# Parents, Schools and Human Capital Differences across Countries*

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**Abstract**

Results from international standardised tests show large cross-country differences in students' performance. Where do these gaps in human capital achievement come from? This paper argues that differences in cultural environments and parental influence are of great importance. We compare the school performance of second-generation immigrants from different nationalities but educated in the same school, and find that those whose parents come from high-scoring countries in the PISA test do better than their peers. The gap is larger among students whose parents have little education and have recently emigrated, suggesting the importance of country-specific cultural traits that parents progressively lose as they integrate in the new host countries. We quantify the overall contribution of parental influence to the observed cross-country differences in the PISA test performance, and show that it accounts for a sizeable part of the gap between East Asia and other regions. This pattern questions the interpretation of PISA scores and other measures of human capital achievement as quality proxies for a country's educational system. They appear to reflect an important intergenerational and cultural component.

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# 1 Introduction

According to available measures, human capital varies greatly across countries. Average years of schooling in 2010 range from 1.24 in Mozambique to 13.42 in the United States (Barro and Lee, 2013). Moreover, international standardized tests show large and persistent cross-country differences in the performance of students of similar age and level of educational attainment. East Asian countries like Korea, Japan, China and Singapore consistently position themselves at the top of international rankings, while several Southern European and Latin American countries show a rather disappointing performance.

An emerging strand of the growth literature puts these facts at the center of the discussion on cross-country differences in economic performance. Kimko and Hanushek (2000), Hanushek and Woessmann (2012a) and Schoellman (2012), among others, argue that standardized tests capture differences in human capital which have great explanatory power for differences in output per worker, while the contribution of schooling quantity is more limited.

Given the role that gaps in human capital measures play in the academic and policy debates, it is important to understand where they come from. Most of the discussion on standardized tests relies on (and argues in favor of) an interpretation of the results as measures of school quality. The popular press is rich of anecdotes on the severity of school curricula in East Asian countries, suggesting that this might be underlying their superior performance.[1] More broadly, the literature on cross-country differences in educational attainment emphasizes how country-specific factors such as access to public education, sectoral composition and skill premia shape the costs and expected benefits of human capital investment.[2]

On the other hand, a large literature studying skill formation at the individual level emphasizes that parents and the home environment are of great importance. Human capital gaps form to a great extent before children start attending any school, and parental actions and characteristics play a crucial role in this process (Almond and Currie, 2011). A natural question then is whether variation in parental influence is relevant also at the country-level, and whether it can contribute to explaining why children in different countries accumulate different levels of human capital. Anecdotal evidence suggests that indeed parenting styles and parental attitudes towards education vary across countries; for example, the international bestseller by Chua (2011) coined the expression "Tiger Mother" to describe the rather strict way in which some Asian parents raise children, pushing on academic excellence and long studying hours.

In this paper we investigate how much of the cross-country variation in test scores can be attributed to differences in parental influence, and what the nature of these differences is in the first place. Discriminating between the contribution of parents and that of other inputs has important implications. For example, it contributes to clarifying whether imitating some of the characteristics of the East Asian school system can raise students' performance in other

[1] See for example Jeevan Vasagar, "Why Singapore's kids are so good at maths", *Financial Times*, July 22, 2016.

[2] This literature is reviewed in greater detail below.

countries, or whether achievement gaps are due to deeper cultural factors, perhaps harder to affect by policy makers.

The analysis involves a set of difficult challenges. Parental influence is typically hard to measure, and, even when proxies are available, cross-country comparisons cannot separately identify its contribution from the one of school quality or other institutional factors. In this paper we overcome these difficulties by adopting an indirect approach, which does not require an explicit specification and measurement of all kinds of parental inputs relevant for human capital formation. Our methodology is based on the analysis of second-generation immigrants. We identify the importance of country-specific parental influences by comparing the performance of students born and educated in a given country and, for part of the analysis, in the same school, but with parents of different nationalities. Since factors such as the school curriculum, teachers and school infrastructure (as well as other individual-level characteristics) are being kept fixed in this comparison, we argue that we can reasonably attribute any residual difference to differential influences exerted by parents. We then show that the results from this empirical exercise can be used to decompose the cross-country variation in test scores between different sources, shedding light on the nature of these gaps.

Our results point towards a substantial role for parents. We document that the PISA performance of second-generation immigrant students, living in the same country and studying in the same school, is very closely related to the one of natives from the country of origin of their parents.[3] In particular, second-generation immigrants from high PISA countries score better than their peers from low PISA countries, even when they are observed in the same school and even if their parents have the same level of education and socio-economic status. This pattern is present also when we focus on a different schooling outcome in a specific host country, which is grade repetition in the United States. Once again, the best performing second-generation immigrants are those whose parents come from countries where natives are particularly successful in standardized tests. As we discuss at length, these results are unlikely to be driven by a pattern of differential selection of emigrating parents from different countries, which, if anything, seems to go against finding our results. According to our estimates, between 10% and 27% of the total cross-country variation in test scores can be accounted for by differences in observable and unobservable parental characteristics. Parents are responsible for a substantial share of the East Asian out-performance: on average, between 22% and 62% of the gap between Chinese and non-Chinese native students is persistent across second-generation immigrants.

We then focus on the US data to explore the nature of these differences in terms of parental influence. We first show that the relationship between the performance of second-generation immigrants and the average score in the parents' country of origin is strongest for parents with little or no formal education. This suggests that our results are not driven by the quality of education received by parents in their home country. Moreover, the relationship weakens if

[3]Throughout the paper, we call natives those students born in the country where they are taking the test and whose parents are born in the same country as well. Students born in a country different from the one where they are taking the test are excluded from all the analyses that follow.

parents have spent more years in the host country, suggesting the importance for school performance of country-specific "cultural" traits, that are progressively lost by emigrants as they integrate in their new host country. This interpretation is reinforced by the fact that part of the variation in second-generation immigrants' performance is accounted for by proxies for cultural traits likely to be conducive to human capital investment, such as long-term orientation, locus of control and attitudes towards leisure. We also look at time use surveys on immigrants in the US, to investigate whether differences in parental influence are reflected in measurable practices and activities. Indeed, parents from high PISA countries systematically spend more time on various forms of child care, with the gap once again being larger for parents with little education and few years spent in the US.

This paper contributes to the debate on cross-country differences in human capital. Several papers study the importance of various characteristics of the school system; Hanushek et al. (2014) and Woessmann (2016), among others, show that the average performance in the PISA test is positively related to teacher quality, instruction time, external exit exams and the degree of competition between schools. Other contributions focus on country-specific factors that influence the returns to human capital investment, both in terms of years spent in formal education and exerted effort; for example, Bils and Klenow (2000) and Manuelli and Seshadri (2014) emphasize TFP-induced differences in the wage rate per unit of human capital, Cordoba and Ripoll (2013) study credit frictions and their interaction with access to public education and Restuccia and Vandenbroucke (2014) stress the interplay between gaps in productivity and life expectancy. We contribute to this literature by studying a setting where all these country-specific channels are arguably shut down, and the importance of parental influence can be isolated.

Our results also speak to a wide literature across economics and sociology on the school performance of first- and second-generation immigrant children (see Levels et al., 2008; Dustmann et al., 2012, for broad reviews). Differently from these papers, our objective is to understand gaps in performance between natives of different nationalities, and our focus on second-generation immigrants is mostly instrumental in that it provides us with an empirical strategy to discriminate between possible sources for these gaps. As a consequence of this, our empirical approach is also different: we relate gaps between second-generation immigrant groups to gaps between natives in the corresponding countries of origin, while most papers have focused on the comparison between immigrants and natives in the host country (Schnepf, 2004; Marks, 2005; Song, 2011, among others).[4] In addition, by combining several waves of the PISA test we can conduct our analysis on a broad sample of host countries and countries of origin (while, for example, Dustmann et al. (2012) focus on Turkish immigrants, and Jerrim (2015) on East Asian

[4]As a partial exception, Levels et al. (2008), Dronkers and de Heus (2012) and Dronkers and de Heus (2016) compare the performance of (a combination of) first- and second-generation immigrants across countries of origin. However, they do not relate those to the performances of natives in the countries of origin, nor explore the implications in terms of cross-country gaps in performance. Yet another distinct strategy is the one in Borjas (1992), who relates the average educational attainment of ethnic groups residing in the US (what he calls "ethnic capital") to schooling and wages of the following generation.

immigrants), and we rely on several additional sources to provide evidence on the mechanisms underlying our results.

From a methodological perspective, our paper shares the approach of a large literature that looks at first- and second-generation immigrants to identify the importance of "portable" cultural components for various different outcomes (the so-called "epidemiological approach"; see among others Giuliano, 2007; Fernandez and Fogli, 2009; Alesina and Giuliano, 2010; Fernandez, 2011; Alesina et al., 2013). Differently from these papers, we study the school performance of the second-generation as our main outcome, and, for part of the analysis, we can relate it to the same outcome measured on the population in the country of origin. Moreover, while most of the focus in the literature is on immigrants observed in the US, our sample includes a large set of both host and source countries, allowing us to exploit variation in both dimensions.[5]

The paper is structured as follows. Section 2 discusses different forms of parental influences that might be relevant for human capital formation, and clarifies which our indirect empirical approach is able to capture. Section 3 describes the data, while Section 4 shows empirical evidence on the performance of second-generation immigrants as a function of their parents' country of origin. Section 5 addresses different issues in relation to selection. Section 6 quantifies the overall importance of parental influence for cross-country differences in test scores, while Section 7 explores more in detail the possible mechanisms behind our results. Finally, Section 8 concludes.

## 2 Parental Influence: Definition and Discussion

Parental influence on children's human capital can manifest itself through a number of different channels. The activities that parents do with their children (or push them to do on their own), the teachings they pass them and the resources they provide them with all plausibly affect their human capital development. Moreover, parents also shape children's attitudes towards education and effort, and at the same time might have an indirect influence through the example they provide. Finally, the genetic transmission of traits that affect learning ability and preferences could in principle also play an important role.

The indirect measure of parental influence that we propose in this paper includes in principle the effect of all inputs listed above. While our evidence in Section 7 does speak to the relative importance of some of these channels, the extent to which we can discriminate between them is limited by data availability, and in particular by the fact that most of these factors are difficult or impossible to measure.

[5]In more recent and independent work, Figlio et al. (2016) adopt a similar methodology to study the effect of long-term orientation on educational performance. Compared to their paper, we do not restrict attention to a specific cultural trait, but study and quantify the overall importance of observables and unobservables parental characteristics for the cross-country variation in human capital achievement. In Section 7 we do look explicitly at long-term orientation, among other cultural traits, and confirm the Figlio et al. (2016)'s result that it affects students' performance, even though it cannot account for the whole cross-country variation in parental influence.

An important qualification for our purposes, however, concerns the *reason* behind the supply of different levels of parental inputs. Part of the variation in parents' choices is plausibly driven by *context-specific* incentives: for example, higher expected returns to skills in the labour market might induce parents to emphasize the importance of education and hard work (Doepke and Zilibotti, 2012), as might do school quality if there are complementarities or substitutabilities between parental and schooling investments (Houtenville and Conway, 2008). On the other hand, factors that are *embedded* into parents, independently of the context-specific incentives they face, are also likely to be important: for example, preferences on education and parental productivity in the process of skill-transmission would fall into this category.

What do we pick up by comparing second-generation immigrants? As emphasized in the introduction, institutional factors and features of the educational system that might directly impact human capital formation are being kept fixed, allowing us to focus on parental influences. In addition, parents in our sample experience similar *context-specific* incentives, since their children face the same educational system and, ruling out differential intentions in terms of future relocation, labour markets with similar characteristics. The relevant source of variation is therefore represented by *embedded* factors, which might differ across parents because of cultural traits or skills inherited from their country of origin.[6]

Taking stock of this discussion, our methodology allows us to isolate the importance of inputs driven by factors *embedded* into parents for cross-country differences in human capital. While the focus on this source of variation in parental influence is imposed by our empirical approach, we emphasize that this is a relevant dimension for the analysis of cross-country gaps, since factors that lead parents to invest differentially in their children independently from the local economic and social conditions are likely to be very persistent over time, and perhaps particularly hard to affect through policy.

# 3 Data

Our main data come from the 2003, 2006, 2009 and 2012 waves of the PISA test. PISA is a triennial survey of the knowledge and skills of 15-year-old children, explicitly designed to allow comparisons across countries. Since 2003, 73 countries have administered at least one wave of the test, covering all OECD members as well as some partner countries. Typically, each country selects between 4,500 and 10,000 students through a two-stage stratified sampling technique, where a random sample of at least 150 schools enrolling 15-year-old students is drawn first, and then 35 students within each school are randomly selected to take part to the test. Throughout the analysis, we make use of the sample weights provided by the OECD.

The PISA test covers three subjects: reading comprehension, science and mathematics. Neither students nor teachers are informed on the outcome of the test, so these are rather low stake exams. Since each student is tested on a random subset of questions, to maximize compa-

[6]This distinction will be further explored in Section 7.

rability across groups test results are not presented as point estimates but rather as "plausible values". In particular, the OECD estimates for each student a probability distribution of test scores based on their answers, and randomly draws from it five values (see OECD (2011) for details). The average across plausible values can be taken as a metric of individual-level performance, even though, as pointed out in OECD (2011), measures of dispersion need to be adjusted to reflect the associated measurement error.[7] For each subject, we standardize scores to have mean 0 and individual-level standard deviation 1 across all countries (pooled, equally weighted) participating in at least one wave of the test.[8]

Results for all subjects vary greatly across countries. Figure 1 shows the average score of native students for all countries that participated to at least one wave of the PISA test.[9] Chinese students score 1.3 standard deviations higher than the average, and almost 3 standard deviations better than the worst-performing countries.[10] These magnitudes are striking; according to OECD (2012a), a gap of 0.4 on this scale corresponds to what is learned in an average year of schooling. There is substantial geographical clustering: East Asian countries occupy the first positions of the ranking, followed by several Western European countries; Southern European countries concentrate in the middle of the distribution, while all Latin American countries are below the average. Table 1 summarizes the average scores across countries in these and other broadly defined regions. The superior performance of Chinese and other East Asian students is stronger in mathematics, but the ranking across regions is quite stable across subjects.

The PISA data include a Student Questionnaire in every wave, which provides basic demographic information on students and parents, including their country of birth, education, employment and the ISEI index of socioeconomic status.[11] The exact country of origin of the parents is, however, not available in all participating countries questionnaires and for the wave 2000.[12] In addition, for some countries and waves further information is available from the

[7]Throughout the analysis on the PISA data, we follow OECD (2009) by computing variances of all functions of test scores as the average of the 5 variances estimated with each set of plausible values, and standard deviations as the square root of the corresponding quantities. Moreover, we inflate the standard errors of our estimates to reflect the the measurement error associated with the use of plausible values, as recommended in OECD (2009) and already implemented in the literature (Dustmann et al., 2012).

[8]The reported statistics for the science test refer only to the 2006, 2009 and 2012 waves. This is because the scale for this subject was established in 2006, and results from 2003 are not fully comparable with the subsequent ones.

[9]Throughout the paper we use the term natives to refer to the group of children born and educated in a certain country, whose mother/parents were born in the same country. On average, across countries participating to the PISA test, 78% of the target population can be classified as native, according to this definition.

[10]The PISA test in China is held in Shanghai only, and as such is not representative of the whole country. On the other hand, in our sample second-generation immigrants from China might come from any part of the country, since we do not have information on the region of origin. This mismatch is likely to work against our main finding, since Shanghai is one the wealthiest are of China and Chinese second-generation immigrants in our sample will be negatively selected. See section 5 for a discussion on this issue.

[11]The ISEI index, developed by Ganzeboom et al. (1992), is a measure of occupational status that assigns to each occupation a score from 16 to 90 based on an optimal scaling procedure combining information on average income and education of full-time employed men across several countries. As such, it is highly correlated with parental education and provides a rough proxy for parental income.

[12]Individual countries moreover have some flexibility on how to classify parents' country of origin. While most have indicators for each country, some group small countries in broader categories. We construct a set of

School Questionnaire and the Parent Questionnaire. In particular, we use the School Questionnaire to construct some measures of school quality, and the Parent Questionnaire to get additional information on parents' age and education.

The final sample includes 40,067 second-generation immigrants on the mother side and 40,304 on the father side, from 49 and 48 different countries of origin and distributed across 39 host countries. Table 2 displays the number and main destination countries of second-generation immigrants from each country of origin with at least one observation per parent, while Table 3 provides a similar breakdown across host countries. Sample sizes vary greatly, and for some countries of origin we have only a few parents to work with. To account for this, we weight countries of origin by the number of second-generation immigrants in the sample when considering cross-country patterns, and we present country-specific estimates only for a "core sample" of 37 countries from which we observe at least 100 immigrant parents. Solid bars in Figure 1 correspond to countries for which we observe second-generation immigrants, and the black ones identify countries that belong to the "core sample". Even when imposing this restriction, our sample covers most of the scores distribution, and includes countries from all regions.

Descriptive statistics for second-generation immigrants on the mother side are provided in Panel A of Table 4. The Table provides also a breakdown between immigrants from countries where native students score below and above the sample median, which allows a first rough comparison between the two groups. Students from countries above the median score substantially better than their peers, a result whose relevance and robustness will be discussed at length throughout the rest of paper. It is interesting to notice that emigrant mothers from high PISA countries are slightly less educated and likely to work compared to emigrant mothers from low PISA countries, even though parental education and PISA scores are on average positively correlated across countries. As discussed in Section 5, this finding will be useful to shed light on the underlying pattern of emigrants' selection across countries.

