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Selective Immigration Policies as Screening Devices and the Immigrant-Native Educational Achievement Gap

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Abstract: The literature on the immigrant-native educational achievement gap is suggestive of a better performance of immigrant students in countries practising selective immigration policies. However, the origin of such differences has not been investigated. I considered both important observed characteristics as well as the role of unobservables in the formation of immigrant-native achievement differences in four selective immigration countries. I found that, if the comparison is between selective immigration countries as a group and other European/OECD countries, immigrant students in selective immigration countries perform better. However, the results are heterogeneous and different conclusions apply to each of the four countries. The findings are discussed in the context of successful immigration policies as screening devices, which induce a self-selection of immigrants with transferable and adaptive skills. Potentially important are also institutional differences with respect to how inclusionary and conducive to integration of immigrants into the host country policies are.

Keywords: Educational achievement gap; selective immigration policies; unobservables.

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Introduction

In the great majority of countries (such as most European countries), an achievement gap in favour of native vs immigrant students has been found with few exceptions (e.g., Andon, Thompson, & Becker, 2014). However, there is considerable heterogeneity in the extent and statistical significance of the disadvantage, and in rare cases, immigrant students perform better than natives. The common finding of a disadvantage in achievement of immigrant students can be partly attributed to the fact that these students tend to be concentrated in disadvantaged schools; more specifically, findings from the Programme for International Student Assessment (PISA) indicate that it is primarily the concentration of disadvantage, not the concentration of immigrant students that has detrimental effects on learning (Organization for Economic Cooperation and Development, 2015).

Immigrant receiving countries can be differentiated into three categories: first, traditional immigration countries (mainly the USA, Canada, Australia, and New Zealand); second, mostly European countries which received immigration flows either after the colonial period (such as the United Kingdom, France and the Netherlands), or were receiving temporary labour migration (such as Germany); and lastly, new migration countries which were previously emigration countries (such as Ireland, Italy, Spain and Greece). A sub-group of countries, which mostly comprises traditional immigration countries, namely Canada, Australia, and New Zealand, are referred to as countries which practice selective immigration policies. A fourth country which follows a strict selection of new permanent residents is Singapore.

In selective immigration countries, a large proportion of admitted immigrants are skilled workers. Although several other countries have more recently introduced specific skill migration programmes, in Canada, Australia, New Zealand, and Singapore, large-scale selective immigration policies have been present for decades. On the other hand, in the USA

(whose situation is influenced by its Mexican border), the immigration system is quite different; for example, in 2002 only a relatively small proportion of immigrants were selected based on skill, with nearly two-thirds being either immediate relatives or family sponsored migrants (Antecol, Cobb-Clark, & Trejo, 2004).

It has been highlighted in the literature (e.g., Entorf & Minoiu, 2005, p. 2) that Australia, Canada, and New Zealand did very well in the PISA tests compared to other countries such as Germany, France, and the US, with German students performing below the OECD average while Singapore performed better. Such differences in performance were linked at least partly to the performance of students with migrant background who differ across nations with respect to the socioeconomic background of parents. In countries with skill-based immigration policies the socioeconomic status of migrants usually exceeds that of natives, while the opposite tends to be the case in countries such as Germany, France, and the USA.

In Singapore, a top performing country in international assessment tests, both first and second-generation immigrant students outperformed native students in PISA tests. While several other countries seek to attract skilled immigrants, Singapore has been single-minded in attracting highly skilled workers (“Foreign Talent”) as “a matter of life and death¹” in the long term for the preservation of jobs for local workers. Furthermore, Singapore has been successful in attracting internationally mobile talent, with individuals and foreign firms left in no doubt about Singapore’s unwavering commitment to attracting quality migrants. In 2004, Singapore ranked third among countries with the least restrictive immigration laws and Singapore’s talent management policies are among the friendliest in the world (Pang, 2006).

The next section outlines the immigration policies in selective immigration countries, summarizes the related literature and states the research hypotheses and research questions.

The following sections discuss the methodological approach, present the results and discuss the findings. The last section summarizes the findings.

Literature Review

Policies

Canada, Australia, and New Zealand (along with the USA) are, by and large, the world's immigration nations. In more recent times, these countries strived to strike a balance between needs to reunite families and give passage to refugees on the one hand and increasing the skill base of the population on the other. Australia, Canada, and New Zealand have in recent decades placed more emphasis on encouraging skilled migration, reversing earlier policies which were based on national origin.

Australia's immigration system is broadly modelled after that of Canada, with non-humanitarian immigration² in both countries consisting of two components: one based on close family relationships with citizens/residents and the other based on applicants' potential contribution to the labour market. There are also programmes that assess applicants on both skills and less close family relationships; these are the Skilled-Australian Linked migration programme in Australia and the Assisted Relative Class in Canada. With respect to proportions by class of admission, in 2002 in both countries, the highest proportion (about half) entered under the skilled category. The proportion under the family relationships category is of similar magnitude in the two countries, at about one-third of the total. In contrast, in the USA, only about 16% entered under the skilled/employment-based category (Antecol et al., 2004, p. 50).

New Zealand, with its new immigration act of 1987 (coming into effect in 1991), ended its race-based immigration (and preference for immigrants from Britain, Europe, and North America) and moved to a system based on a points scale which assesses applicants based on

their potential contribution to the country, also paying attention to their proficiency in English language (New Zealand Government, 2002). As of 2005, in New Zealand, 60% of successful applicants were selected under the “Skilled” category (New Zealand Government, 2006).

Singapore, besides hosting large numbers of non-resident work permit holders (foreign workers) performing unskilled jobs in sectors that cannot attract enough local workers (such as construction and certain service sub-sectors), has been actively pursuing skilled foreigners as a vital ingredient for its future growth and competitiveness. Pang (2006) links the urgency of filling current and future skill gaps to two factors: (1) demographic considerations, as the indigenous skill pool is insufficient to meet the projected demand for skill in an evolving economy; and (2) the firm belief that absorbing carefully identified foreign talent will add dynamism to Singapore’s economy.

In contrast to the much more restrictive policy towards unskilled foreign workers, Singapore allows great flexibility to employers in employing foreign skilled workers who are in short supply domestically. There are various types of employment passes for foreigners with approved qualifications who come to Singapore. The “P” employment pass which specifies a monthly salary of at least S\$3,600, can be renewed, and workers can bring their dependents with them. The “S” work pass, is intended for middle-level skilled workers earning at least S\$2,200 and in many cases can bring their dependents with them. Finally, pass-holders with an approved background are encouraged to apply for permanent residence in Singapore. It is estimated that in the decade of the 1990s 230,000 pass holders and their dependents were granted permanent residence (Pang 2006).

Background and Literature

Students from Singapore, Canada, Australia, and New Zealand performed very well in the 2012 PISA tests, with Singapore topping the country tables and the other three countries

ranking in the top 25 (OECD, 2014). Based on raw PISA data, immigrant students from these four countries performed at least as well as native students and often better. This contrasts with most European countries, the USA, as well as countries from other parts of the world (OECD, 2015).

However, unlike other countries, in skill-based immigration countries, the socioeconomic status of immigrants generally exceeds the national average. For example, Massey and Parr (2012) using 2006 Census of Population and Housing data for Australia found that migrants in regional and rural Australia had a substantially higher level of education compared to the native population, especially recent immigrants. Using the 2012 PISA country samples, I found that the socioeconomic background of first-generation immigrant students in Australia, New Zealand, and Canada and both first - and second generation immigrant students in Singapore exceeded that of natives (see Appendices 1 to 4).

