Parents, Schools and Human Capital Differences across Countries*

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Abstract

We argue that differences in parental influence contribute to cross-country gaps in human capital achievements. 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 international standardized tests do better than their peers. The gap is larger when 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. Parental influence accounts for between 14% and 20% of the cross-country variance in test scores.

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1 Introduction

Human capital varies greatly across countries, in terms of both years of schooling (Barro and Lee, 2013) and results in international standardized tests. East Asian countries consistently position themselves at the top of international test rankings, while several Southern European and Latin American countries perform poorly. An emerging strand of the growth literature argues that human capital accounts for a substantial part of cross-country differences in economic performance (Schoellman, 2012; Jones, 2014; Lagakos et al., 2016), especially when measured by standardized tests (Hanushek and Woessmann, 2012a).

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.[1] More broadly, the literature on cross-country differences in educational attainment emphasizes country-specific factors such as access to public education, sectoral composition and skill premia that shape the costs and expected benefits of human capital investments. On the other hand, studies on skill formation at the individual level argue that parents and the home environment are of great importance (Almond and Currie, 2011). A natural question then is whether variation in these factors is relevant also at the country level.[2]

In this paper we investigate how much of the cross-country variation in test scores can be attributed to differences in broadly defined parental influence, and what the nature of these differences is in the first place. The analysis involves difficult challenges. Parental influence is generally unobservable, and, even when proxies are available, cross-country comparisons cannot separately identify its contribution from the one of school quality or other institutional factors. We overcome these difficulties by adopting an indirect approach, based on the analysis of second-generation immigrants. We compare 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 educational curriculum, teachers and the institutional setting (as well as other individual-level characteristics) are kept fixed in this comparison, we argue that we can reasonably attribute any residual difference to differential influences exerted by parents. We then use the results from this empirical exercise to decompose the cross-country variation in test scores between different sources, shedding light on the nature of these gaps.

[1] The popular press is rich of anecdotes about the severity of school curricula in East Asian countries. For a recent example, see Jeevan Vasagar, "Why Singapore's kids are so good at maths", *Financial Times*, July 22, 2016.

[2] 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 demanding Asian mothers, focusing on their children's academic excellence.

Our results point towards a substantial role for parents. First, we document that the PISA performance of second-generation immigrant pupils, living in the same country and studying in the same school, is closely related to the one of natives from the country of origin of their parents: the best performing second-generation immigrants are those whose parents come from countries where natives are particularly successful in standardized tests.[3] This holds true when controlling for parental education, socio-economic status and other characteristics of parents' countries of origin. Moreover, we find a similar result for a different schooling outcome in a specific host country, which is grade repetition in the United States. These findings do not appear to be driven by a pattern of differential selection into emigration.

We construct a country-specific measure of parental influence, which combines the estimated effect of average observable and unobservable (as captured by country of origin fixed effects) parental characteristics. According to our estimates, between 14% and 20% of the total cross-country variation in test scores can be accounted for by differences in this term. Parental influence is responsible for a substantial share of the East Asian out-performance: on average, between 22% and 58% 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 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 parents have spent more years in the host country, suggesting the importance 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. Finally, time use data for immigrants in the US show that parents from high PISA countries spend more time on various forms of child care.

This paper contributes to the debate on cross-country differences in human capital. Several papers study the importance of characteristics of the school system (Woessmann, 2016), while other contributions focus on country-specific factors that shape human capital investment (Bils and Klenow, 2000; Manuelli and Seshadri, 2014; Schoellman, 2016). Our emphasis on parents is shared by Doepke and Zilibotti (2017), who develop a model of preference transmission to explain the international variation in parenting styles as a function of

[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. On average, across countries participating to the PISA test, natives represent 78% of the target population. Students born in a country different from the one where they are taking the test are excluded from the analysis.

local economic conditions. We contribute to this literature by quantifying and characterizing cross-country differences in parental influence, in a setting where other country-specific factors are arguably not operative.

We also relate 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.[4] In addition, we conduct our analysis on a broad sample of host and origin countries (while, for example, Dustmann et al. (2012) focus on Turkish immigrants, and Jerrim (2015) on East Asian immigrants), and we rely on several additional sources to provide evidence on the mechanisms underlying our results.

Our paper shares the approach of a large literature that looks at first- and second-generation immigrants to identify the importance of "portable" cultural traits for various outcomes (the so-called "epidemiological approach"; see among others Giuliano, 2007; Fernandez and Fogli, 2009; Fernandez, 2011). Differently from these papers, we study the school performance of the second generation, and use the results to quantify the importance of parents for cross-country differences in the same outcome. While most of the focus in this literature is on immigrants 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 influence, and clarifies which our empirical approach can capture. Section 3 describes the data, while Section 4 shows evidence on the performance of second-generation immigrants. Section 5 addresses selection. Section 6 quantifies the importance of parental influence, while Section 7 explores the mechanisms behind our results. Finally, Section 8 concludes.