The second source of data is the Integrated Public Use Microdata Series (IPUMS) created by the US Census Bureau. The IPUMS consists of individual and household level data from the decennial census in the US and includes nearly all the details originally recorded by the census enumerations. We use the 1% samples from the 1970 and 5% sample from the 1980 censuses. Even if the US Census has little information on children's outcomes, it does, however, contain information on each individual's exact grade attending at school.[13] We follow Oreopoulos and Page (2006) in combining this information with children's age to construct an indicator of whether or not each student has repeated any grade. As pointed out by Oreopoulos and Page (2006), grade repetition is a widespread phenomenon in the United States and is correlated with many commonly used measures of educational achievement and socioeconomic success. We classify a child as a repeater if his or her educational attainment is below the mode for the corresponding state, age, quarter of birth, and census year cell. Following Oreopoulos

countries/regions consistently defined over time. See Appendix A for the details.

[13] This information is only available until 1980, which prevents us from using more recent years.

and Page (2006), we focus on children between the ages of 8 and 15, since younger children have not had many opportunities to repeat a grade, and older children are more likely to have left home already or dropped out of school. To adjust for the fact that older sample members have had more opportunities to repeat a grade, all regressions include controls for age dummies. Moreover, we experimented with several alternative definitions of grade repetition and our results are robust throughout. The final sample includes 53,081 second-generation immigrants on the mother side and 46,410 on the father side, from 61 different countries of origin. Descriptive statistics for second-generation immigrants on the mother side are provided in Panel B of Table 4.

For Section 7.2, we use the ATUS-US Time Use Survey to analyze how immigrant parents spend their time. We pool together all waves between 2002 and 2013. The ATUS survey was administered only to one person per household, chosen randomly among all individuals at least 15 years old. We construct a variable measuring the total time (in minutes) spent on child care on the previous day, and three subcategories that split total child care in educational, recreational and basic activities.[14]

Finally, we rely on several other sources to construct our controls at the level of parents' country of origin. We take real GDP per capita from the PWT, average years of schooling for different demographic groups from Barro and Lee (2013), measures of school quality from Bartik (2008), various answers from the World Value Survey to proxy for cultural differences and data on the religion composition in 1970 from Barro and McCleary (2003).

# 4 Reduced Form Evidence

In this section we examine whether the school performance of second-generation immigrants is related to the one of natives in their parents' country of origin. Throughout the section, we focus on second-generation immigrants on the mother's side only. This is done only to simplify the exposition, and alternative specifications in Appendix B show that our results hold without exception when we look at second-generation immigrants on the father's side or at the whole sample of second-generation immigrants and natives.[15] We present results for the PISA and the US Census samples in turn.

[14]We follow Aguiar and Hurst (2007) for the construction of these variables. See Appendix A for the details.
[15]This more complete specification will be used for our decomposition in Section 6.

## 4.1 PISA

Let $T^m_{icst}$ denote the PISA math score in year $t$ of child $i$, studying (and born) in country $c$ and in school $s$, whose mother was born in country $m$.[16,17] We start from the following specification:

$$T^m_{icst} = \theta_0 + \theta_1 T^m + \theta_2' X^m_{icst} + \theta_{cs} + \theta_t + \varepsilon^m_{icst} \tag{1}$$

where $T^m$ is the average score of native students in the mother's country of origin, $X^m_{icst}$ is a vector of individual characteristics of student and parents, $\theta_{cs}$ is a country or school (depending on the specification) fixed effect, $\theta_t$ is a PISA wave fixed effect and $\varepsilon^m_{icst}$ is an error term.[18,19] The main coefficient of interest is $\theta_1$, which captures the relationship between a given second-generation immigrant's performance and the average score of native students in country $m$.

Here, $T^m$ is used as a proxy for the bundle of unobservable characteristics of parents born in country $m$ which affect the school performance of their children. The average test score in a given country reflects a combination of school quality, economic, cultural and institutional factors. However, by analyzing children educated in the same country/school, who differ just because their parents come from different countries, we disentangle the part of their tests scores related to the institutional environment from the part related to parental influences. The main worry is of course that omitted inputs for students' performance might be correlated with $T^m$, i.e. that, for example, second-generation immigrants whose parents come from high PISA countries might receive higher investments in their educational development for reasons unrelated to their parents' nationality. The school fixed effect takes care of the possibility that they might attend schools of higher quality. In addition, we control for parental characteristics which might be correlated with human capital investments on children and with PISA scores, such as parental education, employment status and, for those who are employed, the ISEI index of occupational status.[20] The possibility that our results are driven by differential selection on unobservables of second-generation immigrants will be discussed in great detail in Section 5.

Table 5 shows our main results. The sample is limited to second-generation immigrants on the mother's side, and a dummy is included in all specifications to control for whether the father is also foreign born.[21] Standard errors are clustered at the level of the mother's country

[16]The results are similar for the reading and science tests (see Appendix B). The Math test is often preferred for international comparisons for the relative easiness of defining and quantifying a common set of expected skills (Hanushek and Woessmann, 2012a).

[17]Throughout the paper, subscripts refer to the location and characteristics of students, while superscripts refer to the country of origin of parents.

[18]Since the PISA test in not administered in the same schools across different waves, the school fixed effects are effectively wave-specific.

[19]In this setting the dominant information is found in cross-country variation. A panel data approach would be of difficult implementation because the main regressor is indeed persistent over time (see Kimko and Hanushek (2000)), and short run shocks and variations in PISA scores are likely to be caused by cohort effects rather than significant changes in the cultural and educational environment. Moreover, PISA tests are available for few points in time and for recent years only.

[20]Information on parental age and number of siblings is available only for a small set of host countries and waves. Our results are robust to the inclusion of these controls in this sub-sample.

[21]This specification therefore ignores the variation in parental influence associated with the country of origin

of origin, and inflated by the estimated measurement error in test scores.[22]

We proceed by progressively adding controls. Column 1 of Table 5 displays the raw correlation between PISA scores of second-generation immigrant students whose mother comes from country $m$ and the average PISA score of natives in country $m$. It is strong and highly significant: a gap of one (individual-level) standard deviation in the average score in the mother's country of origin is reflected in a gap 66% of a standard deviation among second generation immigrants. The coefficient shrinks when we restrict the comparison to students that are observed in the same country (Column 2) and, especially, in the same school (Column 3), but is still positive and significant. The difference in the size of the coefficient between the first two specifications and Column 3 is quite illuminating, since it suggests that mothers from high PISA countries send their children to better schools. We will show further evidence of this and discuss the implications for our empirical exercise in Section 5.

The specification in Column 4 adds controls for parental education, with the coefficient of interest being hardly affected. This finding is useful for the interpretation of the mechanisms behind our results: it suggests that the estimate of $\theta_1$ is unlikely to be driven by some parents' unobservable skills (like ability), since we would expect these unobservables to be correlated to parental education, and therefore the inclusion of this last variable to matter a lot for our coefficient of interest. What drives our result seems to be something not correlated with parents' education level.[23] Similarly, the introduction of controls for employment and occupational status in Column 5 does not change the coefficient on $T^m$. Finally, the last column of Table 5 shows that results are not driven only by the particularly good performances of East Asian students, since the coefficient is robust to the exclusion of East Asian mothers.

Figure 2 summarizes the results presented in this section. The left panel displays, for all countries with at least 100 second-generation immigrants on the mother's side in the sample, the strong and positive relationship between the average score of second-generation immigrants and the average score of natives in the mother's country of origin country. The right panel shows that the correlation weakens but is still positive and significant when we clean the scores

of the father. As mentioned earlier, specifications that focus on fathers or that include the whole sample of second-generation immigrants and natives give very similar results, and are shown in Appendix B.

[22]As recommended in OECD (2009), each regression is estimated separately for each set of plausible values, and the sampling variance is computed from the average estimated variance-covariance across these specifications. In addition, standard errors are corrected for the imputation variance, which is proportional to the variance of the estimated coefficients across sets of plausible values.

[23]A possible concern, though, is that $\theta_1$ is not much affected because parental education for immigrant parents is measured with error. Indeed, the estimated coefficients for these variables are quite small and, with the exception of the tertiary education dummy for fathers, not statistically significant. Moreover, the presence of some measurement error is quite realistic, given that PISA questionnaire are filled in by students, who may have difficulties reporting their parents' educational level, especially if parents were educated in a different country. To address this possibility, we exploit the fact that for countries and waves where the Parents Questionnaire was administered, parents were asked to report their education as well. We therefore instrument the mother's and father's educational levels, as reported by children, with those reported by the parents themselves. Since the sample that allows this exercise is considerably smaller, we focus on the specification that includes both natives and second-generation immigrants on either parent's side. The results (available in Appendix F) show that, while there is some degree of measurement error, the coefficient of interest $\theta_1$ does not vary much in magnitude between the OLS and the IV specifications.

of second-generation immigrants from the effect of observable characteristics, including school fixed effects.

## 4.2 US Census

We apply a similar specification as in equation (1) on the US Census data, using a dummy which takes value one if a child has never repeated any grade as our dependent variable. We notice that this outcome, while still related to school performance, captures quite a different dimension compared to the PISA score, given that the variation in this case comes only from the bottom part of the distribution (more than 80% of the students in the sample has never repeated a grade, as shown in Table 4). On the other hand, while the PISA dataset contains only 15 years old children, the US data allows us to look at students between 8 and 15 years old. We therefore find quite noteworthy that our results generalize to this setting as well.

The US Census does not include any information on the particular school children are attending, making it impossible to compare second-generation immigrants in the same school, as we did for Table 5. In an attempt to capture some of the differences across educational systems within the US, we control for Commuting Zone fixed effects.[24] However, the US Census provides us with precious information on parents' immigration history, so that we can control for the number of years passed since the mother has first migrated to the US. In addition, we can control for a richer (compared to the PISA sample) set of observable characteristics on family background, such as number of siblings, child's and parents' age and family income.

Table 6 shows our results. Once again, the coefficient on $T^m$ is positive and significant throughout. Commuting zones fixed effects and controls for parental education, mother's years since migration and family income explain about two thirds of the gap in performance between second-generation immigrants from high and low PISA countries. According to column 5, the most complete specification, an increase of a standard deviation in the PISA score of students in the mother's country of origin is associated with a higher probability of not having repeated any grade by 2.7 percentage points (3% over the average). This effect is not trivial, given that, as mentioned earlier, most students do not repeat any grade. As for the PISA specification, the result is robust to the exclusion of East Asian parents (column 6).

# 5 Selection

In this section we discuss some possible forms of selection with different implications for our analysis: selection into emigration and, conditional on emigration, selection into host countries and schools.

[24]Commuting Zones are constructed following Autor and Dorn (2013).

## 5.1 Selection into Emigration

As our analysis relies on emigrant parents to make inference on all parents of a given nationality, an obvious concern is represented by the fact emigrants are not a random sample of the population, and might be selected on unobservable characteristics that also matter for children's school performance.

What type of selection should we worry about in this context? Figure 3 displays various possibilities. In these plots the solid line represents the selection-free relationship between the score of second-generation immigrants and the one of natives from the parents' country of origin, i.e. the relationship that we would be able to observe in a world where emigrant parents were randomly selected from the population. The dashed line represents instead what we would observe in our data under different patterns of selection into emigration. Our parameter of interest is the slope of the solid line, or, more generally, the extent to which the relative performance of natives is reflected in the relative performance of second generation immigrants with "representative" parents in terms of unobservable characteristics.

The first panel depicts the case where the extent of selection into emigration (as measured by the gap between the two lines) is the same across countries of origin with different PISA scores. In this case only the estimated intercept is biased, while the inferred slope is not affected. In the second panel we have the case where parents emigrated from countries with high PISA scores are more positively selected than parents emigrated from countries with low PISA scores, while in the third panel we have the opposite case. These patterns of differential selection would lead to a biased estimate of our coefficient of interest, and in particular the case depicted in the second panel could rationalize the findings of the previous sections.

While the main threat to our approach is represented by differential selection on unobservables, it is helpful to consider whether emigrant parents are differentially selected on observable characteristics. The idea here is that parents' unobservables traits that positively affect children's school performance (like ability, motivation etc) are likely to be positively correlated with observables like education and socio-economic status. We can therefore somehow alleviate the concerns on differential selection if we can show that the relative "quality" of emigrants compared to stayers is not higher for high PISA countries.[25]

Before turning to our data to do that, it is useful to consider what the extensive literature on emigrants' selection suggests we should expect in terms of differential selection with respect to our variable of interest. While, to our knowledge, the PISA score itself has not been explicitly considered in this literature, this variable is correlated with several others that have been

[25]Ideally, we would want to perform such an exercise with a measure of quality pre-determined with respect to migration. Clearly, parental education, as any other socio-economic control available in the PISA dataset, does not satisfy this condition, since parents might have acquired part of their education in the host countries or, more subtly, have based their educational choices in their countries of origin anticipating their future relocation. In the Census data it is possible to alleviate the first of these concerns, since we observe year of migration and therefore we can focus on parents that completed their education in the country of origin (see Appendix C). For both datasets however, we want to emphasize that this "contamination" of our proxy for unobservable parental skills is problematic for our purposes only to the extent that is differential across countries of origin.

advocated as measuring direct determinants of emigrants' selection. In Figure 4 we plot some of these variables against the PISA score of native students in the country of origin; since in the PISA sample we do not know the exact date of migration, we use data on selection determinants in 1985 or the closest available data, which should plausibly approximate the pre-migration conditions for the average migrant in our sample.[26]

First, the seminal contribution of Borjas (1987) gives a central role to the difference in income inequality between the origin and destination countries, predicting positive selection if the wage structure of the host country is such that skills are rewarded more compared to the country of origin, and negative selection in the opposite case. Panels (a) and (b) of Figure 4 show that on average emigrant parents from high PISA countries do emigrate to countries more unequal (as measured by the Gini coefficient and the estimated return to education) than their countries of origin, implying that they would be more positively selected according to Borjas' theory.[27] However, this theory has received mixed support in the data (Chiquiar and Hanson, 2005; Belot and Hatton, 2012), and in particular Grogger and Hanson (2011) argue that the absolute (as opposed to the relative) wage gap between high and low earners provides a better rationalization of the patterns of selection observed in the data. Panel (c) shows that, according to the preferred measure in Grogger and Hanson (2011), emigrants from high PISA countries (if anything) face a relatively lower absolute earning spread in their host countries, implying that they would be more negatively selected.[28]

Another strand of the literature emphasizes the importance of liquidity constraints (Chiswick, 2000; Belot and Hatton, 2012). These papers suggest that emigrants' self-selection should be more negative from richer countries, where facing emigration costs is affordable for a larger share of the population. Not surprisingly, the average PISA score is positively correlated with real GDP in 1985 (Panel d), so that we should expect negative differential selection according to this mechanism as well. Panel (e) shows instead the extent to which emigrants choose countries with a large pre-existing community from the same country of origin, since McKenzie and Rapoport (2010) among others, argue that stronger social networks act to reduce the effective cost of migration inducing negative selection.[29] We can see that China is an outlier on this dimension, since many Chinese are observed in Macao and Hong Kong, where Chinese-born represented respectively the 37% and 36% of the population in 1980; therefore, this "chain migration" view would predict negative selection for China, and no systematic pattern of dif-

[26]In the Census data, where we do observe years since migration, the average mother of a 15 year old student born in the US migrated 20 years earlier.

[27]We take the Gini Index from the cross-country dataset constructed in Brueckner and Lederman (2015), and we use the 1985 observation when available and 1990 or 1995 when not. The Mincerian coefficients come from Psacharopoulos and Patrinos (2004), who collect estimates from a large set of papers; most observations refer to the 1980s.

[28]Grogger and Hanson (2011) combine information from the Luxembourg Income Study and the WIDER dataset to construct an estimate of the absolute income gap in real terms between the $80^{th}$ and $20^{th}$ percentiles of the income distribution in each country.

[29]We construct a matrix of bilateral migration shares in 1980 from the Global Bilateral Migration Database, discussed in Ozden et al. (2011) Each entry of this matrix gives us the share of the resident population in country $i$ that was born in country $j$.

ferential selection for the other countries.[30] Finally, Panel (f) shows that emigrants from high PISA countries are not systematically located in a country closer or farther from their country of origin.[31] This is relevant since higher geographical distance has been shown to be associated with negative selection (Grogger and Hanson, 2011; Belot and Hatton, 2012), most likely due to its effect on the cost of migrating.