Perspectives vary as to what contributes to the formation of immigrant-native educational achievement gaps. One argues that differences can largely be attributed to differences in family socioeconomic background (Blau & Duncan, 1967; Heath, Rethon & Kilpi, 2008). Another assigns importance to language ability differences as a predictor of achievement differences (Schnepf, 2007). Finally, institutional differences have been proposed as a predictor of educational achievement, specifically government policies and attitudes towards incorporating immigrants into host societies. According to this argument, institutional variations with respect to the inclusion of foreigners into host societies are important determinants, over and above individual characteristics of immigrants. Buchmann and Parrado (2006) find that immigrant-native achievement gaps are smallest in countries with inclusionary systems.

Avato (2009) studied the self-selection of immigrants and the impact of selective immigration policies using European Training Foundation data for four countries. He

attributes the positive selection found in the literature to strong out-selection of immigrants, rather than any self-selection. In other words, while immigration policies do not affect the intention to migrate, when people are under pressure to migrate, the realization of their intentions affects the selection into migration destinations. The study also confirms that the European Union attracts relatively lower skilled migrants compared to other destinations, such as Australia, with more selective immigration, which generates a positive out-selection compared to countries with no such policies.

Entorf and Minoiu (2004) used PISA data to evaluate the importance of social class, migration background (living in Australia, New Zealand, or Canada vs. living in five countries not practising selective immigration policies) and command of the national language, to evaluate differences in educational performance. Their results show that the impact of the socioeconomic status of parents on educational performance is strongest in countries such as Germany, the UK, and the US, compared to Canada, Australia, and Scandinavian countries (see also Marks, 2005).

Literature addressing the objectives of this study is rare. Akther and Robinson's (2014) working paper used the same group of countries and dataset as this study to examine whether immigrant students have an advantage in these four selective immigration countries. They reported that in Australia and Singapore, first and second generation immigrant students showed an advantage in academic performance. However, the analysis in the paper is exploratory and focuses on whether any advantage can be attributed to just a few observable personal characteristics and academic resources (sense of belonging in school, attitude towards learning, student-teacher relationship, and teacher support). They found that these resources did not account for differences in performance. Ma (2003) used Canadian PISA data to examine the effects of student and school characteristics on the academic achievement of immigrant and non-immigrant students. No differences were found in

mathematics achievement, but non-immigrant students outperformed immigrant students in both reading and science achievement.

Summarizing, past findings using multicounty studies or one-country case studies find that there is a tendency for smaller native-immigrant achievement gaps in countries practising selective immigration policies and that in these countries the impact of parents' socioeconomic background is not as strong as in many other countries. The literature on the role of policies finds that institutional differences and policies are important and that the native-immigrant achievement gap is smaller in countries with more inclusionary societies and systems.

Motivation, Hypothesis and Research Questions

What motivates this paper is literature suggestive of a better performance of immigrant students in countries practising selective immigration policies, compared to immigrant students in most other countries and attempts to associate the findings to selective immigration practices (e.g., Akther & Robinson, 2014; Entorf & Minoiu, 2005; Ma, 2003). Existing studies point to the lack of evidence of an immigrant disadvantage and the possibility of an immigrant advantage. A detailed investigation of what shapes the immigrant-native gap in these countries, which considers both observed characteristics, as well as the possible role unobservables play, is lacking.

The hypothesis underlying the research objectives of the study is that immigrant students and their parents, besides observed individual and family background characteristics such as family socioeconomic status, are expected to differ from native students in various unobserved qualities. Such unobserved qualities are expected to influence the immigrant status-educational achievement association, even after accounting for individual, family, and other observed characteristics. Successful selective immigration policies can result in an immigrant educational advantage by impacting the skill composition of immigrants. Given

that selective immigration policies are screening devices, the mechanisms behind successful policies work through incentives for individuals with desirable observed skills as well as unobserved attributes to self-select into the pool of applicants. Whether a destination country experiences a favourable selection could also be influenced by institutional factors, such as how inclusionary host societies are.

I made use of the data samples of four countries known for practising selective immigration policies (Australia, New Zealand, Canada, and Singapore), to investigate the following research questions: (1) To what extent any achievement advantage in favour of immigrant students remains after controlling for observed individual, family and school characteristics? And (2) what role do immigrant unobservable characteristics play in shaping the immigrant-native achievement gap? The link between immigrant unobservable characteristics and self-selection of skilled immigrants based on immigration policies is discussed along with other findings.

Since this study relates to selective immigration countries and policies, the findings can only be generalized to the countries being investigated. However, I compare and contrast the findings for the four selective immigration countries with those for four immigrant-receiving countries with less selective policies.

Data and Methodology

Data

PISA 2012, like its predecessors, intends to measure what 15-year old students approaching the end of their compulsory schooling can do with what they learn at school. It contains information on student, family background, school, and teacher characteristics, as well as information on the socioeconomic background (such as occupational status and educational level of parents), immigrant and language background, measures of engagement with/at school and student self-beliefs. The survey also contains the constructed index of Economic,

Social and Cultural Status (ESCS), which is derived from three other indices: (a) highest occupational status of parent, (b) highest educational level of parents in years of education and (c) home possessions.

The proportion of missing values for important variables such as immigrant status and social-cultural and economic status is small (generally under 3%). Missing values were imputed using the method of relating observations in the original data to a set of fundamental variables (e.g., Rubin, 1987). Cases were organized by patterns of missing data so that the missing-value regressions can be conducted efficiently. Fundamental variables with none or very few missing values on which the imputation is based are socioeconomic status and basic demographic variables.

I distinguished five groups of students by immigrant status, considering age at immigration and distinguishing native students into those with both parents born in the country versus students with a mixed-parentage background. The groups are: (1) first-generation immigrants who migrated before school age (between the ages of 0 and 5 years); (2) first-generation immigrants who migrated between the ages of 6 and 16 years; (3) second-generation immigrants (native-born, with both parents born abroad); (4) students of mixed parentage (one parent born abroad); and (5) native students (native-born, with both parents born in the country). Two achievement scores were used as outcomes and were namely the Mathematics score and the Reading score.

Methodology

Base Estimates – Controlling for Observables

When handling data with a nested structure (such as the PISA data) the preferred methodology is multi-level modelling, implemented by estimating a mixed-effects model. A mixed-effects model has both random and fixed effects as opposed to a standard linear regression model which has only fixed effects. When students are clustered in groups such as schools, classrooms, etc., randomly selected students in the same school are expected to be

more similar compared to students in another school; consequently, clustering needs to be considered otherwise, the standard errors of regression coefficients will be underestimated. Furthermore, using ordinary least squares (OLS) estimation, the correlation between the student level error terms would be ignored.

However, considering that (1) appropriate standard errors can be derived within OLS estimation by obtaining standard errors clustered at the school level and using the appropriate weights; and (2) the bias-adjusted estimates after considering selection on unobservables follow OLS estimation, I made use of OLS estimation to derive the base estimates using all plausible test score values³, appropriate weights and standard error estimates. The estimated model is:

$$Y_i = X_i\beta + S_j + \varepsilon_i$$

where X_i are the individual and family characteristics of student i identified in the literature as relevant determinants of school performance and S_j are the characteristics (resources) of school j shared by all students attending school j , including average characteristics at the school level (such as quality of peer groups and proportion of immigrant students). Finally, ε_i is a student level residual.

It is worth clarifying that, since the immigrant achievement gap is largely a school-wide phenomenon, the estimation models used in this and the overwhelming majority of related studies do not “explain” the immigrant achievement gap in a strict sense. Rather, the background variables included in the five models share variance with the mean difference between immigrant and native students⁴.

Assessing the Potential Effect of Selection on Unobservables (Omitted Variable Bias)

Any estimated immigrant advantage/disadvantage after accounting for various observed characteristics could still be related to unobservables (omitted variable bias). I assessed the extent of omitted variable bias using a method in which the amount of selection on the

observed explanatory variables in a model provides a guide to the degree of selection on unobservables. Altonji, Elder, and Taber (2005) constructed a test statistic, valid under the null hypothesis of a zero-treatment effect, to assess how important the unobservables would have to be relative to the observables to drive an estimated coefficient (observed effect) to zero. Oster (2017) developed an extension and an estimator which connects omitted variable bias explicitly to coefficient stability and showed that it is necessary to consider both coefficient movements as well as R -squared movements after adding the vector of additional observed controls into the model.