[4] Most papers have focused on the comparison between immigrants and natives in the host country. Like us, Levels et al. (2008) 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. We discuss this and other channels through which immigrant parents' ethnic network might affect children's human capital accumulation in Appendix D.

[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.

2 Parental Influence: Definition and Discussion

Parental influence on children's human capital can manifest itself through a number of 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. Parents shape children's attitudes towards education and effort, and might have an indirect influence through the example they provide. The genetic transmission of traits that affect learning ability and preferences could also play a role.

Our measure of parental influence, based on school performance gaps across second-generation immigrants, includes the effect of all inputs listed above. While Section 7 speaks to the relative importance of some of these channels, the extent to which we can discriminate between them is limited by the fact that most of these factors are difficult to measure.

An important qualification concerns the *reason* behind the supply of different levels of parental inputs. Parents' choices are partially driven by *context-specific* incentives: for example, higher expected returns to skills in the labour market might induce parents to stress the importance of education and hard work (Doepke and Zilibotti, 2017). 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 fall into this category.

What do we pick up by comparing second-generation immigrants? Institutional factors and the educational system are 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, labor markets with similar characteristics. The relevant source of variation is represented by *embedded* factors, which might differ across parents because of cultural traits or skills inherited from their country of origin.

Taking stock of this discussion, our methodology allows us to isolate the importance for cross-country differences in human capital of inputs driven by factors *embedded* into parents. This is an interesting 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. The test covers three subjects: reading, mathematics and science. 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.[6]

Results for all subjects vary greatly across countries. Figure I shows the average math score of native students for all countries that participated to at least one wave of the PISA test (pooled across all available waves). Chinese students score 1.3 standard deviations higher than the average, and almost 3 standard deviations better than the worst-performing countries.[7] 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 Latin American countries are below the average. The superior performance of East Asian students is stronger in mathematics, but the ranking across regions is quite stable across subjects (see Table A.1 in the Appendix for the average scores in these and other broadly defined regions).

[Figure I about here]

A Student Questionnaire provides basic demographic information on students and parents, including their country of birth, education, employment and the ISEI index of socioeconomic status.[8] Our sample includes 40,067 second-generation immigrants on the mother's side and 40,304 on the father's side, from 49 and 48 different countries of origin and distributed across 39 host countries.[9] Sample sizes vary greatly, and for some countries of origin we have only a few parents to work with (see Tables A.2 and A.3 in the Appendix for summary statistics by origin and host country). 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 for a "core sample" of 37 countries from which we have at least 100 emigrant parents. Solid bars in Figure I correspond to countries for which we observe second-generation immigrants, and the black ones

[6]The results are not presented as point estimates but rather as "plausible values": the OECD estimates for each student a probability distribution of scores, and randomly draws from it five values. Following OECD (2009), we compute 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.

[7]The PISA test in China is held in Shanghai only, and is not representative of the whole country. In contrast, Chinese-born emigrant parents in our sample might come from any part of the country. This suggests a pattern of selection likely to work against our main result; see Section 5 for a detailed discussion.

[8]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 combining information on average income and education of full-time employed men across several countries.

[9]Individual countries have flexibility on how to classify parents' country of origin. We construct a set of countries consistently defined over time. See Appendix A for the details.

identify the “core sample”. Descriptive statistics for second-generation immigrants on the mother’s side are provided in Panel A of Table I.

[Table I about here]

Our second source is the US Census. We use the 1% sample for 1970 and 5% sample for 1980. We follow Oreopoulos and Page (2006) in combining information on children’s age and grade currently attended to construct an indicator of whether or not students have repeated any grade.[10] 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.[11] We focus on children between the ages of 8 and 15. The final sample includes 53,081 second-generation immigrants on the mother’s side and 46,410 on the father’s side, from 61 countries of origin. Descriptive statistics are provided in Panel B of Table I.

We use the 2002 to 2013 waves of the ATUS-US Time Use Survey to analyze how immigrant parents spend their time. The survey is administered to one person per household, chosen randomly among all individuals at least 15 years old. We compute the total time (in minutes) spent on child care on the previous day, and, following Aguiar and Hurst (2007), three subcategories that split total child care in educational, recreational and basic activities.

Finally, we rely on several other sources to construct our controls at the level of parents’ country of origin. We use 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) and various proxies for cultural differences from the World Value Survey.