Overall, the determinants of self-selection considered in the literature suggest that, if anything, we should expect parents emigrating from high PISA countries to be relatively negatively selected. To verify whether this is the case, we construct for each parent a measure of selection by computing the difference between his or her years of schooling and the average years of schooling of non-emigrant parents from the same country, and dividing this quantity by the country of origin-specific standard deviation.[32] Taking into account differences in standard deviation is potentially important, since on average countries with a higher PISA score feature smaller variation in parental education, implying that a given degree of self-selection in terms of standard deviations would be underestimated for those countries.[33]

Figure 5 plots the average of this measure of selection across mothers' countries of origin against the average score of native students in those countries. First, we notice that for a majority of countries of origin emigrant parents are positively selected (that is, our measure is greater than 0), a finding which is consistent with most of the recent literature (for example, Feliciano (2005b) documents that US immigrants from most nationalities are positively selected on education). In terms of differential selection, if anything the relationship seems to be negative, suggesting that emigrants from high PISA countries are more adversely selected (at least in terms of observable characteristics) than emigrants from low PISA countries (panel 3 of Figure 3).[34]

In addition, Table 7 shows results of a regression of our measure of selection of emigrant parents on the average PISA score in their country of origin, controlling for country (columns 1 and 3) and school (columns 2 and 4) fixed effects. The pattern is rather similar for mothers and

[30]The results of the paper are robust to the omission of Macao and Hong Kong as host countries, and to their aggregation to China as well. If anything, the relative overperformance of Chinese second-generation immigrants compared to other countries of origin is weaker in these two countries, perhaps due to the patterns of selection discussed in this section.

[31]The geographical distance data comes from the CEPII's GeoDist dataset (Mayer and Zignago, 2011). We use the simple distance between the most pupulated cities, expressed in chilometers.

[32]We construct a mapping between the ISCED classification of educational levels and equivalent years of schooling by using the country-specific conversion table in OECD (2012b).

[33]In practice, however, results are very similar (and if anything slightly stronger) when we use the simple difference or the ratio between parental education and the country of origin-average.

[34]The fact that Chinese emigrant parents are negatively selected might appear in contrast with evidence in Feliciano (2005a), which argues that Chinese immigrants in the US are among the most positively selected in terms of education. Indeed, in Appendix C we show that in the US Census data, while on average the pattern of differential selection with respect to the PISA score is still negative, the Chinese are relatively positively selected. This discrepancy is easily explained by the fact that, as discussed earlier, the PISA test is only administered in Shanghai, and as such it targets a subsample of the Chinese population significantly more educated than the average. Therefore, while Chinese emigrants might be positively selected compared to Chinese non-emigrants as a whole, they are negatively selected compared to the population involved in the PISA test.

fathers: the point estimates are negative and not statistically significant, suggesting that the pattern of differential selection that would invalidate our results is not present neither within host countries nor within schools.[35]

## 5.2 Selection into Host Countries and Schools

A distinct issue, though obviously related, is selection into host countries and schools, conditional on emigration. As mentioned earlier, the introduction of host country and, in particular, school fixed effect lowers our correlation of interest in Table 5, suggesting that parents from high PISA countries might select educational environments more conducive to a good schooling performance. In order to provide direct evidence for this, we use the proxies for school quality we constructed from the information available in the School Questionnaire. Table 8 shows that, after controlling for country fixed effects and the usual observable characteristics, a higher PISA score in the country of origin of the mother is associated with schools where natives score better in the PISA test, no matter whether we take the raw average (column 1) or clean it from observable characteristics (column 2), where admissions are more likely to be based on academic records, the proportion of teachers with at least some tertiary education is higher and the proportion of students dropping out is lower.

This result has important implications when decomposing the importance of differences in parental and school inputs across countries. On the one hand, school selection is a choice in which parents (either directly or indirectly, through the transmission of attitudes and values) play an important role, so that, when comparing second-generation immigrants, the attendance of better schools could be viewed as one of the channels through which parental influence manifests itself. On the other hand, for the purpose of explaining differences in the average performance of natives across countries, the extent to which differences in the in average ability or willingness to select better schools can matter is limited by the available supply of school quality in each country. At one extreme, if all schooling resources that matter are utilized to full capacity, then endowing a country with a higher average parental effectiveness in school selection would not contribute at all to boosting the average score.[36] This scenario is probably too stark however, since in several countries students might be able to access better schools without necessarily displacing others, or parents' drive for school quality could stimulate its supply to start with.[37]

[35]While the point estimate is not significantly different from 0, we notice that the stronger pattern of negative differential selection within schools is consistent with the view that there is assortative matching between the quality of parental inputs and the quality of the school attended by children. The logic is as follows: when we observe two students in the same school, with one of them having received higher quality parental inputs (which in our setting means having parents born in high PISA country), then it must be that the other student, or his parents, are "better" on some other (unobservable) characteristics, otherwise the two students would not be in the same school to start with.

[36]This would not necessarily be true in a world where parental and schooling inputs are complementary in the human capital production function, since then the matching pattern between schools or families would matter for the average performance. In Appendix E we investigate this possibility, and conclude that it is unlikely to be quantitatively important in our setting.

[37]See McMillan (2000) and references therein for a discussion on the role of parental pressure in holding

In our context, specifications with school fixed effects wash out differences in school quality from our correlation of interest, while specifications which only include host country fixed effects "attribute" all of the within-country variation in school quality documented above to parents. In light of the difficulty of establishing the relative merit of these two views, for both our reduced form evidence and decomposition exercise we show results from both specifications, with the understanding that regressions with school fixed effects provide us with a lower bound on the importance of parental influence, while the ones with country fixed effects are likely to overstate its importance.[38]

While the discussion so far has focused on the "absolute" quality of schools to which second-generation immigrants are allocated, an additional concern is that immigrant parents from high PISA countries may be systematically selecting host countries (or schools) where, because of idiosyncratic factors, it is easier for them and their children to integrate and perform well. Of course the quality of the match between parents or children on one side and countries or schools on the other is unobservable, and it is difficult to rule out entirely this possibility. However, we can check whether immigrants from high PISA countries are located in countries which are, according to reasonable proxies, culturally closer to their country of origin. Table 9 explores this possibility. In column 2 we add to the baseline regression of column 1 a dummy variable that takes value of 1 for all students that declare to speak a foreign language at home (which is available only for part of the sample). While the coefficient on this newly added control is, as expected, negative and significant, our main coefficient of interest is virtually unaffected.

In column 4 and 6 we add to the baseline specifications (reported in columns 3 and 5 respectively) controls for cultural distance (from Spolaore and Wacziarg (2015)) and linguistic distance (constructed through the softwares provided by the Automated Similarity Judgment Program (Wichmann and Brown, 2016)); both measures are standardized to have mean 0 and standard deviation 1 across all country pairs in the sample. In both cases the impact on our coefficient of interest is positive and of negligible magnitude.[39]

# 6 Decomposition

For our decomposition we introduce a slightly more general model, which allows both mathernal and paternal influence to differ across countries. Suppose that the test score in wave $t$ of a second-generation immigrant $i$, studying in school $s$ and country $c$, whose mother and father

schools accountable and improving their effectiveness.

[38]The patterns of negative differential selection documented in Table 7 reinforce our interpretation of the school fixed effect specification as lower bound.

[39]In recent work, Isphording et al. (2016) argue that linguistic distance impacts immigrant students' mathematics performance through its effect on reading skills. These results are not in contrast with ours given that we are looking at linguistic distance for immigrant parents, while all students in our sample are born in the country where they attend school.

were born in countries $m$ and $f$ is given by

$$T_{icst}^{mf} = Parents_{icst}^{mf} + \alpha_{cs} + \alpha_t + \rho' X_{icst}^{mf} + \varepsilon_{icst}^{mf} \tag{2}$$

where $Parents_{icst}^{mf}$ is

$$Parents_{icst}^{mf} = \gamma^m + \delta^f + \beta' ParentsEdu_{icst}^{mf} + \lambda' ParentsOcc_{icst}^{mf} + \eta_{icst}^{mf} \tag{3}$$

with $\gamma^m$ and $\delta^f$ being country-specific components capturing a set of average (unobservable) characteristics of mothers and fathers from countries $m$ and $f$ respectively. The parental component of student $i$ includes also the effect of parents' education and occupational status, which potentially might influence his or her performance in school.[40] As before, differences in school quality are captured by host country or, depending on the specification, school fixed effects, which also absorb the effect of any other institutional factor that impacts directly or indirectly students' test scores.[41] Combining (2) and (3) we obtain

$$T_{icst}^{mf} = \beta' ParentsEdu_{icst}^{mf} + \lambda' ParentsOcc_{icst}^{mf} + \gamma^m + \delta^f + \alpha_{cs} + \alpha_t + \rho' X_{icst}^{mf} + u_{icst}^{mf}$$

This model can be estimated on the sample of students for which parents are born in a different country from the one where the PISA test is taking place. However, in order to use all the available information in the data and to obtain more precise estimates for the other controls (including the host country and school fixed effects), we include all second-generation immigrants and native students in the following specification

$$\begin{aligned} T_{icst}^{mf} = {} & \beta' ParentsEdu_{icst}^{mf} + \lambda' ParentsOcc_{icst}^{mf} + \gamma^m + \delta^f \\ & + \theta^m NatMoth_{icst}^{mf} + \zeta^f NatFath_{icst}^{mf} + \rho' X_{icst}^{mf} + \alpha_{cs} + \alpha_t + u_{icst}^{mf} \end{aligned} \tag{4}$$

where $NatMoth_{ist}^{mf}$ and $NatFath_{ist}^{mf}$ are dummies identifying native parents (mothers and fathers, respectively). The coefficient $\theta^m$ (and similarly $\zeta^f$), in the spirit of a difference in differences, captures the extent to which the relative performance of students whose mother is from country $m$, compared to second-generation immigrant students from another country, is larger or smaller in country $m$ (where the mother is native) as opposed to a different host country. Importantly, we allow the "native advantage" to be country-specific for both mothers and fathers: a failure to do so would imply that this kind of variation would be absorbed by the country of origin fixed effects, which, in that case, would not be identified only out of

[40]Specifically, $ParentsEdu_{icst}^{mf}$ contains dummies for primary, secondary or tertiary education for each parent, while $ParentsEdu_{icst}^{mf}$ contains dummies for employment status (full-time employed, part-time employed, not working), as well as interactions between the full-time employed and part-time employed dummies and the ISEI index of occupational status.

[41]Importantly, this includes the effect of all parental influences driven by context-specific factors, which, as discussed in section 2, are not part of our parental component identified out of second-generation immigrants.

second-generation immigrants (see footnote 43 for further discussion on this point).

The object whose variation we are ultimately interested in decomposing is the average score (across all available waves) of native students in country $c$, which is given by

$$T^c = \alpha + Parents^c + \theta^c + \zeta^c + \overline{\alpha}_c + \rho' \overline{X}_c \tag{5}$$

where $Parents^c = \gamma^c + \delta^c + \beta' \overline{ParentsEdu}^c + \lambda' \overline{ParentsOcc}^c$, $\overline{\alpha}_c$ is either a weighted average of the school fixed effects or the fixed effect for host country $c$ (depending on the specification) and $\overline{X}_c$, $\overline{ParentsEdu}^c$ and $\overline{ParentsOcc}^c$ are within country $c$ averages.[42] Equation (5) makes our decomposition explicit: our objective is to evaluate the importance of $Parents^c$ to account for the variation of $T^c$ across countries.[43]

In order to do that, we estimate our country $c$ specific parental component from

$$\widehat{Parents}^c = \widehat{\gamma}^c + \widehat{\delta}^c + \widehat{\beta}' \overline{ParentsEdu}^c + \widehat{\lambda}' \overline{ParentsOcc}^c$$

where $\widehat{\gamma}^c, \widehat{\delta}^c$ and $\widehat{\beta}$ are our estimated parameters from equation (4). As discussed earlier, we focus on two different specifications, one that includes school fixed effects and another with only host country fixed effects. Moreover, we display results for countries for which we have at least 100 immigrant parents in our sample and therefore a reasonably precise estimate of the corresponding fixed effect. Figure 6 plots the parental component obtained from both specifications against the average score of natives (with $Parents^{\text{CHINA}}$ being normalized to 1 in both cases).[44] Not surprisingly, the estimated $Parents^c$ is larger (in absolute terms) for countries that perform better in the PISA test, which means that our parental component does account for some of the cross-country variation (as opposed to masking an even larger dispersion) of average test scores. Consistently with our discussion in Section 5, the dispersion in $Parents^c$ is larger under the country fixed effect specification, which allows the parental component to absorb the within country variation in school quality.

As a simple summary statistic, we compute the share of the total cross-country variance of

[42] The constant $\alpha$ absorbs the average of the wave fixed effects.

[43] Notice that $\theta^c$ and $\zeta^c$ are not included in $Parents^c$. These parameters are identified out of the comparison between native and second-generation immigrant students in country $c$, and we think that various factors different from parental influence (such as the extent to which immigrants manage or are willing to integrate in their host country, or even characteristics of the school curriculum) could drive the international variation in the "native advantage". Instead, we view our focus on second-generation immigrants of different nationalities as one of the main advantages of our empirical approach, as it enables us to clean our estimates from confounders that would be difficult to proxy for. Nevertheless, $\theta^c$ and $\zeta^c$ are both positively correlated with $T^c$, so including them in our parental component would lead us to infer a (moderately) higher role for parental influence.

[44] Table 11 displays $Parents^c$ for all countries.

$T^c$ accounted by $Parents^c$, simply as[45]

$$V_{Parents} = \frac{Var(\widehat{Parents^c})}{Var(T^c)}$$

Moreover, for every country $c$ we can calculate the share of the gap in average test score accounted by the parental component with respect to a given benchmark $b$ as

$$S_{Parents}(c,b) = \frac{\widehat{Parents^b} - \widehat{Parents^c}}{T^b - T^c}$$

Finally, to evaluate the relative contribution of observable and unobservable parental characteristics, we also compute equivalent statistics for the country-specific intercepts only,

$$V_{FE} = \frac{Var(\widehat{\gamma}^c + \widehat{\delta}^c)}{Var(T^c)}$$

$$S_{FE}(c,b) = \frac{(\widehat{\gamma}^b + \widehat{\delta}^b) - (\widehat{\gamma}^c + \widehat{\delta}^c)}{T^b - T^c}$$

Tables 10, 11 and 12 show the results of these calculations, both under the country fixed effect and the school fixed effect specifications. For the pairwise comparisons, we focus on the gap between China and the other countries.

Table 10 shows that $Parents^c$ accounts for at least 10% of the total variation across countries, and up to 27% when we do not clean it from the variation in school quality within countries. More than 80% of the international variation in $Parents^c$ is driven by $\widehat{\gamma}^c + \widehat{\delta}^c$, suggesting that cross-country differences in parents' education and occupational status are of limited quantitative importance. The parental component plays a substantially larger role when accounting for the gap between East Asia and the rest of the world. Table 11 shows that, on average, between 22% and 62% of China's out-performance can be accounted for by parental influence. While some of the country-specific estimates are too imprecise to allow definite conclusions, the gaps in $Parents^c$ are particularly high for several countries in the middle-bottom part of the score distribution (Spain, Portugal, Italy, Croatia, Greece and Turkey in particular), but not so pronounced for the worst performers.

In Table 12 we display the average of $Parents^c$, $S_{Parents}(c, CHINA)$ and $S_{FE}(c, CHINA)$ across regions. Particularly striking are the results for Southern Europe and Middle East/North Africa, which display large gaps with respect to the best performing countries, more than a third (and, under the host country fixed effect specification, the majority) of which is potentially explained by differences in terms of parental influence. On the other hand, it is interesting to notice the relatively limited role that parental influence plays for Latin American countries,

[45] Our decomposition exercise is conceptually similar to the ones proposed in Card et al. (2013) and Finkelstein et al. (2014), who also use (in different contexts) fixed effects identified out of movers to separate the contribution of individual characteristics and geographical or institutional factors. Unfortunately, the lack of a panel dimension on the student side prevents us from implementing an event-study type of analysis as they do.

whose poor performance in standardized test has been object of recent study (Hanushek and Woessmann, 2012b). Once again, the country of origin fixed effects and not the differences in observable characteristics account for the bulk of the contribution of the parental component.[46]

# 7 Mechanism

In this section we attempt to open the black box of parental influence, whose importance was quantified above. What is it about parents from high PISA countries that drives the superior school performance of their children? While answering this question precisely is difficult, we make progress by proceeding in three steps. First, we distinguish between two alternative interpretations on the source of differences in parental influence, one based on an intergenerational effect of parental education and another based on a cultural transmission mechanism. Then we turn to the Time Use data to see whether immigrant parents from high PISA countries differ in some observable practices that might help to explain their children's better performance at school. Finally, we test whether measures relative to countries' of origin economic development, culture or religion can explain our correlation of interest.

## 7.1 Interactions

The results in the previous sections can be rationalized by two conceptually distinct interpretations. One possibility is that the outstanding performance of second-generation immigrants from high PISA countries is a by-product of the fact that their parents received an education of higher quality in their country of origin. While conceptually this would still imply that these students have an advantage in terms of parental influence, the source of this advantage would be the school system in the parents' country of origin, implying a powerful intergenerational multiplier effect of educational quality. In other words, our decomposition would still be valid in an accounting sense, but the underlying force driving the result would be the school system itself, providing an even stronger rationale for policies aiming to replicate the best practices in this domain.

An alternative explanation is that parents from different countries have different attitudes and preferences towards education, which are reflected in the school performance of their children. This variation in cultural traits might have its roots in factors deeply entrenched with a country's history and culture, and improving the educational system might not do much in raising average test scores if these aspects do not change as well.