Starting with a linear model and an outcome determined by a treatment/variable of interest (in this case immigrant status group), a set of observed covariates, a set of unobserved covariates and an (*iid*) error term, one needs to hypothesise on the degree of importance of selection on unobserved variables relative to observed covariates which can be application specific. An accepted upper bound value for the coefficient of proportionality, δ , is $\delta = 1$ (unobservables being as important as observables, or equal selection). In our case, I used two alternative assumptions, that unobservables are half as important as observables ($\delta = 0.5$) for the base results and the upper bound assumption of equal selection ($\delta = 1$).

The implementation also requires an assumption on what the R -squared would have been if we had to our disposal both observed and unobserved controls ($R_{\max}$). Let β_0 be the estimated coefficient of the variable of interest in the regression with only this variable as control and β_1 the corresponding coefficient in the regression with all available controls; similarly, let R_0 and R_1 be the R -squared values in the two regressions. The maximum R -squared can be expressed in relation to R_1 as: $R_{\max} = \Pi R_1$, for a chosen value of Π . Empirically, in Economics applications it is unlikely that $R_{\max}$ would approach 1 (for example due to the presence of measurement error). In this study, I parametrise $R_{\max}$ as: $R_{\max}$

$= \min\{\Pi R_1, 1\}$, with $\Pi = 2$; however, I also examined the sensitivity of estimates to different values of $R_{\max}$.

In this study, after using an extensive set of determinants of achievement as a subset of the complete set which determines the outcome, there is a reasonable expectation that the observables can provide a useful guide on the role of unobservables. This procedure, though unlikely to uncover the ‘true’ effect of immigrant status on student achievement, allows the derivation of a consistent estimate of the bias-adjusted effects, under the chosen assumptions about the values of δ and $R_{\max}$ (for more detail, see Oster 2017). At a minimum, such estimates provide information on the direction of change in coefficients for any amount of unobservables considered.

Estimation and Results

Model Specification and Descriptive Statistics

Two outcome measures were used: Mathematics literacy and Reading literacy. The dependent variables (Mathematics and Reading PISA score) are standardised (mean 0 and standard deviation of 1) to facilitate cross-country comparisons. The estimation sample consists of 14,270 observations for Australia, 4,210 observations for New Zealand, 5,427 observations for Singapore and 20,832 observations for Canada.

The set of controls contain both dichotomous and continuous variables and most of the continuous variables are indices. All index controls have been standardized. The variables of interest are the four immigrant status dummies (with native students the comparison group). In specifying the observable controls, as much as possible I avoided using obviously endogenous controls (for example various attitudinal variables such as drive/motivation, perseverance, sense of belonging, etc. The set of controls include student demographic variables (age, male, single-parent family, location size⁵); whether language spoken at home is not the language of the test (which is English for all four countries); school track/grade⁶ level of student (lower secondary general academic or upper secondary vocational, versus

upper secondary general academic for Australia and lower secondary general academic versus upper secondary general academic for New Zealand, Singapore and Canada); family socioeconomic status of student (Economic, Social and Cultural Status index⁷); family attitudes towards learning (degree of parental pressure and hours of out-of-school study time); school characteristics (school ownership, school size, index of student disciplinary climate, and teacher shortage index); and school characteristics at the school level (school average of ESCS index and percentage of immigrant students).

It might have been useful to utilize information about the ethnic origin of immigrants in each country. However, ethnic origin is not reported for Canada and Singapore; for Australia and New Zealand there is information on parents' ethnic origin but is not reported for 37% of parents for Australia and nearly 50% of parents for New Zealand. Looking at the available information, 57% of parents of immigrant students in Australia were British or New Zealanders, while about 40% came from East Asian countries; similarly, 53% of immigrant students in New Zealand were British or Australians, while 25% came from South Pacific islands and 20% from East Asian countries. Finally, immigration statistics (See UN Department of Economic and Social Affairs, 2015). show that in Singapore the ethnic mix of immigrants resembles the ethnic mix of the native population (majority Chinese and minority Malay and Indian).

Tables A1 to A4 in the appendix contain the summary statistics for each of the four countries by immigrant status. Test score differences in Australia and Singapore are statistically significant and strongly in favour of both first and second-generation immigrants compared to natives. In New Zealand, differences are evident only between native students and first-generation immigrants who arrived before the age of 6 and are in favour of the latter. In Canada, the differences in favour of immigrants, when statistically significant, are generally small.

There are several between-group differences in characteristics which are found in all countries. Immigrant populations are heavily concentrated in large cities while native populations are more evenly spread across cities, smaller towns, and rural areas. Immigrant students report higher out-of-school study time and parental pressure to excel and such differences are highly significant for Australia, New Zealand, and Canada, but less so in Singapore. Socioeconomic status differences are generally in favour of immigrants, especially first-generation immigrants who arrived very young. Peer quality tends to mirror between-group differences in socioeconomic status. Finally, immigrant students attend schools by a much higher proportion of immigrant students compared to native students.

Base Estimates

Tables 1 to 8 contain the estimation results for Mathematics and Reading achievement for the four countries. Model 1 includes only the four immigrant generational dummies, while models 2-5 progressively control for personal characteristics, socioeconomic status, school characteristics, and school socioeconomic composition.

Controlling for personal characteristics increases the estimate of the first-generation immigrant advantage in New Zealand and Singapore, countries where natives have an advantage in personal characteristics such as grade/track attended and language spoken at home, over native students. The opposite is the case for Australia, where immigrant students have an advantage in personal characteristics. Controlling for family socioeconomic status moderates any immigrant advantage in New Zealand and Singapore, countries where immigrants (especially first-generation immigrants) have a socioeconomic status advantage. Controlling for school characteristics is less important, except for school socioeconomic composition (peer group effect) which has a small moderating effect on any remaining immigrant advantage estimates.

[Tables 1-8 near here]

In Australia, after controlling for observable characteristics (model 5), the initially significant advantage of 1st immigration immigrants disappears leaving no evidence of an advantage for first-generation immigrant versus native students in both Mathematics and Reading; however, two other statistically significant differences remain: 2nd generation immigrant students enjoy a significant performance advantage over natives both in Mathematics and in Reading (at about 1.4-1.7 of a standard deviation). On the other hand, as a distinct group (native) students with one parent born abroad performed significantly worse than native students with both parents born in the country. In New Zealand, the base estimates from the fully controlled regression differ from those for Australia; first-generation immigrant students enjoy a considerable performance advantage over natives and this advantage amounts to 0.25-0.3 of a standard deviation in the case of immigrant students who arrived before the age of 6. On the other hand, there are no differences between 2nd generation immigrants or students of mixed parentage and native students.

In Singapore, significant differences in favour of 2nd generation immigrants and students of mixed parentage remain after controlling for observables. These differences are large in the case 2nd generation immigrant students, amounting to 0.25 of a standard deviation in Mathematics and 0.3 of a standard deviation in Reading.

Finally, in Canada, most of the differences favour native students. However, they are generally small and insignificant, except for students of mixed parentage; this group, after controlling for observables, is associated with about 0.25 of a standard deviation lower achievement score compared to native students in both Mathematics and Reading.

Unobservables and Omitted Variable Bias

Having examined the extent to which observables account for raw differences in achievement between natives and immigrants, this section assesses whether unobservables further

contribute to the formation of such differentials. Immigrant students and their parents may differ from native students in various unobserved qualities, such as unobserved motivation and (parents) being less risk-averse. There is also evidence that foreign-born are more optimistic than native-born and that what really matters for child human capital acquisition is mother's optimism (Constant, Tatsiramos, & Zimmermann, 2009; Kao & Tienda, 1995). More generally, immigrant students from certain country origins/ethnicity may have an advantage in education due to selection. An example is East Asian immigrants, whose educational success has been linked to cultural attitudes that "breed success". To the extent that East Asian immigrant families are a self-selected group, their children may have attributes that predispose them for different achievement levels compared to native students (Brand, 1987; Yeung, 2009).