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. We focus here on second-generation immigrants on the mother’s side only. This is only to simplify the exposition, and in Appendix B we 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. We present results for the PISA and the US Census samples in turn.

[10] Current grade is only available until 1980, which prevents us from using more recent years.

[11] This grade-for-age measure induces some misclassification, as, for example, students entering school late will be classified as grade repeaters. As discussed in Cascio (2005), this type of misclassification will lead to some attenuation bias in all regressions using the grade repetition proxy as outcome variable.

4.1 PISA

The left panel of Figure II plots the average score of second-generation immigrants against the average score of natives in the country of origin of their mother, pooled across all available waves. The relationship is positive and tight. While the cross-country variation in natives' performance reflects a combination of school quality, economic, cultural and institutional factors, the fact that these gaps are largely preserved across second-generation students in other countries suggests that parents might play an important role. Of course, this pattern might be driven by factors unrelated to systematic differences in parental influence across countries. We investigate several potential confounders in our regression analysis.

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.[12] We estimate variants of the following specification:

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

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 students and parents, θ_{cs} is a host country or school (depending on the specification) fixed effect, θ_t is a PISA wave fixed effect and ε^m_{icst} is an error term. We include in X^m_{icst} various parental characteristics likely to be correlated with human capital investments on children, such as parental education, employment status and, for those who are employed, the ISEI index of occupational status.[13] Moreover, by introducing host country (or school) fixed effects we control for differences in the characteristics of the institutional context (or specific school) students are exposed to. The main coefficient of interest is θ_1, which captures the relationship between a second-generation immigrant's performance and the average score of native students in country m.

Table II shows our 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. Standard errors are clustered at the level of the mother's country of origin, and inflated by the estimated measurement error in test scores.[14]

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

[13]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.

[14]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. In Appendix B we discuss the details of this procedure, and show that the statistical significance of our results is robust to alternative ways to construct the standard errors.

[Table II about here]

We proceed by progressively adding controls. Column 1 controls for students' baseline characteristics (gender and age in months), fathers' immigrant status and wave fixed effects only. The correlation of interest 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 of 66% of a standard deviation among second generation immigrants. The coefficient shrinks when we introduce host country (column 2) and, especially, school (column 3) fixed effects, but is still positive and significant. A comparison between the first two specifications and column 3 suggests that, within the same host country, mothers from high PISA countries might send their children to better schools.[15]

Column 4 adds controls for parental education, with the coefficient of interest being hardly affected. This suggests that the estimate of θ_1 is unlikely to be driven by some unobservable parental skills, since we would expect those to be correlated with parental education, and therefore the inclusion of this last variable to matter a lot for our coefficient of interest. Similarly, the introduction of controls for employment and occupational status in column 5 does not change the coefficient of T^m.[16] The last column of Table II shows that results are not driven only by the performances of students with East Asian origins, since the coefficient is robust to the exclusion of East Asian mothers.

The right panel of Figure II displays the main result of this section. After we clean the scores of second-generation immigrants from the effect of observable characteristics, including school fixed effects, the relationship between the performance of second-generation immigrants and natives in the mother's country of origin country weakens but is still positive and significant.

4.2 US Census

We apply a similar specification as in equation (1) on the US Census data. The dependent variable is a dummy which takes value one if a child has never repeated any grade. This outcome, while still related to school performance, captures quite a different dimension compared to the PISA score, given that the variation here 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 I) and from students aged 8-15 (while PISA is administered to 15-year-old students only).

[15] In Appendix C we show that indeed, after controlling for country fixed effects and the usual observable characteristics, a higher PISA score in the country of origin of the mother is positively correlated with several proxies for school quality.

[16] In Appendix B we show that the results are robust to the inclusion of alternative measures of socio-economic status available in the PISA dataset.

The US Census does not include any information on the school children are attending. To capture some of the differences across educational systems within the US, we control for Commuting Zone fixed effects.[17] Compared to the PISA sample, we can control here for a richer set of family characteristics, such as number of siblings, child's and parents' age and family income, as well as for the number of years passed since the mother has migrated to the US.

Table III 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 2.8 percentage points (3% over the average). As for the PISA specification, the result is robust to the exclusion of East Asian mothers (column 6).

[Table III about here]

5 Selection

As our analysis relies on emigrant parents to make inference on all parents of a given nationality, a concern is that emigrants are not a random sample of the population, and might be selected on unobservable characteristics (such as skills and preferences for education) that matter for children's school performance.[18]

What type of selection should we worry about? Figure III displays various possibilities. 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.