To discriminate between these views, we explore the heterogeneity of country-specific parental influences with respect to parental characteristics. If the intergenerational transmission of educational quality is important, we expect the correlation between school performance and the PISA score in the parents' country of origin to be particularly strong for students whose par-

[46]For several geographic regions, and notably for the US, $S_{FE}(c, EA)$ is considerably larger than $S_{Parents}(c, EA)$, since in those regions parents are on average more educated than their Chinese counterparts.

ents acquired more education in their home country, and were therefore more exposed to the educational system.[47,48] At the extreme, parents with no education cannot transmit the quality of their home country's school system at all.

On the other hand, if the underlying mechanism is related to cultural traits we expect the country of origin effect to be smaller among parents that are more integrated in their host country and have at least in part converged to its cultural norms. As cultural assimilation takes time, the correlation between children's performance and the average test score in the country of origin should be weaker for parents that have emigrated many years ago.[49] Moreover, there is some evidence that highly educated immigrants have an easier time integrating in their host country: if this is the case, under the "cultural" interpretation, parental years of schooling (acquired either in the home or in the host country), would also alleviate the correlation between their children's performance and the average score in their country of origin.[50]

To summarize, we have testable implications to discriminate between two possible sources of differences in parental influence. The intergenerational transmission of educational quality mechanism would imply a positive interaction term between parental years of schooling acquired in the home country and the average score of natives in the same country. A mechanism based on differences in cultural traits would instead involve a negative interaction between the average test score and parents' years since migration, as well as with parents' years of schooling.

We now turn to the US Census data to put these predictions to empirical scrutiny. We once again restrict attention to second-generation immigrants on the mother's side in the main text.[51] We construct a measure of mothers' years of schooling both in their home and in their host countries based on information on year of immigration and age at the end of education (imputed from the educational level). Year of immigration is available only as a categorical variable, identifying intervals of approximately 5 years. We therefore impute the exact year

[47]This line of reasoning is similar to the one in Schoellman (2012), even though here it is applied to returns to parental education for school outcomes of their children.

[48]It is actually unclear whether only years of schooling in the home country should matter, giver that there could be dynamic complementarities in the human capital accumulation process that make the impact of an additional year of schooling in the host country stronger for parents that have spent the initial part of their educational career in higher quality schools. Moreover, it is possible that parents emigrating from high PISA countries would go to better schools once in the host country. Since we actually find a negative interaction term, this issue is mostly inconsequential for our purposes.

[49]There is widespread evidence that years since migration correlate positively with immigrants' assimilation, as measured by earnings (Chiswick, 1978), naming choices (Sue and Telles, 2007; Abramitzky et al., 2016), intermarriage with natives and other outcomes related to family formation (Glick, 2010). In light of these findings, it is perhaps not surprising that children of parents that have spent more time in the US also fare better in terms of years of schooling, earnings (Abramitzky et al., 2016) and school performance (Nielsen and Schindler Rangvid, 2011), a result that we confirm in our setting (with the caveat that the impact of years since migration is actually heterogeneous depending on the country of origin). Appendix D shows that results are similar when we focus on alternative measures on immigrants' assimilation.

[50]For example, more educated migrants have a higher propensity to intermarry with natives (see Schoen and Wooldredge (1989); Sandefur and McKinnell (1986); Lichter and Qian (2001); Meng and Gregory (2005); Chiswick and Houseworth (2011)), which is an important indicator of integration in the host country. Furtado (2012) considers various possible rationalizations for this pattern, and provides evidence supporting an explanation based on assortative matching on education combined with differences in the schooling distribution across immigrants and natives.

[51]The results for the rest of the sample are available in Appendix B.

of arrival in the US according to two alternative criteria: we assign the middle year of each interval for our baseline results, and the first year for a robustness check.[52]

Table 13 shows our main results. We start by adding to the baseline specification in column 1 an interaction term between $T^m$ and mother's years of schooling, finding a negative and significant coefficient (column 2). When we break down years of schooling between those acquired in the US and those acquired in country $m$ (column 3), we find that the interaction term is negative in both cases, with coefficients of similar magnitudes. Figure 7 plots the coefficient on $T^m$ for different levels of mothers' educational attainment: most of the gap is driven by mothers with either no education or primary schooling only, and the performance of second-generation immigrants from different countries becomes indistinguishable when we focus on mothers with college education. These results are inconsistent with strong intergenerational effects of educational quality.

To offer further visual evidence for this pattern, Figure 9 plots the country-specific (for all countries with at least 100 second-generation immigrants in the sample) intercepts and coefficients on mother's years of schooling from a regression of our outcome of interest on these variables and the usual controls. The correlation between students' performance and the average test score in their mother's country of origin is mostly driven by the intercept, while the variation in returns to education, if anything, works in the opposite direction.[53] This pattern is different from the one documented by Schoellman (2012), who shows that the wage returns to education of US immigrants are positively related to GDP per capita and PISA scores in their home country and interprets this as evidence in favor of the fact that school quality varies across countries. While differences in school quality might be important for immigrants' labor market outcomes, they do not seem to account for the differential school performance of their children.

The study of the heterogeneity with respect to years since migration supports the importance of cultural norms. According to column 4 in Table 13, the correlation between $T^m$ and children's school performance is weaker for mothers that have emigrated many years ago.[54] As shown in Figure 8, the effect of $T^m$ disappears after mothers have spent 25 years in the US, suggesting that a relatively quick convergence of cultural norms might be taking place. Column 5 shows that this pattern (as well as the results on education discussed above) is unaffected by the inclusion of controls for age at migration, which has also been shown to be important

[52] Regardless of the imputation strategy, for a few observations (approximately 2% of the sample) the mother appears to have arrived in the US after her child was born. Since all children in the sample are (according to the Census) born in the US, these might be cases where mothers have moved in and out the US and the recorded date refers to the last time of arrival, or simply instances of coding errors. The results are robust to the exclusion of these observations.

[53] We built the same figure using the PISA data and the results are similar.

[54] This result provides an additional reason why our decomposition exercise in Section 6 might understate the importance of parental influence. If immigrant parents from different countries progressively become more similar to each other as they integrate in their host country, we would find a larger role for parental components by focusing on those who have just emigrated, which are still very comparable to non-emigrants in their country of origin. Unfortunately, the lack of data in the PISA sample on date of immigration prevents us from allowing for this type of heterogeneity.

for the assimilation of immigrants (Bleakley and Chin, 2010; Nielsen and Schindler Rangvid, 2012).

A possible concern is that the imperfect mapping from the information available in the Census to years of schooling accumulated in country $m$ and in the US might confound our results (see the discussion in footnote 48). To alleviate this concern, column 6 in Table 13 shows results for a sub-sample of mothers entirely educated in their country of origin, where year of immigration is imputed according to the most restrictive criterion discussed above. We can see that again the interaction between $T^m$ and mother's years of schooling is negative and significant, and so is the one between $T^m$ and years since migration. Moreover, the magnitudes of the estimated coefficients are virtually identical to the ones obtained with the full sample.

Overall, our results seem supportive of the an interpretation based on country-specific cultural traits, given that our correlation of interest is attenuated by both parental education and integration in the United States.

## 7.2 Time Use

In this section we investigate whether immigrant parents from high PISA countries allocate more time to activities that might plausibly stimulate their children's human capital accumulation.

Table 14 shows our results. Columns 1 to 3 refer to total child care, while columns 4 to 6 break down the time spent with children in the educational, recreative and basic categories described in Section 3. Across all specifications and time use categories, interviewed parents from high PISA countries stand out for spending more time with their children. The result is robust to the inclusion of state fixed effects and several controls on demographic and socio-economic characteristics of both parents and children. Since time use variables are measured in minutes and refer to a single day, from column 3 it emerges that an increase of one (individual-level) standard deviation in the PISA score in a parent's country of origin corresponds to a higher investment of approximately 57 minutes per week in total child care. This extra child care time is quite evenly spread across the three time use subcategories, even though as a proportion of the mean the largest gap is in educational activities.

To parallel the analysis above on the Census data, Figures 10 and 11 show the heterogeneous effects of $T^m$ as a function of the interviewed parent's education and time spent in the US. Unfortunately, the small number of observations in the ATUS prevents us from reaching definite conclusions, but some interesting patterns emerge nevertheless. In Figure 10, while the coefficient for primary school educated parents is estimated very imprecisely, the positive effect of $T^m$ on total time in child care seems to be driven by parents with high-school education, as opposed to college-educated. This is once again inconsistent with an important role for educational quality in parents' country of origin. Figure 11 mimics qualitatively the pattern obtained in Figure 8 for the Census data: the gap in child care time investment is driven only by parents who have migrated recently to the US, with the convergence being rather quick in

this case.

The results in this section indicate that immigrant parents do differ in terms of observable practices as a function of their country of origin. In absence of a credible estimate of the effectiveness of parental child care, it is of course difficult to establish where these differences might be driving the results found in the previous sections.

## 7.3 Country-Level Characteristics

We now present results from specification (1), augmented by a series of controls at the mother's country of origin-level. The main objective of this analysis is to verify whether the estimate of our coefficient of interest picks up variation across country-level characteristics that might plausibly affect second-generation immigrants' school performance.

Table 15 includes controls related to economic development and schooling in country $m$. As on average high-scoring countries in the PISA test are richer and have more educated populations, we want to check whether this gives to second-generation immigrants from those countries some direct advantage which might explain their superior performance. In Columns 2 and 3 we add to the baseline specification in Column 1 controls for contemporaneous log real GDP per capita and average years of schooling in the mother's country of origin, but in both cases the respective coefficients are small and not statistically significant. In Column 5 we further control for a measure of educational quality, the log expenditure per pupil in secondary schools; once again, compared to the baseline regression on the same sample reported in Column 4, the added regressor has negligible explanatory power and our coefficient of interest is not affected.

Table 16 considers controls related to religion and cultural values. Columns 2 includes dummies identifying the religion with the highest adherence in 1970. This is a relevant exercise since the outstanding performance of East Asian students is often anecdotally related to the fact that the Confucian religion places a great emphasis on education and learning, while famously in Weber's thesis the Protestant ethic is associated with virtues like thrift and work ethic that might drive attitudes towards human capital investment. Indeed, religion seems to have explanatory power for student's performance, and our coefficient of interest drops by one third when religion dummies are introduced.

As alternative measures, Column 4 controls for proxies of various cultural traits calculated from answers to the World Value Survey. While, to our knowledge, a direct measure of attitudes towards education is not available, we focus on three proxies that have been studied elsewhere as determinants of labour supply and predisposition to effort in different context: tastes for leisure, locus of control and long-term orientation.[55] All three coefficients are significant and

[55] Among others, Mocan and Pogorelova (2015) and Moriconi and Peri (2015) study country-specific preferences for leisure and labour supply choices, Coleman and DeLeire (2003) and Cebi (2007) estimate the effect of the locus of control on educational and labour market outcomes while Dohmen et al. (2016), Galor et al. (2016) and Figlio et al. (2016) consider how long term orientation shapes human capital investment. Tastes for leisure are measured from a question asking *how important leisure time is in your life*, whose answers (ranging from 1

of the expected signs, in that second-generation immigrants from countries where leisure is considered less important, where people believe to have control on events in their life and are oriented towards the future score better than their peers, even when controlling for school quality. The inclusion of these proxies absorbs some of the effect of our coefficient of interest, which drops by one third.

Overall, the results in Table 16 imply that observable proxies for cultural traits in the parental countries of origin can go some way towards explaining the differential performance across second-generation immigrants. Much of the variation, however, remains unexplained, suggesting that the attitudes or traits underlying educational performance might not entirely captured by the proxies for culture commonly used in the literature.

# 8 Conclusions

While the quality of the educational system and local economic conditions are often named as the key factors for cross-country differences in human capital, this is not the whole story. In this paper we show that an important share of the international variation in test scores is driven by differences in broadly defined parental influences. We arrive to this conclusion through a novel empirical approach, based on the comparison between the performance of second-generation immigrants with parents of different nationalities. While parental influence operates also within schools, a quantitatively relevant channel thorugh which it manifests itself is school choice, highlighting potentially important interactions between parental and schooling inputs for human capital formation.

We also provide suggestive evidence on the importance of deep cultural factors, varying across countries, that lead parents to invest differentially in their children's education. This differential investment is partially reflected in time use practices, but further research is needed to identify the specific activities, attributes or skills responsible for the cross-country variation in parental influence. We do not find any evidence in favor of a mechanism of intergenerational transmission of school quality, and parental education appears to attenuate differences in the supply of culturally-driven parental inputs.

Our paper opens important avenues for future research. If parental attitudes towards education are important determinants of human capital achievement, it becomes crucial to understand how they form and evolve, and why they do so differently across time and space. Historical circumstances experienced in different countries and regions might have played an important role in that respect, and social interactions between people of various origins (brought about, for example, by migration or trade linkages) might have shaped and contributed to the diffusion of different cultural traits.

to 4) are standardized to take mean 0 and standard deviation 1 at the individual level. The locus of control is measured from a question asking *how much freedom of choice and control you feel you have over the way your life turns out*, where answers are again standardized as described above. The measure of long term orientation was developed in Hofstede (1991) and subsequently updated using data from the World Value Survey (Hofstede and Minkov, 2010); it ranges from 0 to 1.

As a whole, our results could be viewed as a sign of caution for policymakers aiming to raise their students' performance in standardized tests. Since cross-country gaps seem to go beyond differences in school quality, it is unclear to what extent traditional policies can be effective to this end, given that the cultural factors that lead parents to invest more or less in children's education might be deeply entrenched and persistent over time.

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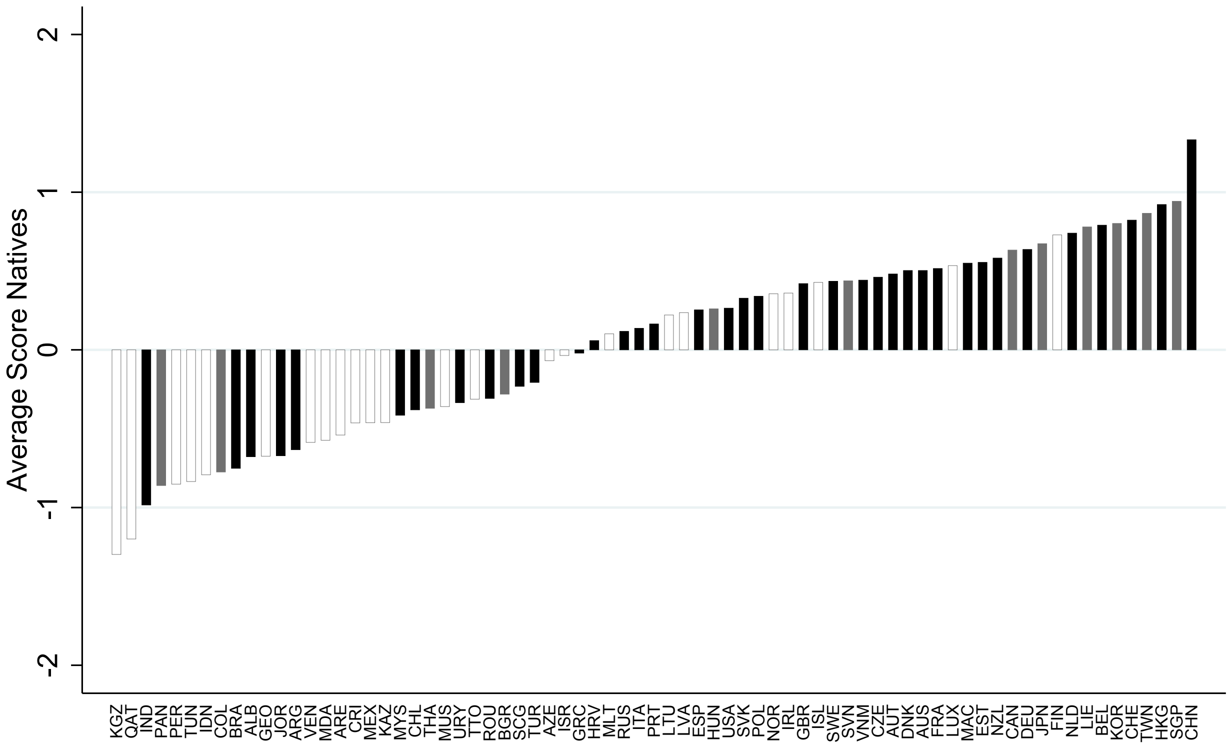
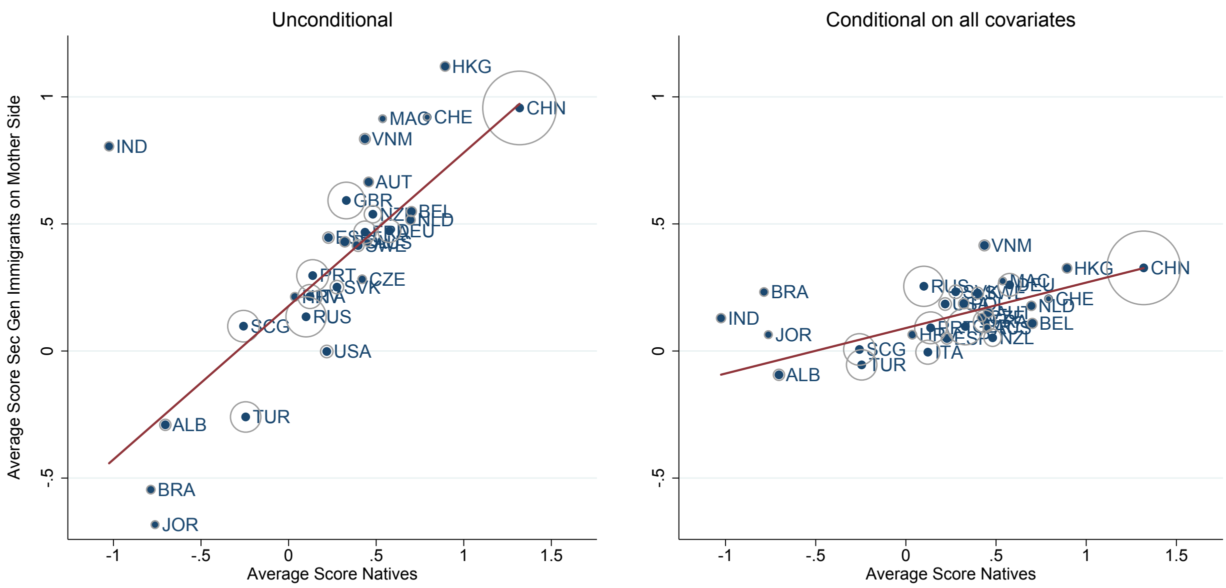
# Figures

