T., & Staerklé, C. (2023). 1016 migration and multiculturalism. In *The Oxford handbook of political psychology* (pp. 1016–1061). Oxford University Press.

Greenaway, V. P., & Turetsky, K. M. (2020). Socioecological diversity and inclusion: A framework for advancing diversity science. *Current Opinion in Psychology, 32*, 171–176. https://doi.org/10.1016/j.copsyc.2019.09.008

Heath, A. F., & Brinbaum, Y. (Eds.). (2014). *Unequal attainments: Ethnic educational inequalities in ten Western countries* (Vol. 196). Oxford: Oxford University Press.

Jerrim, J., Lopez-Agudo, L. A., Marcenaro-Gutierrez, O. D., & Shure, N. (2017a). What happens when econometrics and psychometrics collide? An example using the PISA data. *Economics of Education Review, 61*, 51–58. https://doi.org/10.1016/j.econedurev.2017.09.007

Jerrim, J., López-Agudo, L. A., Marcenaro-Gutiérrez, O. D., & Shure, N. (2017b). To weight or not to weight? The case of PISA data. In J. C. Gómez Gallego, M. C. Pérez Cárceles, & L. Nieto Torrejón (Eds.), *Investigaciones de Economía de la Educación* (Vol. 12, pp. 285–301). Asociación de Economía de la Educación.

Karakus, M., Courtney, M., & Aydin, H. (2023). Understanding the academic achievement of the first-and second-generation immigrant students: A multi-level analysis of PISA 2018 data. *Educational Assessment, Evaluation and Accountability, 35*(2), 233–278. https://doi.org/10.1007/s11092-022-09395-x

Kende, J., Green, E. G. T., & Phalet, K. (2024). Social and institutional inclusion in multi-ethnic schools enable better intergroup relations for majority youth and higher school achievement for minority youth. *International Journal of Intercultural Relations, 103*. https://doi.org/10.1016/j.ijintrel.2024.102088

Kende, J., Sarrasin, O., Manatschal, A., Phalet, K., & Green, E. G. T. (2022). Policies and prejudice: Integration policies moderate the link between immigrant presence and anti-immigrant prejudice. *Journal of Personality and Social Psychology, 123*(2), 337–352. https://doi.org/10.1037/pspi0000376

Macdonald, K. (2023). PV: Stata module to perform estimation with plausible values. https://EconPapers.repec.org/RePEc:boc:bocode:s456951.

Martin, A. J., Collie, R. J., & Malmberg, L. E. (2024). Exploring the roles of academic, personal, and cultural demands and resources in immigrant students' motivation, engagement, and achievement. *Learning and Instruction, 92*, Article 101903. https://doi.org/10.1016/j.learninstruc.2024.101903

McAuliffe, M., & Oucho, L. A. (2024). Report overview: Migration continues to be part of the solution in a rapidly changing world, but key challenges remain. *World Migration Report, 2024*(1), Article e00033. https://doi.org/10.1002/wom3.33

McNeish, D., Stapleton, L. M., & Silverman, R. D. (2017). On the unnecessary ubiquity of hierarchical linear modeling. *Psychological Methods, 22*(1), 114–140. https://doi.org/10.1037/met0000078

OECD. (2009). *PISA data analysis manual: SPSS, second edition*. Paris: OECD Publishing. https://doi.org/10.1787/9789264056275-en. PISA.

OECD. (2019). *PISA 2018 technical report. PISA*. Paris: OECD Publishing.