Tables 9 to 12 present and compare the base estimates from the fully controlled regressions to the corresponding coefficient estimates which have been adjusted for omitted variable bias. Two alternative assumptions about the importance of unobservables relative to observables are considered; (1) unobservables are half-as important as observables ($\delta = 0.5$) and (2) unobservables are as important as observables, i.e., equal selection ($\delta = 1$). The estimates assume that $R_{\max}$ is twice the value of the R -squared in the fully controlled base regression.

In Australia, accounting for omitted variable bias results in lower (more negative) estimates. Under the moderate selection assumption, the advantage of 2nd generation immigrants disappears and first-generation immigrant students who were of school age on arrival are at a disadvantage compared to native students; if unobservables are even more important, the bias-adjusted coefficients are all negative and statistically significant. Considering unobservables for New Zealand is particularly important, as accounting for differences in unobservables between native and immigrant students results in a

strengthening of the immigrant advantage over natives, except for the group of first-generation immigrants who arrived before school age. Under moderate selection, adjusted estimates suggest a substantial advantage for 1st and 2nd generation immigrants over natives. Generally, the immigrant advantage increases as the assumed importance of unobservables increases.

[Tables 9-10 near here]

In Canada, even under moderate selection on unobservables, the bias-adjusted estimates suggest that after considering both observables and unobservables native students are associated with higher achievement than any group of immigrant students, as is the case with students in almost all European and OECD countries. In the case of Singapore, conclusions based on base estimates for the two groups of first-generation immigrants remain, while the substantial advantage of 2nd generation immigrant students reduces as the importance of unobservables increases but remains significant.

[Tables 11-12 near here]

I also examined the sensitivity of the estimates to the assumption about the value of $R_{\max}$. Generally, increasing the value of $R_{\max}$ (for a given value of δ) does not change the direction of the adjustment; however, the numerical value of the adjusted estimate increases. For example, looking at the adjusted coefficient for 2nd generation immigrants in Australia for Mathematics, under the original assumption ($R_{\max}$ is twice the fully controlled R -squared) this coefficient is about 0 (0.016); increasing the value of $R_{\max}$ to three times the fully controlled R -squared results in a coefficient value of -0.175 which is statistically significant at the 1% level.

Finally, for comparison purposes, it is worth looking at the immigrant-native achievement gap and how it is affected by differences in observable and unobservable characteristics in immigrant receiving countries which follow less selective immigration

policies. I derived results (available upon request) for France, the United Kingdom, Germany, and the USA. Results for France, Germany and the USA are in contrast to those of the four selective immigration countries. First, the raw native-immigrant gap is heavily against immigrant students (especially newly arrived first-generation immigrants). However, the gap largely disappears after controlling for observables, because of large differences in the socioeconomic background in favour of native students. After considering the effect of unobservables (even assuming moderate selection on unobservables), the gap is either insignificant (Germany) or in favour of immigrant students (first- and second-generation immigrants in the USA and first-generation immigrants in France).

The picture in the United Kingdom is different; except for newly arrived immigrant students, there are no achievement differences between immigrants and natives. After accounting for observables, the picture remains largely unchanged, as there are no significant differences in socioeconomic background between groups. After considering unobservables, there are no achievement differences between natives and any immigrant subgroup. Between-country differences may be related to the ethnic mix of the immigrant population. In the United Kingdom, the great majority are mostly well-educated immigrants from India and Pakistan as well as Polish immigrants. In Germany, on the other hand, a great majority of immigrants come from Turkey, former Eastern Bloc and Balkan countries. There is no information available in the data on the ethnic mix of immigrants in France and the USA.

Selective Immigration Policies, Institutions, and Immigrant Quality

Briefly summarizing the findings: For Canada, the totality of evidence points to an achievement advantage of native students over all immigrant groups. For Australia, accounting for both observables and unobservables weakens any initial immigrant achievement advantage and strengthens any initial native advantage. For New Zealand, differences in unobservable characteristics between immigrant and native students are

important in shaping the evidence and all considered, an immigrant advantage for all immigrant groups over natives emerges. Finally, for Singapore, while raw differences in achievement are in favour of all immigrant groups, considering both observables and unobservables generally accounts for the initial first-generation immigrant-native gap; however, a significant advantage for second-generation immigrant students (as well as students of mixed-parentage) remains.

We observed that in these four countries with seemingly similar selective immigration policies, the outcomes are somewhat heterogeneous. We also observed that the base model estimates are generally not supportive of the hypothesis that differences in academic performance are mostly due to differences in family background or other individual-level differences (i.e., family socioeconomic status, host country language ability, family size, etc.). While it is not abundantly clear how one can rationalize these findings, some possible explanations based on related research are outlined below.

Immigration policies have an impact on the skill composition of immigrants, not only on the demand side (direct effect) but also the supply (self-selection of immigrants). Bauer, Lofstrom, and Zimmermann (2000) explored the possibility that immigration policies affect the labour market assimilation and success of immigrants by comparing policy priorities by different countries. They found that the success of immigration policies that are based on the selection of immigrants with respect to their labour market characteristics, such as in Australia, New Zealand, and Canada, seems to be mainly because they alter the national origin mix of immigrants. It is not that these countries are better in attracting the most skilled immigrants from a given country, rather they attract individuals from countries with relatively high skill levels (mainly from countries that are similar to the host country), whose skills can easily be transferred and adapted to the labour market needs of the receiving country.

Immigration policies are screening devices; how successful they are proven in attracting quality immigrants depends on the interplay between the effect of the policy on how immigrants are selected from the pool of applicants and the effect of the policy on incentives for an individual to self-select into the pool of applicants (Bertoli, Dequiedt, & Zenou, 2015). One needs to stress the importance of unobserved attributes, such as innate abilities and propensity to take risks, which are correlated with an individual's productivity and influence incentives to migrate; hence, one should be considering how selective immigration policies (which screen potential migrants based on their observable characteristics), influence self-selection on unobservables (which is reflected in the findings of this study). Aydemir (2011) presents evidence that immigrants to Canada admitted based on their characteristics and qualifications (through the point system), while they are significantly more educated than immigrants admitted based on other provisions (such as family reunification), did not perform better in the labour market. Kaushal and Lu (2014), studied changes in selection patterns of immigrants to Canada and the U.S. during 1990–2006 period, using an approach designed to capture labour market selectivity with respect to not only observed but also unobserved immigrant characteristics; they found that the observed human capital endowments do not entirely capture the inherent capabilities of immigrants, with immigrants in the US more positively selected than immigrants to Canada.

It stands to reason that in addition to individual-level contributors to the immigrant-native achievement gap, institutional differences between countries with respect to how inclusionary and conducive to assimilation and integration of immigrants into the host country their policies are, are relevant to immigrant achievement. Buchmann and Parrado (2006), who investigated the degree to which immigrant-native achievement differences correspond to these institutional variations in the host societies for countries with different immigrant incorporation regimes (Northern European, Southern European and Immigrant

Countries), found that in Northern European countries, immigrant achievement disadvantages remain a larger net of family background and language proficiency, compared to other groups of countries. Their findings are generally supportive of the hypothesis that institutional variations between countries in the incorporation and assimilation of immigrants influence the immigrant status-educational achievement association, even after accounting for individual and family characteristics.