Figure 1: Performance of Native Students across Countries



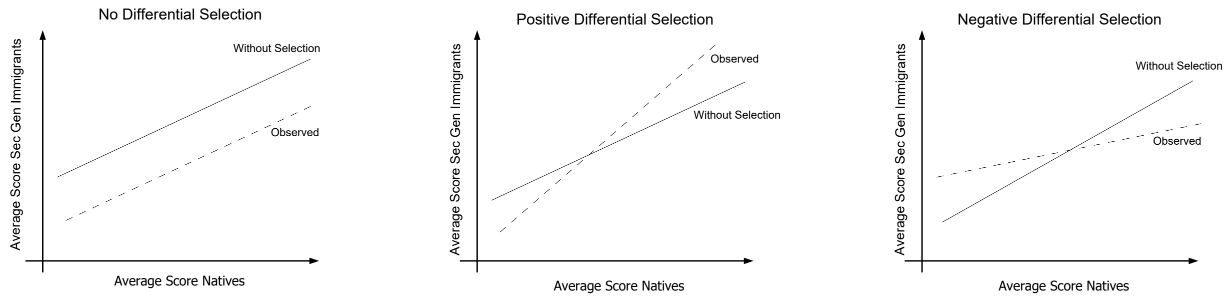

*Notes*: The height of the bar represents the average PISA score in mathematics for native students. Scores are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) 73 countries participating to at least one wave of the test. Black bars refer to countries in the core sample, grey bars to countries for which we observe at least one second generation immigrant but less than 100 immigrant parents.

Figure 2: Performance of Second Generation Immigrants and Natives



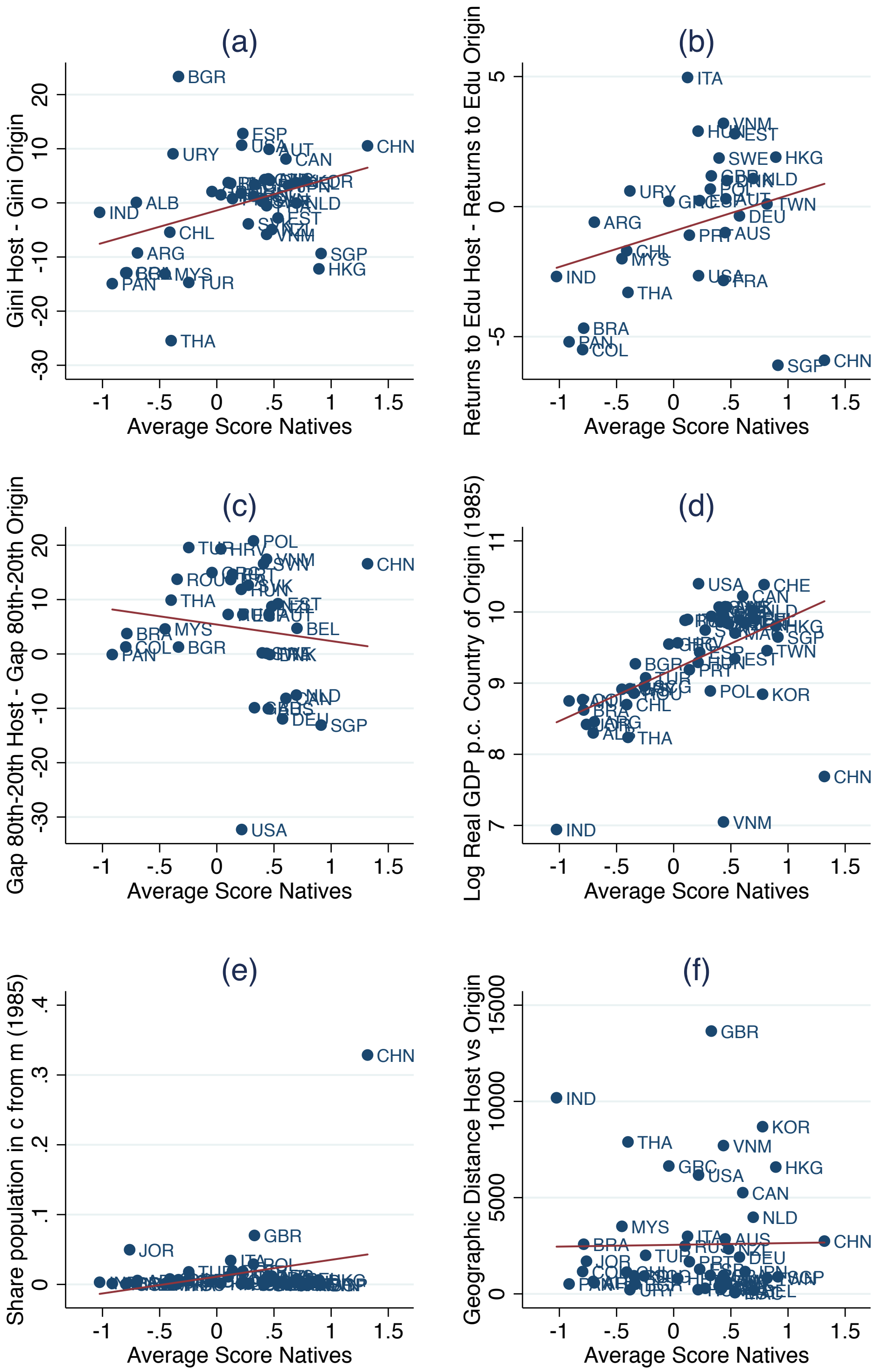

*Notes*: The left panel plots the average PISA score of second generation immigrants whose mother is from country $m$ against the average math PISA score of natives in country $m$, for all countries with at least 100 second generation immigrants on the mother side in the sample. The right panel plots the predicted scores from a regression with individual math scores as dependent variable and fixed effects for mother's country of origin, gender, both parents' education and employment status, father's immigration status and school fixed effects as controls, with all covariates except country of origin fixed effects set at their sample mean and the sample restricted to second generation immigrants on the mother side. The size of the circles is proportional to the number of second generation immigrants on the mother side in the sample. The line shows the best (weighted) linear fit.

Figure 3: Different Types of Selection



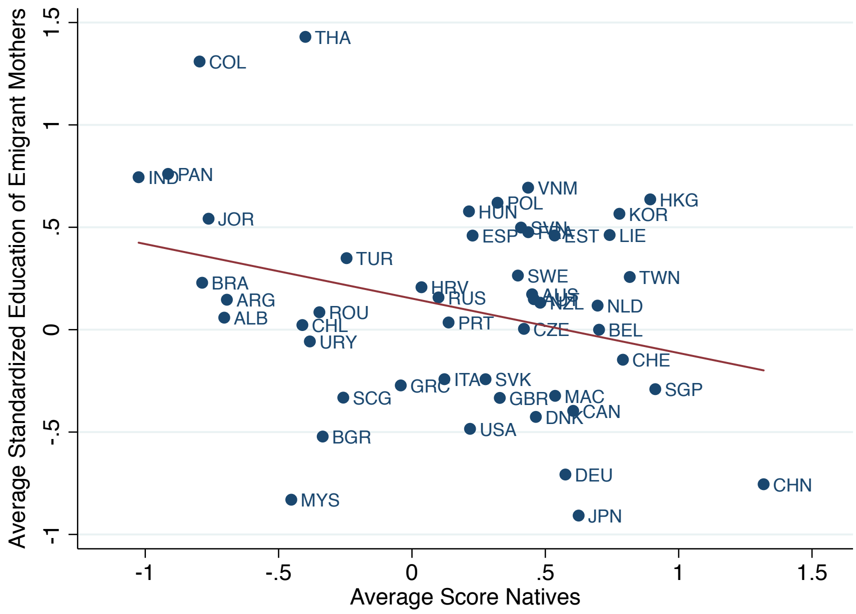

*Notes*: The Figure represents three possible patterns of emigrant parents' selection on unobservables. The first panel refers to the case where emigrant parents are selected to the same extent across all countries of origin. The second (third) panel refers to the case where emigrant parents from high PISA countries are more positively (negatively) selected.

Figure 4: Possible Determinants of Emigrants' Selection



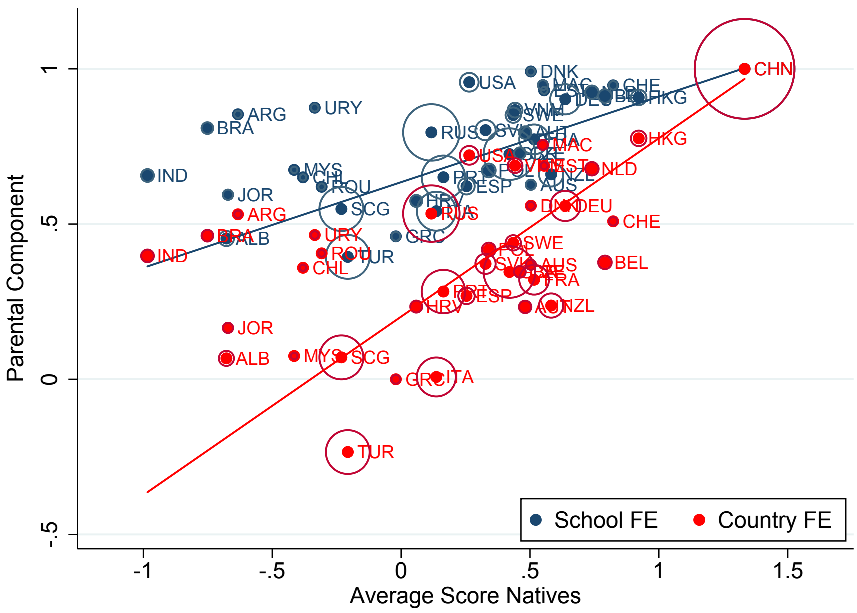

*Notes*: Each Panel plots the relationship between the average score among natives and a possible determinat of emigrants' selection. Panel (a) plots the difference between the average Gini Index faced by emigrants from country $m$ in their respective host countries and the Gini Index in country $m$. Similarly, Panels (b), (c), (e) and (f) plot the difference between the average value faced by emigrants from country $m$ and country $m$'s value for the estimated return to education, the absolute income gap between the $80^{th}$ and the $20^{th}$ percentiles, the share of host country population born in country $m$ and the geographic distance between the host country and country $m$. Panel (d) plots the log real GDP per capita in 1985. The lines show the best linear fits.

Figure 5: Selection on Parental Education



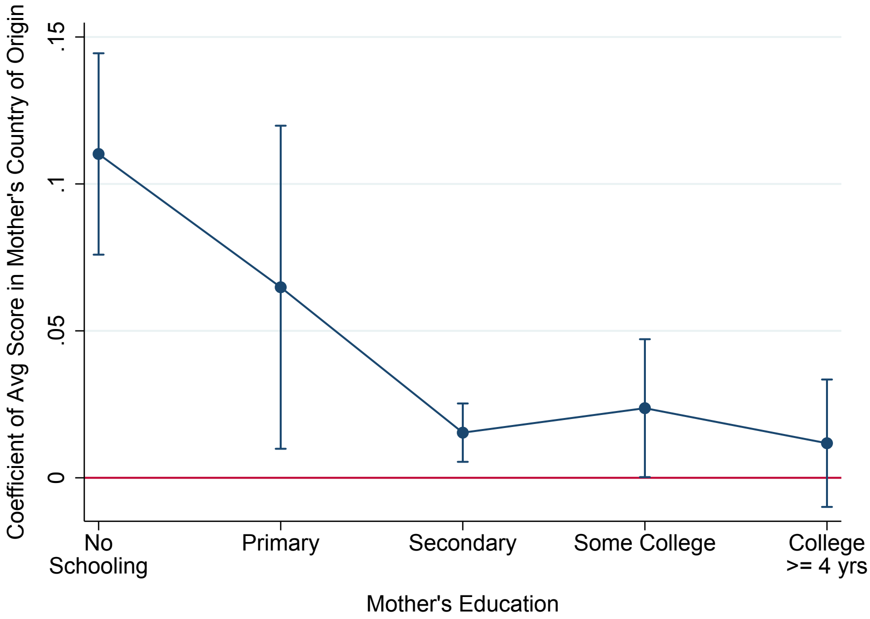

*Notes*: The Figure plots the average years of schooling of emigrant mothers from country $m$ standardized by the average and the standard deviation of years of schooling of non-emigrant mothers in country $m$ (y-axis) against the average PISA score of native students in country $m$ (x-axis). The line shows the best linear fit.

Figure 6: Parental Component



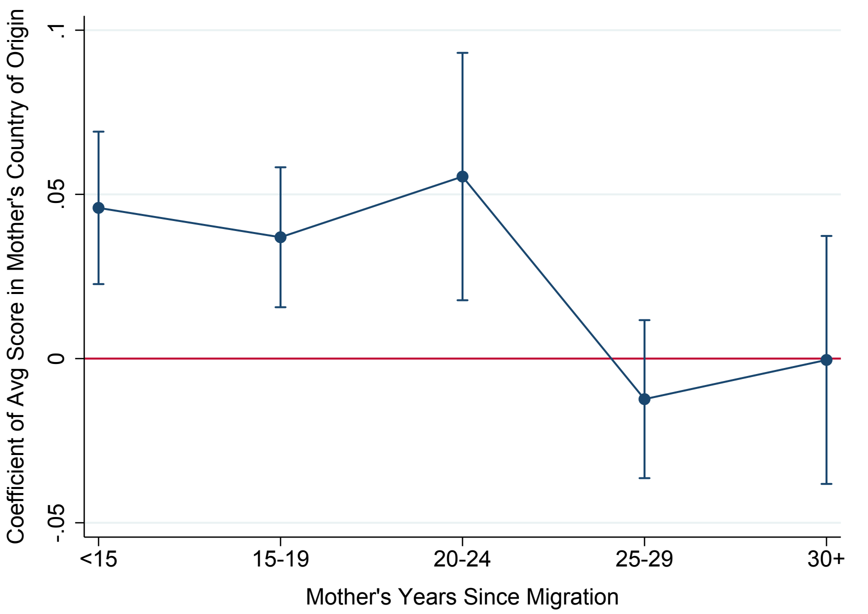

*Notes*: The Figure plots the estimated parental component ($Parents^c$ as defined in Section 6), normalized such that it takes value 1 for China (y-axis) against the average PISA score of natives (x-axis). Only countries with at least 100 immigrant parents in the sample are included. The lines show the best linear fits.

Figure 7: Heterogeneous Effect with respect to Mother's Education - US Census



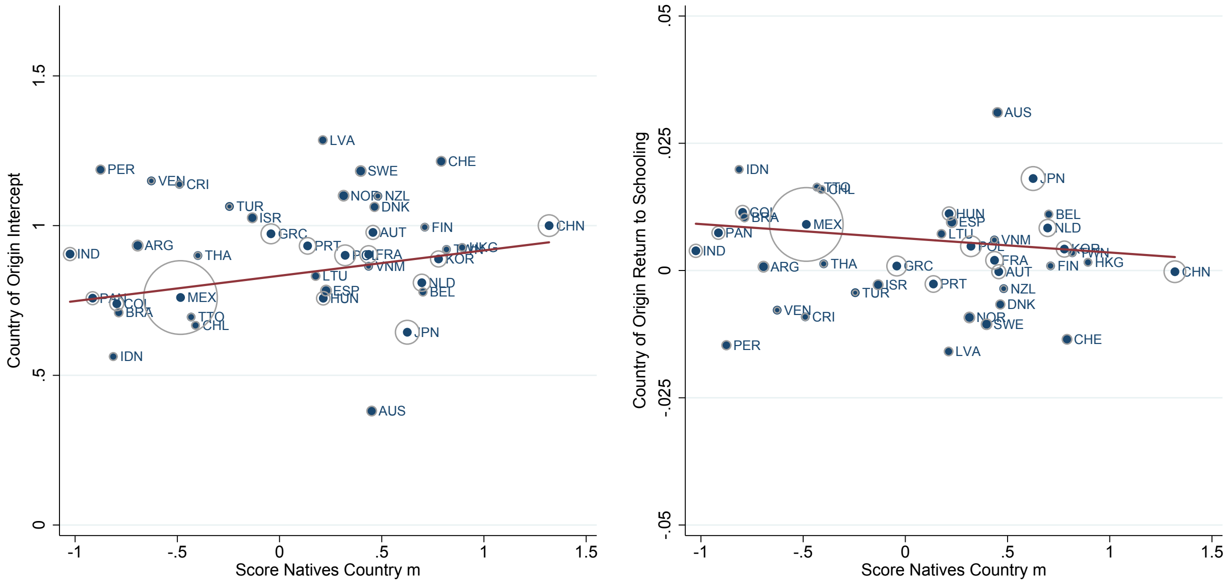

*Notes*: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in mother's country of origin and dummies corresponding to mother's educational achievement, with the dependent variable and other controls being the same as in columns 3-6 of Table 6. Standard errors are clustered by mother's country of origin.