[Figure III about here]

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

[18] The discussion in this session focuses on selection into emigration. A distinct issue is, conditional on emigration, selection into host countries where parents have different prospects of assimilation. In Appendix C we show that controlling for measures of linguistic and cultural distance between the origin and the host country does not affect our results.

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.

To understand which case is relevant in our setting, we look at differential selection in terms of parental education. While the main threat to our approach is differential selection on unobservables, it seems plausible that several unobservable parental traits that positively affect children's school performance (such as skills and attitudes towards schooling) are positively correlated with parents' own educational achievements. We can therefore 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.[19]

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.[20] Figure IV plots the average of this measure across mothers' countries of origin against the average score of native students in those countries. For a majority of countries of origin emigrant mothers are positively selected (that is, our measure is greater than 0), a finding 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 is negative, especially when weighted by the number of second generation immigrants in the sample (the unweighted relationship is flatter, though still negatively sloped). Emigrant mothers from high PISA countries are more adversely selected in terms of education than those from low PISA countries (panel 3 of Figure III).[21]

[19]Ideally, we would like to perform such an exercise with a measure of quality pre-determined with respect to migration. 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 their host countries, or have based their educational choices in their countries of origin anticipating their future relocation. In the Census data it is possible to alleviate these concerns by focusing on parents that completed their education in the country of origin (see Appendix C). However, 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.

[20]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).

[21]The results for China might appear in contrast with 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

In addition, Table IV 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. For both mothers and fathers, the point estimates are negative and not statistically significant, suggesting that the type of differential selection that would invalidate our results is not present neither within host countries nor within schools.

[Figure IV and Table IV about here]

We conclude this section by noticing that our results are consistent with the patterns of selection reported in the development accounting literature. Schoellman (2012) documents that, among migrants (not necessarily parents of school-age children) residing in the US, the education gap compared to non-migrants is higher for poor origin countries. Hendricks and Schoellman (2016) show that emigrants from poor countries are more positively selected in terms of pre-migration wages and occupations.[22]

6 Decomposition

This section quantifies the role of parental influence in accounting for cross-country differences in average test scores. For this purpose, we introduce a more general model, which allows both maternal and paternal influence to differ across countries and includes both natives and second-generation immigrants.[23] Suppose that the test score in wave t of student i, educated in school s and country c, whose mother and father were born in countries m and f is given by

$$T_{icst}^{mf} = Parents_{icst}^{mf} + \theta^m NatMoth_{icst}^{mf} + \zeta^f NatFath_{icst}^{mf} + \rho' Z_{icst}^{mf} + \alpha_{cs} + \alpha_t + \varepsilon_{icst}^{mf} \quad (2)$$

where $Parents_{icst}^{mf}$ represents parental influence, and is given by

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

is still negative, the Chinese are relatively positively selected. This discrepancy is explained by the fact that 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. While Chinese emigrants are positively selected compared to Chinese non-emigrants as a whole, they are negatively selected compared to the population involved in the PISA test.

[22]More broadly, our results are consistent with a large literature studying the determinants of emigrants' self-selection, such as income inequality, migration costs, social networks, geography and school quality. See Appendix C for a detailed discussion.

[23]While the linear specification considered here is still restrictive, in Appendix E we show that considering dfferent types of complementarities does not majorly alter our conclusions.

with γ^m and δ^f being country-specific components capturing a set of average (unobservable) characteristics of mothers and fathers from countries m and f respectively. Parental influence includes also the effect of parents' education and occupational status.[24]

In (2), $NatMoth_{ist}^{mf}$ and $NatFath_{ist}^{mf}$ are dummies identifying native parents (mothers and fathers, respectively). The coefficient θ^m (and similarly ζ^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. 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 (see footnote 28 for further discussion on this point). In addition, Z_{icst}^{mf} includes controls for student's gender and age in months.

Differences in school quality are captured by either host country or school fixed effects.[25] The distinction between the two specifications is important, given that, within the same host country, students from high PISA countries seem to attend better schools. This within-country variation in school quality is attributed to parental influence in the host country fixed effect specification, but not when school fixed effects are introduced. While the selection of better schools is one of the channels through which parental influence manifests itself, for the purpose of explaining differences in the average performance of natives across countries, the extent to which differences in the average ability or willingness to select better schools can matter is limited by the available supply of school quality in each country.[26] We display results from both specifications, with the understanding that controlling for school fixed effects provides us with a lower bound for the importance of parental influence.

Combining (2) and (3) we obtain our main specification

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

[24]Specifically, $ParentsEdu_{icst}^{mf}$ contains dummies for primary, secondary or tertiary education for each parent, while $ParentsOcc_{icst}^{mf}$ 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.