Finally, there are limitations to this study, including data limitations. Controlling for student socioeconomic background is important, but the measure available (Economic, Social and Cultural status index) is a synthesis of single components which are not necessarily comparable between immigrants and natives. For example, educational credentials acquired in the country of origin can be devalued after migration. It would also be useful to have information on the ethnic origin of students to be able to control for differences in ethnic minority composition between countries. While the consequences of such data limitations are not known, it is entirely possible that the relative estimates of the variance that observable and unobservable variables share with the immigration status variable would be different. There are also methodological limitations in assessing the importance of selection on unobservables. Specifically, the methodology used relies on the implicit assumption that unobservables share the same covariance properties as observables. If unobservables are completely unlike the observables, one cannot learn much about the nature of the bias associated with unobservables.

Conclusions

The literature on the immigrant-native educational achievement gap is suggestive of a better performance of immigrant students in countries practising selective immigration policies compared to immigrant students in other countries, such as most European and other OECD countries; there have been attempts to explain the findings by relating them to selective

immigration practices. A detailed investigation of what shapes the immigrant-native gap in these countries, which includes both observed characteristics, as well as the possible role of unobservables, is lacking.

I used PISA 2012 data for Mathematics and Reading literacy to investigate the pattern of the immigrant-native gap in academic skills for 15-year olds in the four countries with selective immigration policies (Australia, New Zealand, Singapore, and Canada). The empirical strategy was to first, use multi-level modelling to investigate the contribution of various important observed characteristics on the raw immigrant-native gap in each of the four countries; subsequently, I investigated the contribution of unobservables to the remaining gap.

The findings show that, if we consider these four countries as a group, even after considering both observables and unobservables immigrant students are better performers if the comparison is between this group of countries and other developed countries (such as in Europe/OECD). However, the results are heterogeneous both within each country (i.e., depending which immigrant group is considered) and between countries (for example, the pattern for Canada is representative of other OECD countries rather than the groups of skill-based immigration countries).

In explaining these findings, one needs to consider how policies can affect the skill composition of immigrants through self-selection of immigrants with respect to their labour market characteristics, i.e., attract individuals from countries with relatively high skill levels, whose skills can easily be transferred and adapted to the labour market needs of the receiving country. In the context of immigration policies as screening devices, one needs also to recognise the importance of unobserved attributes, such as innate abilities and propensity to take risks, which are correlated with an individual's productivity and influence incentives to migrate; hence, one should be considering how selective immigration policies influence self-

selection on unobservables. Finally, institutional differences between countries with respect to how inclusionary and conducive to assimilation and integration of immigrants into the host country their policies are, should not be underestimated, as they are relevant to immigrant achievement.

Notes

1. In the words of former Prime Minister Goh Chong Tong in the 1997 National Day speech.
2. Non-humanitarian immigration excludes those who gain entry on humanitarian grounds, such as refugees needing protection from persecution.
3. I use the **pv** procedure in Stata, designed to estimate statistics when there are multiple plausible values (K. McDonald, 2014).
4. It is a nuanced distinction, but an important one that will help move the literature on this topic forward.
5. Except for Singapore, a city-state.
6. PISA surveys contain information for students who are approximately age 15, not students in a particular grade (who could be of any age). Failure to control for track and grade could create the impression that immigrant students are disadvantaged as they compete against students in higher grades. However, grade retention associated with academic failure is not the only possible reason for immigrant students being over-represented in lower grades; some parents of immigrant students (especially 1st generation) could be deliberately enrolling their children in a lower grade to increase the chance of successfully competing with native students and mature academically (Pong, 2014).
7. Since the Economic, Social, and Cultural Status index combines several sub-components, it could be argued that when applied in the context of the native-immigrant gap, there may be comparability issues for one or more of the sub-components.

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References

- Akther, A. & Robinson, J. (2014, December). *Immigrant students' academic performance in Australia, New Zealand, Canada, and Singapore*. Paper presented at the Joint AARE-NZARE 2014 Conference, Brisbane, Australia.
- Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of Political Economy*, 113(1), 151-184.
- 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(7), 1-20.
- Antecol, H., Cobb-Clark, D. A., & Trejo, S. J. (2004). Selective immigration policy in Australia, Canada, and the United States. *Brussels Economic Review*, 47(1), 45-56.
- Avato, J. (2009). *Migration pressures and immigration policies: New evidence on the selection of migrants* (Discussion Paper No 930). Washington, DC: Social Protection & Labour, The World Bank.
- Aydemir, A. (2011). Immigrant selection and short-term labour market outcomes by Visa category. *Journal of Population Economics*, 24(2), 451-475.
- Bauer, T. K., Lofstrom, M., & Zimmermann, K. F. (2000). *Immigration policy, assimilation of immigrants, and natives' sentiments towards immigrants: Evidence from 12 OECD countries*. IZA Discussion Papers 187, Bonn, Germany: Institute for the Study of Labour.
- Bertoli, S., Dequiedt, V., & Zenou, Y. (2015). *Selective immigration policies and migrant 'quality'*. Centre for Economic Policy Research (CERP) Policy Portal, London, UK: Centre for Economic Policy Research.
- Blau, P. M., & Duncan, O.D. (1967). *The American occupational structure*. New York, NY: John Wiley and Sons.
- Brand, D. (1987, August 31). Education: The new whiz kids. *Time*, pp. 2-5.
- Buchmann, C., & Parrado, E. A. (2006). Educational achievement of immigrant origin and native students: A comparative analysis informed by institutional theory. In D. P. Baker & A. W. Wiseman (Eds.), *The Impact of comparative education research on institutional theory, International Perspectives on Education and Society*, 7 (pp. 345-377). West Yorkshire, UK: Emerald-Insight.
- Constant, A., Tatsiramos, K., & Zimmermann, K. F. (Eds) (2009). *Ethnicity and Labour Market Outcomes (Research in Labour Economics, Special Issue, 29)*. West Yorkshire, UK: Emerald.
- Entorf, H., & Minoiu, N. (2004). *PISA Results: What a Difference Immigration Law Makes* (IZA Discussion Paper No. 1021). Bonn, Germany: Institute for the Study of Labour.
- Entorf, H., & Minoiu, N. (2005). What a difference immigration policy makes: A comparison of PISA scores in Europe and traditional countries of immigration. *German Economic Review*, 6(3), 355-376.

Heath, A. F., Rothon, C., & Kilpi, E. (2008). The second generation in Western Europe: Education, unemployment, and occupational attainment. *Annual Review of Sociology*, 34(1), 211-235.

Kao, G., & Tienda, M. (1995). Optimism and achievement: The education performance of immigrant youth. *Social Science Quarterly*, 76(1), 1-19.

Kaushal, N., & Yao Lu. (2014). Recent immigration to Canada and the United States: A mixed tale of relative selection. *International Migration Review*, 49(2), 479-522.

Ma X. (2003). Measuring up: Academic performance of Canadian immigrant children in reading mathematics and science. *Journal of International Migration and Integration*, 4(4), 541-576.

Marks, G. N. (2005). Accounting for immigrant non-immigrant differences in reading and mathematics in twenty countries. *Ethnic and Racial Studies*, 28(5), 925-946.

Massey, S. J. L., & Parr, N. (2012). The socioeconomic status of migrant populations in regional and rural Australia and its implications for future population policy. *Journal of Population Research*, 29(1), 1-21.

McDonald, K. (2014). PV: Stata module to perform estimation with plausible values [Statistical Software]. Boston, MA: Boston College, Department of Economics.

New Zealand Government. (2002, December 20). *Documents confirm April consideration of language requirement change*. Retrieved from Beehive.govt.nz. New Zealand: The official website of the New Zealand Government.

New Zealand Government. (2006, July 16). *New Zealand popular with migrants we need*. Retrieved from Beehive.govt.nz. New Zealand: The official website of the New Zealand Government.

Organisation for Economic Co-operation and Development. (2014). *PISA results in focus: What 15-year-olds know and what they can do with what they know*. Paris: Programme for International Student Assessment, OECD.

Organisation for Economic Co-operation and Development. (2015). *Immigrant students at school: Easing the journey towards integration*. *OECD Reviews of Migrant Education*. doi:org/10.1787/9789264249509-en, Paris: OECD.