Figure 8: Heterogeneous Effect with respect to Mother's Years Since Migration - US Census



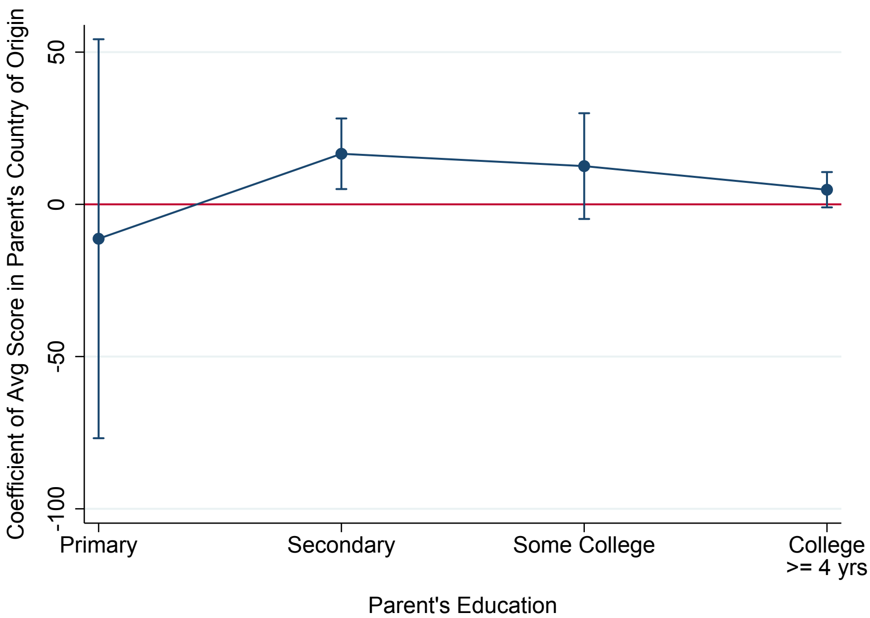

*Notes*: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in mother's country of origin and dummies corresponding to mother's years since migration, with the dependent variable and other controls being the same as in columns 3-6 of Table 6. Standard errors are clustered by mother's country of origin.

Figure 9: Country Specific Intercept and Returns to Parental Education - US Census



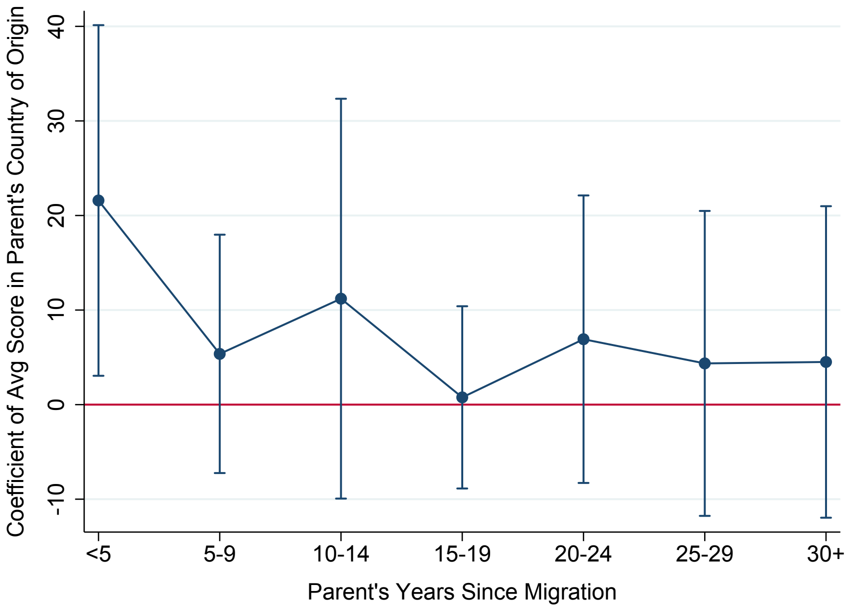

*Notes*: The two panels plot respectively the estimated country-specific intercepts and coefficients on mother's years of schooling from a regression with a dummy for not having repeated any grade as dependent variable. The sample and other controls are the same as in columns 3-6 of Table 6. Only countries with at least 100 second generation immigrants on the mother side are shown. The intercept for China is normalized to 1. The size of the circles is proportional to the number of second generation immigrants on the mother side in the sample. The lines show the best (weighted) linear fits.

Figure 10: Heterogeneous Effect with respect to Parental Education - Time Use




*Notes*: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in the interviewed parent's country of origin and dummies corresponding to parent's educational achievement, with the dependent variable and other controls being the same as in column 3 of Table 14. Standard errors are clustered by mother's country of origin.

Figure 11: Heterogeneous Effect with respect to Years Since Migration - Time Use




*Notes*: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in the interviewed parent's country of origin and dummies corresponding to parent's years since migration, with the dependent variable and other controls being the same as in column 3 of Table 14. Standard errors are clustered by mother's country of origin.

# Tables

Table 1: Average PISA Scores across Regions

| | Math | Reading | Science | # Countries |
|---|---|---|---|---|
| China | 1.33 | 0.96 | 1.07 | 1 |
| Other East Asia | 0.79 | 0.58 | 0.67 | 6 |
| Canada | 0.63 | 0.66 | 0.68 | 1 |
| EU North | 0.57 | 0.53 | 0.58 | 15 |
| Oceania | 0.54 | 0.62 | 0.67 | 2 |
| US | 0.26 | 0.45 | 0.43 | 1 |
| EU South | 0.13 | 0.18 | 0.21 | 5 |
| EU East | -0.08 | -0.16 | -0.06 | 19 |
| Other Asia | -0.42 | -0.38 | -0.36 | 5 |
| Middle East/NA | -0.55 | -0.40 | -0.43 | 7 |
| Latin America | -0.58 | -0.38 | -0.46 | 11 |

*Notes*: The Table shows the average math PISA score across countries belonging to each region, for all available waves (for Science, only waves from 2006 onwards are considered). Country averages are computed using the provided sample weights. Scores are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) 73 countries participating to at least one wave of the test.

Table 2: Second Generation Immigrants by Country of Origin - PISA

| Country of Origin | Mothers: Number | Mothers: # Host Countries | Mothers: Top Host Country | Fathers: Number | Fathers: # Host Countries | Fathers: Top Host Country |
|---|---|---|---|---|---|---|
| Albania | 330 | 5 | Greece (183) | 306 | 5 | Greece (162) |
| Argentina | 69 | 2 | Uruguay (68) | 64 | 1 | Uruguay (64) |
| Australia | 150 | 2 | New Zealand (149) | 117 | 1 | New Zealand (117) |
| Austria | 239 | 2 | Switzerland (181) | 175 | 2 | Switzerland (137) |
| Belgium | 258 | 3 | Luxembourg (244) | 239 | 2 | Luxembourg (219) |
| Brazil | 187 | 4 | Uruguay (78) | 162 | 4 | Uruguay (72) |
| Bulgaria | 30 | 1 | Turkey (30) | 16 | 1 | Turkey (16) |
| Canada | 2 | 1 | Ireland (2) | 2 | 1 | Ireland (2) |
| Chile | 58 | 1 | Argentina (58) | 48 | 1 | Argentina (48) |
| China | 14161 | 12 | Macao (9149) | 13529 | 11 | Macao (8416) |
| Colombia | 5 | 1 | Costa Rica (5) | 5 | 1 | Costa Rica (5) |
| Croatia | 190 | 3 | Serbia-Mont. (101) | 167 | 3 | Serbia-Mont. (81) |
| Czech Republic | 187 | 2 | Slovakia (179) | 176 | 2 | Slovakia (167) |
| Denmark | 75 | 2 | Norway (74) | 91 | 1 | Norway (91) |
| Estonia | 81 | 1 | Finland (81) | 53 | 1 | Finland (53) |
| France | 1312 | 7 | Switzerland (626) | 1110 | 7 | Switzerland (456) |
| Germany | 1364 | 9 | Switzerland (630) | 1086 | 9 | Switzerland (461) |
| Greece | 85 | 2 | Australia (68) | 133 | 2 | Australia (112) |
| Hong Kong | 236 | 2 | Macao (168) | 432 | 3 | Macao (348) |
| Hungary | 16 | 2 | Austria (14) | 15 | 2 | Austria (12) |
| India | 218 | 4 | Australia (189) | 220 | 4 | Australia (187) |
| Italy | 1510 | 9 | Switzerland (1006) | 2606 | 9 | Switzerland (1741) |
| Jordan | 155 | 1 | Qatar (155) | 119 | 1 | Qatar (119) |
| Liechtenstein | 38 | 1 | Switzerland (38) | 27 | 1 | Switzerland (27) |
| Macao | 138 | 1 | Hong Kong (138) | 123 | 1 | Hong Kong (123) |
| Malaysia | 65 | 4 | Australia (53) | 55 | 4 | Australia (45) |
| Netherlands | 226 | 5 | Belgium (195) | 264 | 4 | Belgium (192) |
| New Zealand | 781 | 1 | Australia (781) | 790 | 1 | Australia (790) |
| Panama | 9 | 1 | Costa Rica (9) | 15 | 1 | Costa Rica (15) |
| Poland | 275 | 3 | Germany (211) | 213 | 3 | Germany (173) |
| Portugal | 2646 | 4 | Luxembourg (1762) | 2517 | 5 | Luxembourg (1730) |
| Romania | 49 | 2 | Austria (47) | 55 | 3 | Austria (43) |
| Russia | 4216 | 13 | Estonia (1219) | 4092 | 13 | Estonia (1225) |
| Serbia-Mont. | 2615 | 9 | Switzerland (1548) | 2653 | 9 | Switzerland (1563) |
| Singapore | 8 | 1 | Indonesia (8) | 8 | 2 | Indonesia (7) |
| Slovakia | 472 | 2 | Czech Republic (467) | 569 | 2 | Czech Republic (564) |
| Slovenia | 11 | 2 | Austria (8) | 17 | 2 | Austria (10) |
| South Korea | 42 | 2 | Australia (30) | 43 | 2 | Australia (33) |
| Spain | 334 | 5 | Switzerland (317) | 409 | 4 | Switzerland (391) |
| Sweden | 362 | 2 | Finland (230) | 272 | 2 | Finland (173) |
| Switzerland | 106 | 1 | Liechtenstein (106) | 90 | 1 | Liechtenstein (90) |
| Taiwan | 26 | 1 | Hong Kong (26) | 9 | 2 | Hong Kong (6) |
| Thailand | 13 | 1 | Finland (13) | 2 | 1 | Finland (2) |
| Turkey | 2411 | 8 | Denmark (535) | 2648 | 8 | Switzerland (591) |
| United Kingdom | 3514 | 5 | Australia (2142) | 3659 | 5 | Australia (2313) |
| United States | 407 | 5 | Mexico (198) | 532 | 5 | Mexico (326) |
| Uruguay | 79 | 1 | Argentina (79) | 72 | 1 | Argentina (72) |
| Vietnam | 304 | 4 | Australia (249) | 299 | 3 | Australia (240) |
| Average | 834.69 | 3.38 | | 839.67 | 3.31 | |

*Notes*: The Table shows summary statistics on second generation immigrants from each country of origin in the PISA sample (with at least one observation per parent). *# Host Countries* is the number of different host countries in which second generation immigrants are observed. *Top Host Country* is the host country where the highest number (reported in brackets) of second generation immigrants are observed.

Table 3: Second Generation Immigrants by Host Country - PISA

| Host Country | Mothers | | | Fathers | | |
|---|---|---|---|---|---|---|
| | Number | # Countries of Origin | Top Country of Origin (in PISA) | Number | # Countries of Origin | Top Country of Origin (in PISA) |
| Argentina | 631 | 6 | Uruguay (88) | 585 | 6 | Uruguay (82) |
| Australia | 9022 | 17 | UK (2316) | 9394 | 17 | UK (2500) |
| Austria | 1979 | 15 | Turkey (487) | 1965 | 15 | Turkey (519) |
| Belgium | 3126 | 7 | Turkey (434) | 3524 | 7 | Turkey (492) |
| Costa Rica | 460 | 3 | Panama (11) | 537 | 3 | Panama (16) |
| Croatia | 2160 | 4 | Serbia-Mont. (363) | 1948 | 4 | Serbia-Mont. (348) |
| Czech Republic | 780 | 6 | Slovakia (549) | 1014 | 6 | Slovakia (652) |
| Denmark | 2712 | 6 | Turkey (621) | 2814 | 6 | Turkey (625) |
| Estonia | 1708 | 2 | Russia (1391) | 1839 | 2 | Russia (1390) |
| Finland | 1103 | 10 | Sweden (239) | 1266 | 10 | Sweden (182) |
| Georgia | 97 | 2 | Russia (69) | 76 | 2 | Russia (51) |
| Germany | 1429 | 10 | Turkey (512) | 1515 | 10 | Turkey (559) |
| Greece | 1270 | 3 | Russia (214) | 760 | 3 | Albania (173) |
| Hong Kong | 5447 | 4 | China (4758) | 5296 | 4 | China (4938) |
| Indonesia | 44 | 5 | Singapore (9) | 55 | 5 | Singapore (9) |
| Ireland | 1173 | 17 | UK (946) | 1043 | 15 | UK (814) |
| Israel | 2321 | 5 | Russia (606) | 2474 | 5 | Russia (596) |
| Kazakhstan | 1174 | 2 | Russia (982) | 1117 | 2 | Russia (918) |
| Kyrgyzstan | 480 | 2 | Russia (106) | 297 | 2 | Russia (106) |
| Latvia | 2295 | 4 | Russia (967) | 2593 | 4 | Russia (1107) |
| Liechtenstein | 330 | 11 | Switzerland (114) | 281 | 11 | Switzerland (97) |
| Luxembourg | 4448 | 10 | Portugal (1906) | 4540 | 10 | Portugal (1865) |
| Macao | 10202 | 5 | China (9570) | 9654 | 7 | China (8788) |
| Mauritius | 84 | 4 | China (11) | 57 | 4 | China (8) |
| Mexico | 1085 | 4 | United States (228) | 1398 | 4 | United States (360) |
| Moldova | 203 | 3 | Russia (68) | 192 | 4 | Russia (59) |
| Netherlands | 1741 | 16 | Turkey (203) | 1832 | 16 | Turkey (228) |
| New Zealand | 1989 | 8 | UK (528) | 2144 | 8 | UK (620) |
| Norway | 1145 | 3 | Sweden (144) | 1149 | 3 | Sweden (114) |
| Portugal | 1576 | 5 | Brazil (61) | 1353 | 5 | Brazil (64) |
| Qatar | 5908 | 4 | Jordan (184) | 5159 | 4 | Jordan (145) |
| Serbia-Mont. | 2333 | 4 | Croatia (121) | 1782 | 4 | Croatia (93) |
| Slovakia | 593 | 3 | Czech Republic (206) | 583 | 3 | Czech Republic (177) |
| Slovenia | 1841 | 3 | Italy (8) | 1880 | 3 | Italy (10) |
| South Korea | 29 | 5 | China (11) | - | - | - |
| Switzerland | 8453 | 11 | Serbia-Mont. (1637) | 8320 | 11 | Italy (1844) |
| Turkey | 229 | 5 | Germany (67) | 190 | 5 | Germany (33) |
| UK | 2199 | 7 | China (25) | 2380 | 7 | China (26) |
| Uruguay | 313 | 4 | Brazil (92) | 338 | 4 | Brazil (86) |
| Average | 2156.7 | 6.3 | | 2137.1 | 6.2 | |

*Notes*: The Table shows summary statistics on second generation immigrants observed in each country in the PISA sample, across all available waves. Only host countries with second generation immigrants from at least one country of origin in the PISA sample are included. *# Countries of Origin* is the number of different countries of origin of second generation immigrants in a given host country. *Top Country of Origin (in PISA)* is the country of origin from which the highest number (across all countries in the PISA sample, not considering other countries of origin) of second generation immigrants in a given host country are observed (number reported in brackets).