[25]These fixed effects also absorb the impact of any other institutional factor that influences directly or indirectly students' performance. Importantly, this includes 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.

[26]At one extreme, if all schooling resources are utilized to full capacity, endowing a country with a higher average parental effectiveness in school selection would not contribute at all to boosting the average score. This scenario is probably too stark, 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.

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

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

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 $\overline{Z}_c$, $\overline{ParentsEdu}^c$ and $\overline{ParentsOcc}^c$ are within-country c averages.[27] 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.[28]

We estimate the 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 $\widehat{\gamma}^c, \widehat{\delta}^c$, $\widehat{\beta}$ and $\widehat{\lambda}$ are estimated from (4). As discussed, we focus on two specifications, one that includes school fixed effects and another with host country fixed effects only.

Figure V plots the parental component obtained from both specifications against the average score of natives ($Parents^{\text{CHINA}}$ is normalized to 1 in both cases).[29] $Parents^c$ is larger (in absolute terms) for high scoring countries, which means that parental influence does account for some of the cross-country variation (as opposed to masking an even larger dispersion) in performance. The dispersion in $Parents^c$ is larger for the country fixed effect specification, which allows the parental component to absorb the within-country variation in school quality.

[Figure V about here]

As a simple summary statistic, we define the share of the total cross-country variance of T^c accounted by $Parents^c$ as[30]

$$V_{Parents} = \frac{Var(Parents^c)}{Var(T^c)} \tag{6}$$

[27] The constant α absorbs a weighted average of the wave fixed effects.

[28] Notice that θ^c and ζ^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, θ^c and ζ^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.

[29] Table VI displays $Parents^c$ for all countries.

[30] Our decomposition exercise is similar to the ones proposed in Card et al. (2013) and Finkelstein et al. (2016), who also use (in different contexts) fixed effects identified out of movers to separate the contribution of individual characteristics and geographical or institutional factors.

This can be interpreted as the fraction of the variance that would persist if all relevant factors except parental influence were equalized across countries. To evaluate the relative contribution of observable and unobservable parental characteristics, we also compute an equivalent statistic for the country-specific intercepts only,

$$V_{FE} = \frac{Var(\gamma^c + \delta^c)}{Var(T^c)} \tag{7}$$

As a result of sampling error, the variance of our estimates overstates the true variation in the corresponding quantities. This is particularly relevant for $Parents^c$ and $\gamma^c + \delta^c$, which for some countries are identified out of a limited number of second generation immigrants. As suggested by Aaronson et al. (2007), we adjust variances by subtracting the average squared standard error of our estimates.[31]

Table V shows the results of this variance decomposition. According to the estimates adjusted for sampling error, $Parents^c$ accounts for at least 14% of the cross-country variance, and up to 20% when we do not clean it from the variation in school quality within countries. Most of the variation in $Parents^c$ is driven by $\gamma^c + \delta^c$, suggesting that cross-country differences in parents' education and occupational status are of limited quantitative importance. The adjustment for sampling error approximately halves the inferred contribution of $Parents^c$ and $\gamma^c + \delta^c$ compared to the unadjusted estimates (shown in the first row of Table V).

[Table V about here]

We then investigate the contribution of parental influence for the out-performance of Chinese students. For each country c we define the share of the gap in average test score with respect to China accounted by parental influence as

$$S_{Parents}(c, \text{CHINA}) = \frac{Parents^{\text{CHINA}} - Parents^c}{T^{\text{CHINA}} - T^c} \tag{8}$$

Moreover, as in (7), we isolate the importance of unobservable parental characteristics by computing

$$S_{FE}(c, \text{CHINA}) = \frac{(\gamma^{\text{CHINA}} + \delta^{\text{CHINA}}) - (\gamma^c + \delta^c)}{T^{\text{CHINA}} - T^c} \tag{9}$$

Table VI shows that parental influence plays a substantial role in accounting for the gap between China and the rest of the world. On average, between 22% and 58% of China's out-performance can be accounted for by parental influence. The gap between the school

[31] Standard errors are computed using the provided replicate weights, and inflated to account for the estimated measurement error in test scores. For computational convenience, we used the "unbiased shortcut" procedure described in OECD (2009). See Appendix B for more details on the construction of standard errors with PISA data.

and country fixed effect specifications suggests that school choice is a particularly important factor that sets Chinese parents apart. Virtually all the gap in parental influence is driven by the country-specific intercepts. 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, but not so pronounced for the worst performers.