Oster, E. (2017). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business and Economic Statistics*. Advance online publication. doi:10.1080/07350015.2016.1227711

Pang, E. F. (2006). Foreign talent and development in Singapore. In C. Kuptsch & E. F. Pang (Eds.), *Competing for global talent* (pp. 155-170), Geneva: International Institute for Labour Studies, ILO.

Pong, S. L. (2014). Grade level and achievement of immigrants' children: academic redshirting in Hong Kong. *Educational Research and Evaluation*, 15(4), 405-425.

Rubin, D. B. (1987). *Multiple Imputation for Nonresponse in Surveys*. New York, NY: Wiley.

Schnepf, S. V. (2007). Immigrants' educational disadvantage: an examination across ten countries and three surveys. *Journal of Population Economics*, 20(3), 527-545.

United Nations Department of Economic and Social Affairs. (2015). *Trends in international migrant stock: migrants by destination and origin* (United Nations database, POP/DB/MIG/Stock/Rev.2015).

Yeung, R. (2011). *The Effect of Immigrant Composition on Student Achievement: Evidence from New York City* (Public Administration-Doctoral Dissertations, Paper 83), Syracuse University, Syracuse, NY.

Table 1: Weighted OLS models of standardised Mathematics score - Australia

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	0.097 (0.047)	-0.024 (0.042)	-0.017 (0.038)	-0.005 (0.038)	-0.072 (0.039)
First-generation - age of arrival 0-5	0.325 (0.068)	0.154 (0.059)	0.156 (0.054)	0.165 (0.053)	0.070 (0.049)
Second-generation	0.370 (0.057)	0.210 (0.045)	0.273 (0.043)	0.263 (0.042)	0.174 (0.032)
Born in country-mixed parentage	-0.068 (0.026)	-0.139 (0.024)	-0.118 (0.022)	-0.118 (0.021)	-0.132 (0.021)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.020	0.143	0.194	0.213	0.250
N	14,270	14,270	14,270	14,270	14,270

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Table 2: Weighted OLS models of standardised Reading literacy – Australia

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	0.044 (0.048)	-0.037 (0.044)	-0.030 (0.04)	-0.016 (0.040)	-0.074 (0.040)
First-generation - age of arrival 0-5	0.282 (0.064)	0.130 (0.059)	0.132 (0.055)	0.143 (0.054)	0.060 (0.051)
Second-generation	0.287 (0.048)	0.164 (0.039)	0.224 (0.037)	0.217 (0.037)	0.140 (0.031)
Born in country-mixed parentage	-0.046 (0.028)	-0.103 (0.025)	-0.082 (0.024)	-0.082 (0.023)	-0.093 (0.022)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.012	0.126	0.143	0.224	0.256
N	14,270	14,270	14,270	14,270	14,270

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Table 3: Weighted OLS models of standardised Mathematics score – New Zealand

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	0.037 (0.076)	0.226 (0.062)	0.174 (0.059)	0.172 (0.059)	0.147 (0.059)
First-generation - age of arrival 0-5	0.328 (0.122)	0.381 (0.092)	0.287 (0.092)	0.288 (0.090)	0.249 (0.080)
Second-generation	-0.079 (0.099)	-0.010 (0.086)	0.086 (0.074)	0.089 (0.074)	0.080 (0.065)
Born in country - mixed parentage	0.084 (0.046)	0.070 (0.041)	0.048 (0.039)	0.047 (0.039)	0.041 (0.037)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.009	0.126	0.241	0.253	0.283
N	4,210	4,210	4,210	4,210	4,210

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Table 4: Weighted OLS models of standardised Reading literacy – New Zealand

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	-0.101 (0.071)	0.180 (0.062)	0.133 (0.061)	0.132 (0.061)	0.121 (0.061)
First-generation - age of arrival 0-5	0.230 (0.102)	0.392 (0.091)	0.305 (0.091)	0.307 (0.090)	0.287 (0.083)
Second-generation	-0.154 (0.100)	-0.010 (0.085)	0.078 (0.077)	0.081 (0.077)	0.087 (0.068)
Born in country-mixed parentage	0.058 (0.046)	0.060 (0.042)	0.039 (0.040)	0.039 (0.040)	0.036 (0.038)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.009	0.157	0.254	0.261	0.282
N	4,210	4,210	4,210	4,210	4,210

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Table 5: Weighted OLS models of standardised Mathematics score – Singapore

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	0.200 (0.054)	0.496 (0.064)	0.182 (0.066)	0.195 (0.055)	0.153 (0.058)
First-generation - age of arrival 0-5	0.260 (0.070)	0.340 (0.066)	0.111 (0.062)	0.103 (0.059)	0.058 (0.056)
Second-generation	0.395 (0.066)	0.442 (0.064)	0.314 (0.060)	0.272 (0.051)	0.245 (0.049)
Born in country-mixed parentage	0.090 (0.040)	0.134 (0.037)	0.130 (0.038)	0.125 (0.035)	0.119 (0.035)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.012	0.130	0.195	0.258	0.317
N	5,427	5,427	5,427	5,427	5,427

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Table 6: Weighted OLS models of standardised Reading literacy – Singapore

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	0.004 (0.058)	0.336 (0.055)	0.027 (0.055)	0.036 (0.055)	-0.050 (0.054)
First-generation - age of arrival 0-5	0.262 (0.084)	0.366 (0.078)	0.141 (0.068)	0.132 (0.069)	0.054 (0.064)
Second-generation	0.427 (0.068)	0.501 (0.064)	0.375 (0.061)	0.339 (0.053)	0.299 (0.049)
Born in country-mixed parentage	0.072 (0.040)	0.109 (0.035)	0.106 (0.035)	0.100 (0.034)	0.093 (0.033)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.012	0.182	0.246	0.293	0.351
N	5,427	5,427	5,427	5,427	5,427

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Table 7: Weighted OLS models of standardised Mathematics score – Canada

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	0.056 (0.066)	-0.065 (0.071)	-0.058 (0.064)	-0.027 (0.062)	-0.057 (0.057)
First-generation - age of arrival 0-5	0.111 (0.078)	-0.043 (0.076)	-0.052 (0.070)	-0.029 (0.069)	-0.053 (0.060)
Second-generation	-0.089 (0.058)	-0.220 (0.048)	-0.102 (0.046)	-0.096 (0.046)	-0.114 (0.039)
Born in country - mixed parentage	-0.199 (0.038)	-0.244 (0.037)	-0.242 (0.035)	-0.237 (0.034)	-0.249 (0.034)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.007	0.068	0.135	0.160	0.166
N	20,832	20,832	20,832	20,832	20,832

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Table 8: Weighted OLS models of standardised Reading literacy – Canada

	Model 1	Model 2	Model 3	Model 4	Model 5
First-generation - age of arrival 6-16	0.033 (0.066)	0.009 (0.068)	0.015 (0.063)	0.036 (0.062)	-0.048 (0.054)
First-generation - age of arrival 0-5	0.166 (0.069)	0.073 (0.066)	0.065 (0.061)	0.081 (0.061)	0.001 (0.057)
Second-generation	0.037 (0.051)	-0.069 (0.045)	0.036 (0.044)	0.040 (0.044)	-0.034 (0.041)
Born in country - mixed parentage	-0.175 (0.041)	-0.212 (0.038)	-0.210 (0.036)	-0.207 (0.036)	-0.233 (0.035)
Personal characteristics	No	Yes	Yes	Yes	Yes
ESCS index	No	No	Yes	Yes	Yes
School characteristics	No	No	No	Yes	Yes
School socioeconomic composition	No	No	No	No	Yes
R^2	0.006	0.104	0.159	0.171	0.183
N	20,832	20,832	20,832	20,832	20,832

Note: Estimation with plausible values; standard errors clustered at the school level in parentheses; bold indicates significance at the 5% level or lower.