Table 4: Summary statistics - Second Generation Immigrants on the Mother's Side

| Panel A: PISA Sample | All | | Score Country $m$ Below Median | | Score Country $m$ Above Median | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| Score | 0.29 | 0.92 | 0.10 | 0.87 | 0.75 | 0.88 |
| Score Country $m$ | 0.28 | 0.56 | -0.01 | 0.29 | 0.98 | 0.39 |
| Mother Pri Edu | 0.18 | 0.38 | 0.16 | 0.36 | 0.23 | 0.42 |
| Mother Sec Edu | 0.51 | 0.50 | 0.50 | 0.50 | 0.56 | 0.50 |
| Mother Ter Edu | 0.31 | 0.46 | 0.35 | 0.48 | 0.22 | 0.41 |
| Father Pri Edu | 0.15 | 0.35 | 0.13 | 0.33 | 0.20 | 0.40 |
| Father Sec Edu | 0.51 | 0.50 | 0.49 | 0.50 | 0.55 | 0.50 |
| Father Ter Edu | 0.34 | 0.47 | 0.38 | 0.49 | 0.25 | 0.43 |
| Mother Working | 0.66 | 0.47 | 0.67 | 0.47 | 0.63 | 0.48 |
| Working Mother ISEI | 41.35 | 18.79 | 41.33 | 19.08 | 41.40 | 17.99 |
| Father Working | 0.88 | 0.33 | 0.88 | 0.33 | 0.88 | 0.33 |
| Working Father ISEI | 41.51 | 17.42 | 41.32 | 17.40 | 41.97 | 17.46 |
| Immigrant Father | 0.64 | 0.48 | 0.66 | 0.47 | 0.59 | 0.49 |
| Observations | 40067 | | 20320 | | 19747 | |

| Panel B: US Census Sample | All | | Score Country $m$ Below Median | | Score Country $m$ Above Median | |
|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| No Grade Repeated | 0.81 | 0.39 | 0.76 | 0.43 | 0.85 | 0.36 |
| Score Country $m$ | 0.48 | 0.50 | 0.04 | 0.35 | 0.87 | 0.22 |
| Mother Pri Edu | 0.31 | 0.46 | 0.52 | 0.50 | 0.13 | 0.33 |
| Mother Sec Edu | 0.48 | 0.50 | 0.34 | 0.47 | 0.61 | 0.49 |
| Mother Ter Edu | 0.21 | 0.40 | 0.14 | 0.35 | 0.26 | 0.44 |
| Father Pri Edu | 0.27 | 0.45 | 0.46 | 0.50 | 0.12 | 0.32 |
| Father Sec Edu | 0.39 | 0.49 | 0.32 | 0.47 | 0.46 | 0.50 |
| Father Ter Edu | 0.34 | 0.47 | 0.23 | 0.42 | 0.43 | 0.49 |
| Log Family Income | 10.84 | 0.69 | 10.68 | 0.73 | 10.98 | 0.62 |
| Father Immigrant | 0.46 | 0.50 | 0.63 | 0.48 | 0.31 | 0.46 |
| Yrs Since Migr Mother | 20.08 | 8.75 | 19.20 | 8.85 | 20.84 | 8.59 |
| Student Age | 11.35 | 2.29 | 11.21 | 2.29 | 11.46 | 2.28 |
| Observations | 53081 | | 27071 | | 26010 | |

*Notes*: The Table shows descriptive statistics for second generation immigrants on the mother's side in the PISA (Panel A) and US Census (Panel B) Samples. Only cases where both parents report a country of origin and the country of origin of the mother runs a PISA test on natives are included. Scores are from the math test and are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) 73 countries participating to the test. Observations weighted according to the provided sample weights.

Table 5: Main results - PISA

| | Dependent Variable: Math Test Score | | | | | |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] All | [4] | [5] | [6] No East Asia |
| Score Country $m$ | 0.662*** | 0.499*** | 0.253*** | 0.249*** | 0.240*** | 0.225** |
| | (0.081) | (0.158) | (0.073) | (0.070) | (0.065) | (0.095) |
| Female | -0.140*** | -0.148*** | -0.206*** | -0.204*** | -0.201*** | -0.187*** |
| | (0.032) | (0.028) | (0.022) | (0.022) | (0.022) | (0.024) |
| Father Sec Edu | | | | 0.030 | 0.014 | 0.022 |
| | | | | (0.022) | (0.022) | (0.044) |
| Father Ter Edu | | | | 0.099*** | 0.045 | 0.049 |
| | | | | (0.033) | (0.034) | (0.052) |
| Mother Sec Edu | | | | 0.001 | -0.015 | 0.027 |
| | | | | (0.037) | (0.037) | (0.065) |
| Mother Ter Edu | | | | 0.032 | -0.011 | 0.023 |
| | | | | (0.042) | (0.042) | (0.075) |
| Mother Working × ISEI | | | | | 0.003*** | 0.003*** |
| | | | | | (0.001) | (0.001) |
| Father Working × ISEI | | | | | 0.003*** | 0.003*** |
| | | | | | (0.001) | (0.001) |
| N | 40067 | 40067 | 40067 | 40067 | 40067 | 25454 |
| # Country m | 49 | 49 | 49 | 49 | 49 | 42 |
| R Squared | 0.16 | 0.25 | 0.67 | 0.67 | 0.67 | 0.63 |
| Host Country FE | No | Yes | Yes | Yes | Yes | Yes |
| School FE | No | No | Yes | Yes | Yes | Yes |

*Notes*: The Table shows results for second generation immigrants on the mother's side. The sample includes only cases where both parents report a country of origin and the country of origin of the mother runs a PISA test on natives. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. All specifications control for intercept, students' age (in months), wave fixed effect and a dummy for father's immigrant status; specifications 5-6 additionally control for dummies for parents' employment status (full-time employed, part-time employed, not working). *Working* refers to either full-time or part-time employed. Observations are weighted according to the provided sample weights. Standard errors are clustered by mother's country of origin, and inflated by the estimated measurement error in test scores. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 6: Main results - US CENSUS

| | Dependent variable: 1 = Never repeated a grade | | | | | |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] |
| | | | All | | | No East Asia |
| Score Country $m$ | 0.088*** | 0.059*** | 0.034*** | 0.031*** | 0.028*** | 0.022* |
| | (0.030) | (0.017) | (0.009) | (0.010) | (0.009) | (0.012) |
| Female | 0.068*** | 0.067*** | 0.067*** | 0.068*** | 0.068*** | 0.071*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Mother Sec Edu | | | 0.054*** | 0.051*** | 0.047*** | 0.045*** |
| | | | (0.013) | (0.012) | (0.011) | (0.012) |
| Mother Ter Edu | | | 0.068*** | 0.064*** | 0.054*** | 0.050*** |
| | | | (0.010) | (0.010) | (0.010) | (0.010) |
| Father Sec Edu | | | 0.041*** | 0.041*** | 0.036*** | 0.041*** |
| | | | (0.012) | (0.011) | (0.010) | (0.009) |
| Father Ter Edu | | | 0.072*** | 0.073*** | 0.058*** | 0.063*** |
| | | | (0.015) | (0.014) | (0.011) | (0.011) |
| Log Family Income | | | | | 0.036*** | 0.037*** |
| | | | | | (0.008) | (0.009) |
| N | 53081 | 53081 | 53081 | 53081 | 53081 | 49132 |
| # Country $m$ | 61 | 61 | 61 | 61 | 61 | 54 |
| R Squared | 0.06 | 0.09 | 0.10 | 0.10 | 0.10 | 0.11 |
| Comm Zone FE | No | Yes | Yes | Yes | Yes | Yes |
| Years Since Migr Mother | No | No | No | Yes | Yes | Yes |

*Notes*: The Table shows results for second generation immigrants on the mother's side. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother. All specifications control for intercept, child age dummies, parents' age, number of siblings, year fixed effect, (year specific) quarter of birth fixed effect and father's immigrant status. Observations weighted according to the provided sample weights. Robust standard errors clustered by mother country of origin. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 7: Selection

| | Dependent Variable: Standardized Years of Education | | | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| | Mothers | | Fathers | |
| Score Country $m$ | -0.072 | -0.219 | | |
| | (0.193) | (0.147) | | |
| Score Country $f$ | | | -0.093 | -0.208 |
| | | | (0.193) | (0.145) |
| N | 40067 | 15710 | 40304 | 40304 |
| R Squared | 0.12 | 0.64 | 0.13 | 0.59 |
| Host Country FE | Yes | Yes | Yes | Yes |
| School FE | No | Yes | No | Yes |

*Notes*: The sample includes second generation immigrants on the mother's side for columns (1) and (2) and on the father's side for (3) and (4). The dependent variable is years of education standardized by the average and standard deviation of mothers' (columns 1 and 2) and fathers' (columns 3 and 4) education in the country of origin. *Score Country m* and *Score Country f* are the average math PISA scores of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother and the father. All specifications control for intercept and wave fixed effect. Standard errors are clustered by mother's country of origin in columns (1) and (2) and by father's country of origin in (3) and (4). * denotes significance at 10%, ** at 5%, *** at 1%.

Table 8: Selection into Schools

| | Avg Score School | Estimated School FE | Academic Admission | % Qual Teachers | Dropout Rate |
|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] |
| Score Country $m$ | 0.167* | 0.162* | 0.041* | 0.024** | -0.009** |
| | (0.087) | (0.081) | (0.024) | (0.011) | (0.004) |
| Female | 0.050** | 0.064*** | 0.009 | 0.004 | -0.002 |
| | (0.021) | (0.020) | (0.009) | (0.007) | (0.002) |
| Father Sec Edu | 0.080** | 0.075** | 0.053* | -0.021 | -0.005 |
| | (0.032) | (0.032) | (0.029) | (0.014) | (0.007) |
| Father Ter Edu | 0.161*** | 0.150*** | 0.072** | -0.005 | -0.005 |
| | (0.040) | (0.038) | (0.028) | (0.017) | (0.008) |
| Mother Sec Edu | 0.124*** | 0.122*** | 0.015 | -0.004 | -0.038 |
| | (0.026) | (0.024) | (0.018) | (0.010) | (0.030) |
| Mother Ter Edu | 0.158*** | 0.148*** | 0.009 | -0.010 | -0.039 |
| | (0.039) | (0.037) | (0.027) | (0.016) | (0.028) |
| Mother Working $\times$ Working Mother ISEI | 0.005*** | 0.005*** | 0.001*** | 0.001*** | 0.000 |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) |
| Father Working $\times$ Working Father ISEI | 0.005*** | 0.005*** | 0.000 | 0.001*** | 0.000 |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) |
| N | 42952 | 42903 | 43494 | 32356 | 10184 |
| # Country $m$ | 49 | 49 | 49 | 48 | 41 |
| R Squared | 0.34 | 0.35 | 0.17 | 0.41 | 0.06 |
| Host Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

*Notes*: The sample includes only second generation immigrants on the mother's side. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. All specifications control for intercept and father's immigrant status. Standard errors are clustered by mother's country of origin. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 9: Linguistic and Cultural Distance

| | Dependent Variable: Math Test Score | | | | | |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] |
| Score Country $m$ | 0.220*** | 0.217*** | 0.239*** | 0.241*** | 0.216** | 0.241*** |
| | (0.062) | (0.060) | (0.067) | (0.065) | (0.088) | (0.088) |
| Female | -0.192*** | -0.194*** | -0.201*** | -0.200*** | -0.202*** | -0.201*** |
| | (0.026) | (0.027) | (0.022) | (0.022) | (0.023) | (0.023) |
| Father Sec Edu | 0.012 | 0.010 | 0.015 | 0.015 | -0.015 | -0.018 |
| | (0.022) | (0.023) | (0.021) | (0.021) | (0.057) | (0.059) |
| Father Ter Edu | 0.034 | 0.032 | 0.041 | 0.042 | 0.014 | 0.009 |
| | (0.035) | (0.035) | (0.031) | (0.030) | (0.069) | (0.072) |
| Mother Sec Edu | -0.030 | -0.035 | -0.013 | -0.012 | 0.007 | 0.012 |
| | (0.033) | (0.033) | (0.039) | (0.039) | (0.101) | (0.108) |
| Mother Ter Edu | -0.012 | -0.017 | -0.012 | -0.010 | -0.050 | -0.044 |
| | (0.038) | (0.039) | (0.043) | (0.044) | (0.122) | (0.130) |
| Mother Working $\times$ Working Mother ISEI | 0.002*** | 0.002*** | 0.003*** | 0.003*** | 0.003** | 0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Father Working $\times$ Working Father ISEI | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Foreign Language at Home | | -0.068** | | | | |
| | | (0.028) | | | | |
| Mother Linguistic Distance | | | | -0.001 | | |
| | | | | (0.017) | | |
| Father Linguistic Distance | | | | 0.015 | | |
| | | | | (0.011) | | |
| Mother Cultural Distance | | | | | | 0.002 |
| | | | | | | (0.002) |
| Father Cultural Distance | | | | | | -0.002 |
| | | | | | | (0.003) |
| N | 37827 | 37827 | 38487 | 38487 | 10309 | 10309 |
| # Country m | 49 | 49 | 49 | 49 | 35 | 35 |
| R Squared | 0.67 | 0.67 | 0.67 | 0.67 | 0.68 | 0.69 |
| Host Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: The Table shows results for second generation immigrants on the mother's side, augmented for controls for linguistic and cultural distance. Sample includes only cases where both parents report a country of origin and the country of origin of the mother runs a PISA test on natives. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. All specifications control for intercept, wave fixed effect and a dummy for father's immigrant status. Observations are weighted according to the provided sample weights. Standard errors are clustered by mother's country of origin, and inflated by the estimated measurement error in test scores. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 10: Decomposition Results - Cross-Country Variance

| $V_{Parents}$ (%) | | $V_{FE}$ (%) | |
|---|---|---|---|
| School FE | Host Country FE | School FE | Host Country FE |
| 10.02 | 26.79 | 8.83 | 22.18 |
| (1.90) | (3.71) | (1.88) | (3.75) |

*Notes*: The Table shows the share of the cross-country variance accounted by the whole parental component ($V_{Parents}$) and by the country specific intercept ($V_{FE}$). Only countries with at least 100 immigrant parents in the sample are included in the computation. Standard errors (in parentheses) are computed through a bootstrap with 200 replications at the student level.

Table 11: Decomposition Results - Countries

| | | $Parents^c$ | | $S_{Parents}(c, \text{CHINA})$ (%) | | $S_{FE}(c, \text{CHINA})$ (%) | |
|---|---|---|---|---|---|---|---|
| Country | PISA Score | School FE | Country FE | School FE | Country FE | School FE | Country FE |
| China | 1.33 | 1 | 1 | - | - | - | - |
| | | | | | | | |
| Hong Kong | 0.92 | 0.91 | 0.78 | 22.39 | 54.50 | 20.22 | 41.51 |
| | | | | (19.87) | (19.82) | (19.85) | (19.70) |
| Switzerland | 0.82 | 0.95 | 0.51 | 10.42 | 96.34 | 15.33 | 100.67 |
| | | | | (18.73) | (26.77) | (18.71) | (26.78) |
| Belgium | 0.79 | 0.91 | 0.38 | 16.16 | 115.06 | 22.02 | 121.86 |
| | | | | (23.02) | (34.07) | (23.04) | (34.16) |
| Netherlands | 0.74 | 0.92 | 0.68 | 12.71 | 54.34 | 18.72 | 58.00 |
| | | | | (13.91) | (17.90) | (13.91) | (17.92) |
| Germany | 0.64 | 0.90 | 0.56 | 14.08 | 63.47 | 17.47 | 65.96 |
| | | | | (8.25) | (11.81) | (8.24) | (11.82) |
| New Zealand | 0.58 | 0.66 | 0.24 | 45.30 | 101.61 | 48.11 | 102.28 |
| | | | | (6.36) | (6.96) | (6.37) | (6.92) |
| Estonia | 0.55 | 0.93 | 0.69 | 8.90 | 40.14 | 10.50 | 43.27 |
| | | | | (22.15) | (21.63) | (22.16) | (21.67) |
| Macao | 0.55 | 0.95 | 0.76 | 6.68 | 31.28 | 4.32 | 20.78 |
| | | | | (9.69) | (11.07) | (9.69) | (11.03) |
| France | 0.52 | 0.77 | 0.32 | 27.80 | 83.21 | 29.23 | 85.49 |
| | | | | (5.75) | (8.09) | (5.76) | (8.09) |
| Australia | 0.50 | 0.63 | 0.37 | 45.01 | 76.09 | 48.45 | 78.41 |
| | | | | (14.65) | (18.97) | (14.65) | (18.98) |
| Denmark | 0.50 | 0.99 | 0.56 | 1.01 | 53.18 | 4.13 | 57.76 |
| | | | | (17.87) | (16.93) | (17.89) | (16.94) |
| Austria | 0.48 | 0.79 | 0.23 | 24.10 | 90.07 | 25.15 | 92.06 |
| | | | | (10.44) | (14.77) | (10.44) | (14.79) |
| Czech Republic | 0.46 | 0.73 | 0.35 | 31.17 | 75.01 | 31.06 | 74.56 |
| | | | | (10.05) | (14.41) | (10.07) | (14.40) |
| Sweden | 0.44 | 0.85 | 0.44 | 16.60 | 62.45 | 20.17 | 67.28 |
| | | | | (8.24) | (9.83) | (8.25) | (9.85) |
| Vietnam | 0.44 | 0.87 | 0.69 | 14.92 | 35.01 | 2.79 | 24.01 |
| | | | | (7.25) | (7.81) | (7.24) | (7.77) |
| United Kingdom | 0.42 | 0.73 | 0.35 | 30.11 | 71.74 | 32.09 | 74.09 |
| | | | | (3.88) | (4.09) | (3.89) | (4.08) |
| Poland | 0.34 | 0.67 | 0.42 | 32.98 | 58.65 | 29.61 | 57.28 |
| | | | | (5.70) | (7.53) | (5.70) | (7.52) |
| Slovakia | 0.33 | 0.80 | 0.37 | 19.65 | 62.49 | 17.87 | 61.92 |
| | | | | (7.98) | (9.88) | (7.98) | (9.90) |