[Table VI about here]

The results are particularly striking for Southern European countries, which display large gaps with respect to China in terms of both test scores and parental influence. On the other hand, parental influence plays a limited role for Latin American countries, whose poor performance in standardized test has been object of recent study (Hanushek and Woessmann, 2012b).[32]

7 Mechanism

We now study the nature of differences in parental influence. 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 several possible drivers of cross-country differences in parental influence: the educational system to which parents were exposed, the country-specific cultural context and the genetic transmission of relevant traits. Then we turn to time use surveys to see whether immigrant parents from high PISA countries differ in observable practices that might help to explain their children's better performance at school. Finally, we test whether country level proxies for economic development, educational attainment or culture can explain our relationship of interest.

7.1 Interactions

Cross-country differences in parental influence might be driven by a number of sources. First, the outstanding performance of second-generation immigrants from high PISA countries might reflect the higher quality of the education received by parents in their country of origin. While 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. This

[32]In Appendix F we show in a standard development accounting framework how the relative variation in parental influence maps into its relative contribution for cross-country differences in output. We find that the parental component accounts for about 12% of the covariance between GDP per worker and the PISA score.

would provide an even stronger rationale for policies aiming to replicate the best practices in this domain.

An alternative is that the country-of-origin's cultural context, defined as a shared set of beliefs and preferences within a given country, might have shaped parents' attitudes and beliefs towards education. This variation in cultural traits might have its roots in factors deeply entrenched in 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. Yet another possibility is that individuals from different countries are systematically endowed with different genetic traits that shape their human capital investment. This interpretation would leave little room for policies to affect achievement gaps.

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 parents acquired more education in their home country, and were therefore more exposed to the educational system.[33] 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 what matters is the cultural context in the source country, 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.[34] Moreover, there is evidence that highly educated immigrants have an easier time integrating in their host country (Lichter and Qian, 2001; Meng and Gregory, 2005); therefore, under the "cultural" interpretation parental years of schooling should also alleviate the correlation between children's performance and the average score in parents' country of origin.

To summarize, we have testable implications to discriminate between two 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 story

[33] We might expect a differential effect of years of schooling in the host country as well, if there are dynamic complementarities in the human capital accumulation process that make the impact of an additional year of schooling stronger for parents that have spent the initial part of their educational career in higher quality schools. Moreover, emigrants from high PISA countries might attend better schools once in the host country.

[34] There is widespread evidence that years since migration correlate positively with immigrants' assimilation (Chiswick, 1978). Children of parents that have spent more time in the US 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 heterogeneous depending on the country of origin). Appendix D shows that results are similar when we focus on alternative measures on immigrants' assimilation.

based on differences in cultural environments would instead involve a negative interaction between the average test score and parents' years since migration, as well as parents' years of schooling. A purely genetic view, instead, would not have any obvious implication in terms of differential effects.

We now turn to the US Census data to put these predictions to empirical scrutiny. We compute 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).[35]

Table VII shows the results. We add 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 VI 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 disappears when we focus on mothers with college education. These results are inconsistent with strong intergenerational effects of educational quality.[36]

[Table VII and Figure VI about here]

The study of the heterogeneity with respect to years since migration supports the importance of country-specific cultural environments. According to column 4 in Table VII, the correlation between T^m and children's school performance is weaker for mothers that have emigrated many years ago.[37] As shown in Figure VII, the effect of T^m disappears for mothers that 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 for the assimilation of immigrants (Bleakley and Chin, 2010).

[35] Year of immigration is available as a categorical variable, in intervals of approximately 5 years. We impute the exact year of arrival in the US according to two alternative criteria: the middle year of each interval for our baseline results, and the first year for a robustness check where we consider parents likely to have completed their education in their origin country.

[36] It is interesting to contrast these results to the ones in 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.

[37] 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 influence by focusing on those who have just emigrated, which are still very comparable to non-emigrants in their country of origin. Unfortunately, date of immigration is not available in the PISA data.

[Figure VII about here]

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. Column 6 in Table VII shows results for a sub-sample of mothers entirely educated in their country of origin. 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. The magnitudes of the estimated coefficients are virtually identical to the ones obtained with the full sample.

Overall, our results are supportive of an interpretation based on country-specific cultural environments. While we cannot entirely rule out a role for genetic traits, the fact that gaps in performance disappear when focusing on more educated and integrated parents is difficult rationalize with a purely genetic transmission story.

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. The analysis complements and extends the work of Ramey (2011), who compares time use practices across ethnic groups.

Table VIII 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. 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. [38]

[Table VIII about here]

These results indicate that immigrant parents do differ in terms of observable practices as a function of their country of origin and this may lay behind the results found in the previous sections.