OECD. (2023). *PISA 2022 results (volume I): The State of Learning and Equity in Education, PISA*. Paris: OECD Publishing. https://doi.org/10.1787/53f23881-en

Paluck, E. L., Porat, R., Clark, C. S., & Green, D. P. (2021). Prejudice reduction: Progress and challenges. *Annual Review of Psychology, 72*(1), 533–560. https://doi.org/10.1146/annurev-psych-071620-030619

Paluck, E. L., Shepherd, H., & Aronow, P. M. (2016). Changing climates of conflict: A social network experiment in 56 schools. *Proceedings of the National Academy of Sciences, 113*(3), 566–571. https://doi.org/10.1073/pnas.1514483113

Payne, B. K., Vuletich, H. A., & Lundberg, K. B. (2017). The bias of crowds: How implicit bias bridges personal and systemic prejudice. *Psychological Inquiry, 28*(4), 233–248. https://doi.org/10.1080/1047840X.2017.1335568

Phalet, K., & Baysu, G. (2020). Fitting in: How the intergroup context shapes minority acculturation and achievement. *European Review of Social Psychology, 31*(1), 1–39. https://doi.org/10.1080/10463283.2020.1711627

Pit-ten Cate, I. M., & Glock, S. (2019). Teachers' implicit attitudes toward students from different social groups: A meta-analysis. *Frontiers in Psychology, 10*, 2832. https://doi.org/10.3389/fpsyg.2019.02832

Porcu, M., Sulis, I., Usala, C., & Giambona, F. (2023). Will the gap ever be bridged? A cross-national comparison of non-native students' educational achievements. *Genus, 79*(1), 19. https://doi.org/10.1186/s41118-023-00199-5

Quinn, D. M. (2017). Racial attitudes of preK–12 and postsecondary educators: Descriptive evidence from nationally representative data. *Educational Researcher, 46*(7), 397–411. https://doi.org/10.3102/0013189X17727270

Schmidt, K. (2021). The dynamics of attitudes toward immigrants: Cohort analyses for Western EU member states. *International Journal of Comparative Sociology, 62*(4), 281–310. https://doi.org/10.1177/002071522110525

Shehaj, A., Shin, A. J., & Inglehart, R. (2021). Immigration and right-wing populism: An origin story. *Party Politics, 27*(2), 282–293. https://doi.org/10.1177/13540688198498

Sommet, N, & Lipps, O (2025). A Primer on Fixed Effects and Fixed-Effects Panel Modeling Using. *Advances in Methods and Practices in Psychological Science, 8*(4). https://doi.org/10.1177/25152459251392843

Sprong, S., & Skopek, J. (2022). Academic achievement gaps by migration background at school starting age in Ireland. *European Societies, 24*(5), 580–604. https://doi.org/10.1080/14616696.2022.2084558

Starck, J. G., Riddle, T., Sinclair, S., & Warikoo, N. (2020). Teachers are people too: Examining the racial bias of teachers compared to other American adults. *Educational Researcher, 49*(4), 273–284. https://doi.org/10.3102/0013189X209127

Timmermans, A. C., de Boer, H., Amsing, H. T., & van der Werf, M. P. (2018). Track recommendation bias: Gender, migration background and SES bias over a 20-year period in the Dutch context. *British Educational Research Journal, 44*(5), 847–874. https://doi.org/10.1002/berj.3470

Turetsky, K. M., Sinclair, S., Starck, J. G., & Shelton, J. N. (2021). Beyond students: How teacher psychology shapes educational inequality. *Trends in Cognitive Sciences, 25*(8), 697–709. https://doi.org/10.1016/j.tics.2021.04.006

Van Assche, J., Roets, A., De Keersmaecker, J., & Van Hiel, A. (2017). The mobilizing effect of right-wing ideological climates: Cross-level interaction effects on different types of outgroup attitudes. *Political Psychology, 38*(5), 757–776. https://doi.org/10.1111/pops.12359

Visintin, E. P., Green, E. G. T., Falomir-Pichastor, J. M., & Berent, J. (2020). Intergroup contact moderates the influence of social norms on prejudice. *Group Processes & Intergroup Relations, 23*(3), 418–440. https://doi.org/10.1177/1368430219839485

Anatolia Batruch is a social and educational psychologist examining the structural antecedents of educational inequalities as well as the psychological consequences of belonging to a social class.

Nicolas Sommet is a social and educational psychologist working on the consequences of economic inequality, achievement motivation, and making statistics more accessible.

Eva Green is a Professor in social psychology examining how normative climates shape immigration attitudes, and intergroup phenomena more generally.