Immigrant status	Mathematics			Reading		
	Base:	Bias-adjusted:		Base:	Bias-adjusted:	
	$\delta = 0$	$\delta = 0.5$	$\delta = 1$	$\delta = 0$	$\delta = 0.5$	$\delta = 1$
First-generation - age of arrival 6-16	-0.072 (0.039)	-0.179 (0.042)	-0.291 (0.055)	-0.074 (0.040)	-0.137 (0.044)	-0.214 (0.059)
First-generation - age of arrival 0-5	0.070 (0.049)	-0.066 (0.057)	-0.203 (0.078)	0.060 (0.051)	-0.054 (0.063)	-0.180 (0.079)
Second-generation immigrant	0.174 (0.032)	0.016 (0.042)	-0.233 (0.062)	0.140 (0.031)	0.023 (0.045)	-0.155 (0.072)
Born in country - mixed parentage	-0.132 (0.021)	-0.131 (0.021)	-0.123 (0.028)	-0.093 (0.022)	-0.089 (0.021)	-0.082 (0.029)

Table 9: Base and Bias-adjusted estimates – Australia

Note: Bootstrap standard errors in parentheses; bold indicates statistical significance at the 5% level or lower.

Immigrant status	Mathematics			Reading		
	Base:	Bias-adjusted:		Base:	Bias-adjusted:	
	$\delta = 0$	$\delta = 0.5$	$\delta = 1$	$\delta = 0$	$\delta = 0.5$	$\delta = 1$
First-generation - age of arrival 6-16	0.147 (0.059)	0.291 (0.079)	0.563 (0.180)	0.121 (0.061)	0.356 (0.090)	0.777 (0.141)
First-generation - age of arrival 0-5	0.249 (0.080)	0.208 (0.089)	0.143 (0.130)	0.287 (0.083)	0.329 (0.080)	0.370 (0.106)
Second-generation immigrant	0.080 (0.065)	0.242 (0.065)	0.471 (0.115)	0.087 (0.068)	0.293 (0.074)	0.579 (0.107)
Born in country - mixed parentage	0.041 (0.037)	0.027 (0.044)	0.008 (0.052)	0.036 (0.038)	0.013 (0.043)	-0.015 (0.047)

Table 10: Base and Bias-adjusted estimates – New Zealand

Table 11: Base and Bias-adjusted estimates – Singapore

Immigrant status	Mathematics			Reading		
	Base:	Bias-adjusted:		Base:	Bias-adjusted:	
	$\delta = 0$	$\delta = 0.5$	$\delta = 1$	$\delta = 0$	$\delta = 0.5$	$\delta = 1$
First-generation - age of arrival 6-16	0.153 (0.058)	0.166 (0.078)	0.185 (0.162)	-0.050 (0.054)	-0.043 (0.086)	-0.026 (0.193)
First-generation - age of arrival 0-5	0.058 (0.056)	-0.025 (0.076)	-0.117 (0.093)	0.054 (0.064)	-0.042 (0.070)	-0.149 (0.095)
Second-generation immigrant	0.245 (0.049)	0.192 (0.056)	0.129 (0.065)	0.299 (0.049)	0.250 (0.053)	0.186 (0.071)
Born in country - mixed parentage	0.119 (0.035)	0.172 (0.031)	0.227 (0.039)	0.093 (0.033)	0.132 (0.032)	0.171 (0.037)

Table 12: Base and Bias-adjusted estimates - Canada

Immigrant status	Mathematics			Reading		
	Base:	Bias-adjusted:		Base:	Bias-adjusted:	
	$\delta = 0$	$\delta = 0.5$	$\delta = 1$	$\delta = 0$	$\delta = 0.5$	$\delta = 1$
First-generation - age of arrival 6-16	-0.057 (0.057)	-0.177 (0.062)	-0.349 (0.090)	-0.048 (0.054)	-0.126 (0.061)	-0.237 (0.099)
First-generation - age of arrival 0-5	-0.053 (0.060)	-0.175 (0.072)	-0.310 (0.078)	0.001 (0.057)	-0.110 (0.063)	-0.236 (0.081)
Second-generation immigrant	-0.114 (0.039)	-0.165 (0.045)	-0.254 (0.098)	-0.034 (0.041)	-0.124 (0.050)	-0.293 (0.094)
Born in country - mixed parentage	-0.249 (0.034)	-0.290 (0.031)	-0.324 (0.037)	-0.233 (0.035)	-0.268 (0.032)	-0.294 (0.039)

Note: Bootstrap standard errors in parentheses; bold indicates statistical significance at the 5% level or lower.

Appendix

Table A1: Weighted summary statistics by immigrant status: Australia

	First-generation: Arrival 0-5 years	First-generation: Arrival 6-16 years	Second-generation immigrants	Mixed parentage	Natives
Mathematics score	0.395 (1.00)	0.158 (0.991)	0.460 (1.05)	0.000 (1.01)	0.073 (0.918)
Reading score	0.365 (0.965)	0.119 (0.996)	0.369 (0.963)	0.026 (1.02)	0.074 (0.923)
Age	15.76 (28.0)	15.79 (28.0)	15.79 (28.0)	15.79 (28.0)	15.78 (28.9)
Male (%)	47.41 (50.0)	49.74 (50.0)	52.37 (50.0)	53.22 (49.9)	50.91 (50.0)
Single parent family (%)	13.80 (34.54)	11.24 (31.60)	13.07 (33.72)	14.90 (35.62)	12.80 (33.41)
City (%)	85.97 (34.78)	79.79 (40.18)	86.35 (34.34)	71.31 (45.23)	53.64 (49.87)
Town (%)	10.64 (30.88)	15.11 (35.84)	10.45 (30.6)	17.26 (37.80)	25.34 (43.50)
Small Town/Village (%)	3.39 (18.12)	5.10 (22.01)	3.19 (17.58)	11.42 (31.81)	21.02 (40.75)
Language at home: Other (%)	28.78 (43.85)	36.34 (46.70)	31.59 (45.54)	7.10 (23.84)	2.29 (14.83)
Lower Sec. Gen. Acad. (%)	75.30 (43.19)	70.90 (45.45)	80.45 (39.67)	81.45 (38.87)	82.18 (38.27)
Upper Sec. VET (%)	1.87 (13.57)	2.04 (14.16)	1.16 (10.71)	1.42 (11.82)	1.46 (12.01)
Out-of-school study time	12.31 (10.64)	11.79 (10.27)	12.03 (9.72)	9.93 (7.79)	9.13 (8.00)
Strong parental pressure (%)	49.09 (50.01)	38.20 (48.60)	47.52 (50.0)	36.92 (48.26)	31.58 (46.48)
ESCS index	0.168 (1.03)	0.071 (1.04)	-0.034 (1.03)	0.077 (0.983)	0.092 (0.946)
School size	1089.2 (451.0)	1071 (503.0)	1070 (473.0)	986 (442.3)	945 (454.5)
Student climate index	0.201 (0.97)	0.086 (0.987)	0.273 (0.983)	0.107 (1.101)	0.014 (0.990)
Private school (%)	38.52 (48.73)	35.55 (47.90)	41.10 (49.22)	41.46 (49.27)	41.94 (49.35)
Peer group quality index	0.289 (0.993)	0.060 (1.02)	0.146 (1.00)	0.094 (0.994)	0.072 (0.938)
% immigrant students (school)	34.81 (19.73)	32.83 (18.07)	39.21 (22.04)	21.02 (17.12)	12.99 (13.27)
N	345	831	1,321	3,431	8,382

Note: Standards deviation in parentheses.