[38] We find again that the effect is mostly concentrated among low educated parents and those of more recent immigration. These results are available upon request.

7.3 Country-Level Characteristics

We now augment specification (1) with a series of controls at the mother's country of origin-level. The objective 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 IX includes controls related to economic development and schooling in country m. As 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; the coefficients are small and not statistically significant. In column 5 we further control for 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.[39]

[Table IX about here]

Table X controls for proxies for various cultural traits from 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 labor supply and effort: tastes for leisure, locus of control and long-term orientation.[40,41]

[Table X about here]

Columns 1 to 3 introduce our cultural proxies in regressions controlling for the usual parental characteristics and school fixed effects. All three coefficients are significant and of the expected sign; 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 if school quality is controlled for. A

[39] We use average years of schooling for 35- to 45-year-old adults in 2005, and expenditure per pupil in secondary schools in 2000 (the year with the largest number of observations in Bartik (2008)'s dataset). Using different years and reference groups yields very similar results.

[40] Among others, Moriconi and Peri (2015) study country-specific preferences for leisure and labor supply choices, Coleman and DeLeire (2003) estimate the effect of the locus of control on educational and labor market outcomes while Dohmen et al. (2016), Galor and Ömer Özak (2016) and Figlio et al. (2016) consider how long term orientation shapes human capital investment.

[41] Tastes for leisure are measured from the question *how important leisure time is in your life?*. Answers (ranging from 1 to 4) are standardized to take mean 0 and standard deviation 1 at the individual level. The locus of control is measured from the question *how much freedom of choice and control you feel you have over the way your life turns out?*, where answers are standardized as above. The measure of long term orientation was developed by Hofstede (1991) and updated in Hofstede et al. (2010) using data from the World Value Survey; it ranges from 0 to 1.

similar message emerges when the cultural proxies are included simultaneously (column 4). In column 6 we further control for the average performance of native students in the mother's country of origin, which retains its statistical significance and drops by one third compared to the baseline specification without cultural proxies (reported in column 5).

Proxies for cultural traits in the parental countries of origin can go some way towards explaining the parental country of origin effect across second-generation immigrants. Much of this 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. We show that an important share of the international variation in test scores is driven by cross-country differences in broadly defined parental influence. We arrive to this conclusion through an indirect empirical approach, based on the comparison between the performance of second-generation immigrants with parents of different nationalities. Parental influence operates both within schools and through school choice, highlighting potentially important interactions between parental and schooling inputs for human capital formation.

We do not find evidence for a mechanism of intergenerational transmission of school quality, as parental education appears to attenuate rather than reinforce the relevance of the standardized test performance in parents' country of origin for explaining their children's achievements. Our results support instead the importance of cultural factors, varying across countries, that shape parents' attitudes towards their children's education. Differences in parental influence across nationalities are partially reflected in observable time use practices.

These results have important implications for the study of human capital in a cross-country perspective. Models of human capital accumulation should be consistent with an important role for parents in the transmission of knowledge. Moreover, parental attitudes towards education potentially represent a competing mechanism to gaps in TFP and local economic conditions for generating human capital and output gaps across countries. A systematic quantitative analysis of the interaction between these factors is left for future work.

Our paper opens other important avenues for future research. If parental attitudes towards education are important determinants of human capital achievement, it is crucial to understand how they form and evolve, and why they do so differently across time and space. Historical circumstances experienced in different countries might have played an important role, and social interactions between people of various origins (brought about by migration or trade linkages) might have shaped the diffusion of different cultural traits. Further research is also needed to identify the specific activities, attributes or skills responsible for the cross-country variation in parental influence.

Our results are relevant for policymakers aiming to raise their students' performance in standardized tests. Cross-country gaps go beyond differences in school quality, and policies aimed at replicating school practices successful in other countries might be uneffective. Parents are an important factor, and it is an open question whether policy should and could play a role in this respect.

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Tables

Table I: 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 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 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
Working Mother ISEI	41.35	18.79	41.33	19.08	41.40	17.99
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 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 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
Immigrant Father	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 participates to PISA 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 II: Main results - PISA

	Dependent Variable: Math Test Score					
	[1]	[2]	[3]	[4]	[5]	[6]
			All			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 $\times$ Mother ISEI					0.003***	0.003***
					(0.001)	(0.001)
Father Working $\times$ Father 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 participates to PISA. *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 III: 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's country of origin. * denotes significance at 10%, ** at 5%, *** at 1%.

Table IV: 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 emigrant mothers (columns 1 and 2) and fathers (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' (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 clustered by mother's (columns 1 and 2) and father's (3 and 4) country of origin. * denotes significance at 10%, ** at 5%, *** at 1%.