*Continued on next page*

| Country | PISA Score | $Parents^c$ | | $S_{Parents}(c, \text{CHINA})$ (%) | | $S_{FE}(c, \text{CHINA})$ (%) | |
|---|---|---|---|---|---|---|---|
| | | School FE | Country FE | School FE | Country FE | School FE | Country FE |
| United States | 0.26 | 0.96 | 0.72 | 4.04 | 26.08 | 7.59 | 29.48 |
| | | | | (5.59) | (8.14) | (5.59) | (8.11) |
| Spain | 0.25 | 0.62 | 0.27 | 35.05 | 67.80 | 32.58 | 64.00 |
| | | | | (5.66) | (10.20) | (5.66) | (10.21) |
| Portugal | 0.16 | 0.65 | 0.28 | 29.89 | 61.40 | 25.14 | 51.82 |
| | | | | (3.70) | (5.24) | (3.70) | (5.25) |
| Italy | 0.14 | 0.54 | 0.01 | 38.35 | 83.00 | 37.27 | 81.87 |
| | | | | (4.19) | (5.91) | (4.19) | (5.92) |
| Russia | 0.12 | 0.80 | 0.53 | 16.85 | 38.37 | 17.77 | 41.78 |
| | | | | (3.97) | (4.25) | (3.97) | (4.26) |
| Croatia | 0.06 | 0.57 | 0.23 | 33.40 | 60.13 | 32.60 | 61.39 |
| | | | | (6.76) | (10.07) | (6.76) | (10.06) |
| Greece | -0.02 | 0.46 | 0.00 | 39.88 | 73.92 | 39.65 | 73.19 |
| | | | | (7.13) | (8.55) | (7.13) | (8.54) |
| Turkey | -0.21 | 0.39 | -0.23 | 39.35 | 80.19 | 34.42 | 71.52 |
| | | | | (2.57) | (3.30) | (2.57) | (3.28) |
| Serbia-Mont. | -0.23 | 0.55 | 0.07 | 28.87 | 59.42 | 28.61 | 60.99 |
| | | | | (2.60) | (3.76) | (2.60) | (3.78) |
| Romania | -0.31 | 0.62 | 0.41 | 23.16 | 36.23 | 21.56 | 37.30 |
| | | | | (5.50) | (6.66) | (5.50) | (6.65) |
| Uruguay | -0.34 | 0.87 | 0.46 | 7.50 | 32.10 | 5.09 | 29.03 |
| | | | | (8.37) | (11.75) | (8.38) | (11.77) |
| Chile | -0.38 | 0.65 | 0.36 | 20.40 | 37.41 | 17.35 | 35.92 |
| | | | | (8.35) | (12.58) | (8.35) | (12.58) |
| Malaysia | -0.41 | 0.67 | 0.07 | 18.63 | 52.94 | 16.71 | 51.62 |
| | | | | (9.85) | (15.45) | (9.85) | (15.46) |
| Argentina | -0.63 | 0.85 | 0.53 | 7.45 | 23.84 | 5.96 | 21.75 |
| | | | | (6.20) | (7.81) | (6.19) | (7.80) |
| Jordan | -0.67 | 0.59 | 0.17 | 20.23 | 41.63 | 19.62 | 41.65 |
| | | | | (3.31) | (3.80) | (3.31) | (3.80) |
| Albania | -0.68 | 0.45 | 0.07 | 27.19 | 46.40 | 24.64 | 45.47 |
| | | | | (2.80) | (3.37) | (2.79) | (3.37) |
| Brazil | -0.75 | 0.81 | 0.46 | 9.16 | 25.79 | 6.31 | 22.26 |
| | | | | (5.09) | (8.45) | (5.09) | (8.46) |
| India | -0.98 | 0.66 | 0.40 | 14.83 | 26.02 | 11.13 | 22.44 |
| | | | | (2.47) | (3.35) | (2.47) | (3.35) |
| Average | 0.17 | 0.73 | 0.32 | 22.24 | 61.93 | 21.91 | 61.15 |
| | | | | (3.32) | (4.11) | (3.32) | (4.13) |

*Notes*: The Table shows the decomposition results across countries. Only countries with at least 100 immigrant parents in the sample are shown. $Parents^c$ is the estimated parental component, normalized such that $Parents^{\text{CHINA}} = 1$. Standard errors (in parentheses) are computed through a bootstrap with 200 replications at the student level.

Table 12: Decomposition Results - Regions

| | | $\overline{Parents}^{c}$ | | $\overline{S_{Parents}(c,\text{CHINA})}$ (%) | | $\overline{S_{FE}(c,\text{CHINA})}$ (%) | |
|---|---|---|---|---|---|---|---|
| Region | PISA Score | School FE | Country FE | School FE | Country FE | School FE | Country FE |
| China | 1.33 | 1 | 1 | - | - | - | - |
| Other East Asia | 0.74 | 0.93 | 0.77 | 14.53 | 42.89 | 12.27 | 31.15 |
| | | | | (11.65) | (11.69) | (9.99) | (10.24) |
| EU North | 0.59 | 0.87 | 0.45 | 17.00 | 76.65 | 20.48 | 80.35 |
| | | | | (5.90) | (8.29) | (5.35) | (7.40) |
| Oceania | 0.54 | 0.64 | 0.30 | 45.15 | 88.85 | 48.28 | 90.34 |
| | | | | (8.34) | (10.52) | (8.65) | (10.93) |
| US | 0.26 | 0.96 | 0.72 | 4.04 | 26.08 | 7.59 | 29.48 |
| | | | | (5.59) | (8.14) | (5.59) | (8.11) |
| EU South | 0.13 | 0.57 | 0.14 | 35.79 | 71.53 | 33.66 | 67.72 |
| | | | | (3.61) | (4.99) | (3.66) | (4.95) |
| EU East | 0.07 | 0.68 | 0.35 | 24.68 | 52.98 | 23.80 | 53.77 |
| | | | | (3.89) | (4.47) | (3.22) | (3.73) |
| Other Asia | -0.32 | 0.73 | 0.39 | 16.13 | 37.99 | 10.21 | 32.69 |
| | | | | (4.39) | (6.05) | (4.13) | (6.02) |
| Middle East/NA | -0.44 | 0.49 | -0.03 | 29.79 | 60.91 | 27.02 | 56.58 |
| | | | | (2.42) | (2.90) | (2.50) | (2.95) |
| Latin America | -0.53 | 0.80 | 0.45 | 11.13 | 29.79 | 8.68 | 27.24 |
| | | | | (5.23) | (7.39) | (5.09) | (7.21) |

*Notes*: The Table shows the average decomposition results across the (equally weighted) countries within each region. $Parents^{c}$ is normalized such that $Parents^{\text{CHINA}} = 1$. Standard errors (in parentheses) are computed through a bootstrap with 200 replications at the student level.

Table 13: Interactions - US CENSUS

| | Dependent variable: 1 = Never repeated a grade | | | | | |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] All | [4] | [5] | [6] Mothers Educated in $m$ |
| Score Country $m$ | 0.030*** | 0.097*** | 0.097*** | 0.150*** | 0.168*** | 0.159*** |
| | (0.008) | (0.024) | (0.025) | (0.033) | (0.038) | (0.038) |
| Female | 0.067*** | 0.067*** | 0.067*** | 0.067*** | 0.067*** | 0.068*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.005) |
| Yrs Edu Father | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Yrs Edu Mother | 0.006*** | 0.007*** | | | | |
| | (0.001) | (0.001) | | | | |
| Score Country $m$ * Yrs Edu Mother | | -0.006*** | | | | |
| | | (0.002) | | | | |
| Yrs Edu Mother in US | | | 0.007*** | 0.003** | 0.006*** | |
| | | | (0.001) | (0.002) | (0.001) | |
| Yrs Edu Mother in $m$ | | | 0.007*** | 0.007*** | 0.007*** | 0.006*** |
| | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Score Country $m$ * Yrs Edu Mother in US | | | -0.007*** | -0.003* | -0.003** | |
| | | | (0.001) | (0.001) | (0.002) | |
| Score Country $m$ * Yrs Edu Mother in $m$ | | | -0.006*** | -0.007*** | -0.007*** | -0.007*** |
| | | | (0.002) | (0.002) | (0.002) | (0.002) |
| Yrs Since Migr Mother | | | | 0.003*** | 0.003*** | 0.004*** |
| | | | | (0.001) | (0.001) | (0.001) |
| Score Country $m$ * Yrs Since Migr Mother | | | | -0.003*** | -0.003*** | -0.003** |
| | | | | (0.001) | (0.001) | (0.001) |
| Age Migration Mother | | | | | 0.006*** | 0.005** |
| | | | | | (0.002) | (0.002) |
| Score Country $m$ * Age Migration Moth | | | | | -0.001 | -0.000 |
| | | | | | (0.001) | (0.001) |
| N | 53081 | 53081 | 53081 | 53081 | 53081 | 29963 |
| # Country $m$ | 61 | 61 | 61 | 61 | 61 | 61 |
| R Squared | 0.10 | 0.10 | 0.10 | 0.11 | 0.11 | 0.12 |
| Comm Zone FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: The Table shows results for second generation immigrants on the mother's side. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. All specifications control for intercept, child age dummies, parents' age, number of siblings, log family income, year fixed effect, (year-specific) quarter of birth fixed effect and father's immigrant status. Observations are weighted according to the provided sample weights. Standard errors are clustered by mother's country of origin. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 14: Time Use of Parents

| | Total | Total | Total | Educational | Recreational | Basic |
|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] |
| Score Country $p$ | 14.636* | 12.822** | 8.188** | 2.208** | 4.087** | 1.894 |
| | (8.489) | (6.319) | (3.448) | (1.100) | (1.711) | (1.857) |
| Mother | | | 66.413*** | 8.449*** | 0.903 | 57.061*** |
| | | | (4.000) | (0.885) | (3.179) | (2.416) |
| Parent Sec Edu | | | -2.355 | 4.482*** | -2.827 | -4.011* |
| | | | (5.617) | (0.674) | (3.285) | (2.138) |
| Parent Ter Edu | | | 4.232 | 3.826*** | -2.526 | 2.932 |
| | | | (3.469) | (1.220) | (2.174) | (1.901) |
| Spouse Sec Edu | | | 3.107 | -1.783* | 6.519** | -1.628 |
| | | | (2.905) | (0.894) | (2.611) | (1.322) |
| Spouse Ter Edu | | | 12.839*** | 2.409 | 7.242*** | 3.188 |
| | | | (3.376) | (1.728) | (2.516) | (2.608) |
| Log Family Income | | | 6.228*** | 0.719 | -1.407 | 6.915*** |
| | | | (2.140) | (0.630) | (0.959) | (1.353) |
| Age Parent | | | 0.234 | 0.097 | 0.064 | 0.073 |
| | | | (0.369) | (0.072) | (0.339) | (0.191) |
| Age Spouse | | | 0.345 | 0.151 | 0.014 | 0.181 |
| | | | (0.235) | (0.094) | (0.198) | (0.251) |
| Number of Children | | | 20.072*** | 3.451** | 1.003 | 15.617*** |
| | | | (2.810) | (1.379) | (0.690) | (1.640) |
| Avg Age Children | | | -8.898*** | -0.263* | -3.338*** | -5.297*** |
| | | | (1.065) | (0.141) | (0.439) | (0.577) |
| Number of Male Children | | | -1.138 | 0.849 | -0.950 | -1.036 |
| | | | (1.680) | (0.545) | (1.046) | (1.031) |
| Yrs Since Migration | | | -0.162 | -0.128*** | -0.120 | 0.086 |
| | | | (0.201) | (0.037) | (0.133) | (0.102) |
| N | 5659 | 5659 | 5659 | 5659 | 5659 | 5659 |
| # Country $p$ | 59 | 59 | 59 | 59 | 59 | 59 |
| Mean Dep. Var. | 89.87 | 89.87 | 89.87 | 10.53 | 22.27 | 57.07 |
| St. Dev. Dep. Var. | 119.98 | 119.98 | 119.98 | 32.30 | 58.06 | 88.63 |
| R Squared | 0.01 | 0.03 | 0.24 | 0.06 | 0.10 | 0.22 |
| State FE | No | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes | Yes | Yes |

*Notes*: The sample includes only immigrant parents of children with at most 18 years. *Parent* refers to the interviewed parent, *Spouse* to the other one; *Mother* is 1 when the interview parent is the mother. *Total* refers to the total time spent in child care activities, while *Educational*, *Recreational* and *Basic* refer to the sub-categories defined in the text. *Score Country p* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the interviewed parent, across all available waves. Additional controls in specifications (3) to (6) are dummies for native spouses and for retired, full time students and disabled parents. Standard errors are clustered by the interviewed parent's country of origin. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 15: Country of Origin Characteristics - Economic and Educational Development

| | Dependent variable: Math Test Score | | | | |
|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] |
| Score Country $m$ | 0.240*** | 0.254*** | 0.210*** | 0.214*** | 0.214*** |
| | (0.065) | (0.061) | (0.063) | (0.065) | (0.063) |
| Female | -0.201*** | -0.201*** | -0.200*** | -0.216*** | -0.216*** |
| | (0.022) | (0.022) | (0.022) | (0.019) | (0.019) |
| Father Sec Edu | 0.014 | 0.012 | 0.013 | 0.014 | 0.014 |
| | (0.022) | (0.022) | (0.022) | (0.023) | (0.023) |
| Father Ter Edu | 0.046 | 0.044 | 0.045 | 0.053 | 0.053 |
| | (0.034) | (0.034) | (0.034) | (0.041) | (0.041) |
| Mother Sec Edu | -0.015 | -0.015 | -0.022 | -0.036 | -0.036 |
| | (0.036) | (0.037) | (0.036) | (0.032) | (0.032) |
| Mother Ter Edu | -0.012 | -0.010 | -0.020 | -0.055 | -0.055 |
| | (0.042) | (0.042) | (0.045) | (0.041) | (0.042) |
| Mother Working $\times$ ISEI | 0.003*** | 0.003*** | 0.003*** | 0.003** | 0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Father Working $\times$ ISEI | 0.003*** | 0.003*** | 0.003*** | 0.003** | 0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Log GDP | | -0.038 | | | |
| | | (0.036) | | | |
| Avg Years Edu in $m$ | | | 0.011 | | |
| | | | (0.011) | | |
| Log Exp per Pupil in $m$ | | | | | -0.003 |
| | | | | | (0.024) |
| N | 40029 | 40029 | 40029 | 31502 | 31502 |
| # Country m | 48 | 48 | 48 | 42 | 42 |
| R Squared | 0.67 | 0.67 | 0.67 | 0.70 | 0.70 |
| Host Country FE | Yes | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes | Yes |

*Notes*: The Table shows results for second generation immigrants on the mother's side. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. Observations are weighted according to the provided sample weights. Standard errors are clustered by mother's country of origin, and inflated by the estimated measurement error in test scores. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 16: Country of Origin Characteristics - Religion and Culture

| | Dependent variable: Math Test Score | | | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| Score Country $m$ | 0.240*** | 0.161*** | 0.251*** | 0.158*** |
| | (0.065) | (0.055) | (0.071) | (0.060) |
| Female | -0.201*** | -0.198*** | -0.201*** | -0.198*** |
| | (0.022) | (0.022) | (0.022) | (0.023) |
| Father Sec Edu | 0.014 | 0.014 | 0.016 | 0.014 |
| | (0.022) | (0.022) | (0.022) | (0.022) |
| Father Ter Edu | 0.045 | 0.045 | 0.047 | 0.043 |
| | (0.034) | (0.034) | (0.034) | (0.034) |
| Mother Sec Edu | -0.015 | -0.026 | -0.014 | -0.020 |
| | (0.037) | (0.034) | (0.038) | (0.034) |
| Mother Ter Edu | -0.011 | -0.028 | -0.010 | -0.020 |
| | (0.042) | (0.043) | (0.043) | (0.043) |
| Mother Working $\times$ ISEI | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Father Working $\times$ ISEI | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Eastern Religion | | 0.326*** | | |
| | | (0.077) | | |
| Hindu | | 0.336*** | | |
| | | (0.101) | | |
| Muslim | | -0.114** | | |
| | | (0.056) | | |
| Orthodox | | 0.036 | | |
| | | (0.050) | | |
| Protestant | | 0.115** | | |
| | | (0.045) | | |
| Leisure Important in Life | | | | -0.247*** |
| | | | | (0.070) |
| Locus of Control | | | | 0.266** |
| | | | | (0.112) |
| Long Term Orientation | | | | 0.237* |
| | | | | (0.125) |
| N | 40029 | 40029 | 39882 | 39882 |
| # Country $m$ | 48 | 48 | 46 | 46 |
| R Squared | 0.67 | 0.68 | 0.67 | 0.68 |
| Host Country FE | Yes | Yes | Yes | Yes |
| School FE | Yes | Yes | Yes | Yes |

*Notes*: The Table shows results for second generation immigrants on the mother's side. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. Observations are weighted according to the provided sample weights. Standard errors are clustered by mother's country of origin, and inflated by the estimated measurement error in test scores. * denotes significance at 10%, ** at 5%, *** at 1%.