Table A2: Weighted summary statistics by immigrant status: New Zealand

	First-generation: Arrival 0-5 years	First-generation: Arrival 6-16 years	Second-generation immigrants	Mixed parentage	Natives
Mathematics score	0.295 (1.17)	-0.005 (1.03)	-0.124 (1.09)	0.043 (0.996)	-0.043 (0.959)
Reading score	0.230 (1.09)	-0.113 (1.03)	-0.169 (1.05)	0.051 (1.00)	-0.009 (0.969)
Age	15.75 (28.23)	15.76 (29.75)	15.78 (27.52)	15.75 (28.72)	15.76 (28.62)
Male (%)	56.88 (49.65)	51.62 (50.00)	55.35 (49.78)	52.97 (49.94)	49.36 (50.00)
Single parent family (%)	15.90 (36.62)	18.42 (38.41)	20.37 (40.33)	23.91 (42.67)	23.64 (42.49)
City (%)	72.04 (44.99)	65.87 (47.47)	70.07 (45.85)	52.73 (49.96)	39.06 (48.80)
Town (%)	21.62 (41.26)	25.20 (43.47)	26.21 (44.03)	34.03 (47.41)	39.91 (48.98)
Small Town/Village (%)	6.34 (24.43)	8.92 (28.54)	3.72 (18.95)	13.23 (33.91)	21.03 (40.76)
Lower Sec. Gen. Acad. (%)	7.49 (26.49)	13.05 (33.73)	2.43 (15.43)	6.33 (24.34)	5.48 (22.75)
Language at home: Other (%)	48.72 (49.87)	58.11 (49.34)	40.46 (48.35)	5.97 (22.59)	3.57 (18.40)
Out-of-school study time	11.90 (10.55)	10.82 (7.14)	9.50 (5.91)	8.84 (5.79)	7.98 (5.50)
Strong parental pressure (%)	58.01 (49.47)	49.03 (50.04)	44.20 (49.72)	37.44 (48.43)	37.34 (48.38)
ESCS index	0.286 (0.942)	0.048 (1.03)	-0.297 (1.07)	0.075 (0.970)	-0.027 (0.999)
School size	1480 (777.3)	1343 (712.5)	1211 (618.7)	1154 (592.2)	1077 (592.2)
Student climate index	0.190 (1.01)	0.110 (0.992)	-0.034 (0.901)	-0.020 (0.988)	-0.034 (0.992)
Private school (%)	8.50 (27.95)	5.30 (22.43)	4.70 (0.213)	5.33 (22.47)	3.75 (19.00)
Peer group quality index	0.260 (1.03)	0.055 (0.985)	-0.167 (1.19)	0.040 (1.06)	-0.057 (0.948)
% immigrant students (school)	43.95 (24.15)	39.15 (22.53)	44.04 (21.30)	24.88 (17.92)	18.82 (15.12)
N	205	450	381	806	2,348

Note: Standards deviation in parentheses.

Table A3: Weighted summary statistics by immigrant status: Singapore

	First-generation: Arrival 0-5 years	First-generation: Arrival 6-16 years	Second-generation immigrants	Mixed parentage	Natives
Mathematics score	0.258 (1.04)	0.192 (0.920)	0.392 (0.974)	0.083 (0.965)	-0.010 (1.01)
Reading score	0.278 (1.11)	-0.002 (0.958)	0.449 (0.969)	0.082 (0.979)	0.007 (0.992)
Age	15.79 (30.28)	15.80 (27.90)	15.77 (28.69)	15.77 (29.13)	15.78 (29.04)
Male (%)	52.79 (50.05)	47.65 (50.00)	55.22 (49.81)	47.42 (49.96)	51.62 (49.98)
Single parent family (%)	14.46 (32.26)	25.71 (43.75)	8.05 (27.52)	10.61 (30.82)	8.78 (23.31)
Language at home: Other (%)	33.41 (46.15)	17.86 (37.98)	32.51 (45.81)	44.52 (48.58)	52.29 (48.31)
Lower Sec. Gen. Acad. (%)	4.11 (19.90)	19.66 (39.99)	1.29 (11.31)	1.75 (13.11)	0.29 (5.36)
Out-of-school study time	16.59 (10.76)	15.71 (9.05)	15.84 (8.98)	14.53 (9.23)	15.04 (9.57)
Strong parental pressure (%)	53.36 (49.84)	51.48 (50.03)	61.04 (48.84)	58.83 (49.24)	57.14 (49.50)
ESCS index	-0.085 (0.869)	-0.056 (0.932)	-0.413 (1.02)	-0.724 (1.05)	-0.660 (0.954)
School size	1375 (547.1)	1319 (482.8)	1419 (554.7)	1303 (433.6)	1318 (458.0)
Student climate index	0.233 (1.07)	0.155 (1.09)	0.241 (1.11)	0.050 (1.06)	0.010 (1.01)
Private school (%)	6.37 (24.47)	6.73 (25.08)	2.41 (15.36)	2.62 (15.98)	1.32 (11.43)
Peer group quality index	-0.681 (1.30)	-0.745 (1.27)	-0.979 (1.08)	-1.235 (1.01)	-1.262 (0.925)
% immigrant students (school)	29.61 (26.53)	31.82 (28.41)	21.18 (10.11)	16.07 (9.14)	15.51 (7.79)
N	197	449	311	1,093	3,383

Note: Standards deviation in parentheses.

Table A4: Weighted summary statistics by immigrant status: Canada

	First-generation: Arrival 0-5 years	First-generation: Arrival 6-16 years	Second-generation immigrants	Mixed parentage	Natives
Mathematics score	0.259 (1.07)	0.202 (1.08)	0.053 (0.989)	-0.061 (1.07)	0.144 (0.981)
Reading score	0.326 (1.01)	0.187 (1.04)	0.192 (0.950)	-0.030 (1.13)	0.153 (0.952)
Age	15.85 (29.09)	15.92 (28.75)	15.84 (29.14)	15.85 (28.27)	15.83 (28.32)
Male (%)	50.47 (50.04)	52.33 (49.97)	49.76 (50.01)	52.47 (49.95)	49.96 (50.00)
Single parent family (%)	15.30 (36.03)	14.36 (35.08)	11.54 (31.95)	13.45 (34.12)	11.84 (32.30)
City (%)	85.37 (35.37)	86.12 (34.59)	87.49 (33.09)	55.46 (49.71)	37.60 (48.44)
Town (%)	10.64 (30.86)	9.30 (29.06)	8.36 (27.68)	23.25 (42.25)	29.87 (45.77)
Small Town/Village (%)	3.99 (19.59)	4.58 (20.91)	4.15 (19.95)	21.30 (40.95)	32.54 (46.85)
Language at home: Other (%)	55.46 (49.75)	70.39 (45.67)	36.04 (48.02)	6.57 (24.78)	3.98 (19.56)
Lower Sec. Gen. Acad. (%)	9.07 (28.74)	13.95 (34.65)	6.74 (25.08)	13.19 (33.84)	16.59 (37.20)
Out-of-school study time	12.60 (9.33)	12.42 (9.22)	11.47 (9.24)	9.35 (6.67)	8.04 (6.04)
Strong parental pressure (%)	45.04 (49.80)	35.96 (48.01)	40.21 (49.04)	33.17 (47.09)	27.61 (44.71)
ESCS index	0.186 (1.02)	0.056 (1.07)	-0.260 (1.09)	0.099 (0.942)	0.044 (0.991)
School size	1283 (435.3)	1231 (468.1)	1244 (447.9)	1026 (490.5)	935 (493.2)
Student climate index	0.058 (0.930)	-0.011 (0.920)	0.038 (1.08)	0.034 (0.982)	0.024 (1.03)
Private school (%)	5.84 (23.46)	3.85 (19.26)	6.34 (24.37)	7.43 (26.22)	8.09 (27.26)
Peer group quality index	0.188 (1.12)	0.130 (1.12)	-0.080 (1.14)	0.128 (1.05)	0.001 (0.986)
% immigrant students (school)	58.68 (27.98)	57.51 (27.02)	60.02 (26.78)	26.45 (25.31)	14.10 (17.88)
N	544	1,084	1,951	2,758	14,495

Note: Standards deviation in parentheses.