Table V: Decomposition Results - Cross-Country Variance

	$V_{Parents}$ (%)		V_{FE} (%)	
	School FE	Host Country FE	School FE	Host Country FE
Unadjusted	24.25	34.65	23.22	30.59
Adjusted	14.13	19.94	13.10	15.91

Notes: The Table shows the ratio (in percent) between the cross-country variance of either the whole parental component ($V_{Parents}$) or the country specific intercept (V_{FE}) and the cross-country variance of the average math PISA score of natives. Columns denoted by *School FE* (*Host Country FE*) refer to specifications that include school fixed effects (host country fixed effects). Adjusted variances are computed by subtracting the average squared standard errors (constructed using the provided replicate weights, and inflated by the estimated measurement error in test scores).

Table VI: 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	0.79	22.39	52.15	20.22	41.11
				(25.66)	(31.83)	(25.69)	(31.76)
Switzerland	0.82	0.95	0.56	10.42	86.15	15.33	101.30
				(20.63)	(30.10)	(20.65)	(30.29)
Belgium	0.79	0.91	0.43	16.16	104.93	22.02	122.00
				(27.44)	(35.82)	(27.37)	(36.22)
Netherlands	0.74	0.92	0.75	12.71	42.65	18.72	59.06
				(14.76)	(20.78)	(14.94)	(21.03)
Germany	0.64	0.90	0.62	14.08	54.13	17.47	64.04
				(9.20)	(15.54)	(9.22)	(15.88)
New Zealand	0.58	0.66	0.29	45.30	95.09	48.11	102.03
				(8.84)	(11.36)	(8.97)	(11.84)
Estonia	0.55	0.93	0.70	8.90	38.38	10.50	43.78
				(25.76)	(29.80)	(25.79)	(29.82)
Macao	0.55	0.95	0.74	6.68	33.07	4.32	21.98
				(11.51)	(14.04)	(11.49)	(14.04)
France	0.52	0.77	0.35	27.80	79.93	29.23	84.99
				(7.17)	(10.21)	(7.26)	(10.50)
Australia	0.50	0.63	0.44	45.01	67.68	48.45	76.76
				(16.63)	(16.39)	(16.62)	(16.56)
Denmark	0.50	0.99	0.61	1.01	46.57	4.13	56.13
				(20.69)	(20.39)	(20.65)	(20.42)
Austria	0.48	0.79	0.26	24.10	87.41	25.15	91.85
				(14.01)	(18.45)	(14.08)	(18.75)
Czech Republic	0.46	0.73	0.37	31.17	72.36	31.06	72.64
				(13.32)	(19.85)	(13.32)	(19.84)
Sweden	0.44	0.85	0.48	16.60	57.55	20.17	68.25
				(9.03)	(10.89)	(9.02)	(11.06)
Vietnam	0.44	0.87	0.49	14.92	57.18	2.79	23.78
				(8.74)	(9.43)	(8.66)	(9.53)
United Kingdom	0.42	0.73	0.38	30.11	67.52	32.09	73.71
				(5.27)	(7.35)	(5.34)	(7.56)
Poland	0.34	0.67	0.36	32.98	64.81	29.61	57.33
				(7.15)	(10.10)	(7.15)	(10.12)
Slovakia	0.33	0.80	0.35	19.65	65.13	17.87	61.59
				(9.48)	(11.97)	(9.51)	(12.15)
United States	0.26	0.96	0.79	4.04	20.00	7.59	29.26
				(9.46)	(10.28)	(9.48)	(10.43)
Spain	0.25	0.62	0.23	35.05	71.03	32.58	63.92
				(6.85)	(9.34)	(6.86)	(9.42)
Portugal	0.16	0.65	0.22	29.89	67.05	25.14	51.60
				(4.99)	(7.26)	(5.00)	(7.32)
Italy	0.14	0.54	-0.01	38.35	84.36	37.27	82.02
				(5.98)	(7.70)	(6.02)	(7.77)
Russia	0.12	0.80	0.54	16.85	38.11	17.77	41.79
				(4.11)	(6.19)	(4.13)	(6.23)
Croatia	0.06	0.57	0.22	33.40	61.57	32.60	60.59
				(8.98)	(11.64)	(8.97)	(11.68)

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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
Greece	-0.02	0.46	0.01	39.88	73.52	39.65	72.61
				(10.17)	(11.39)	(10.18)	(11.44)
Turkey	-0.21	0.39	-0.34	39.35	87.29	34.42	71.19
				(3.78)	(5.66)	(3.79)	(5.29)
Serbia-Mont.	-0.23	0.55	0.05	28.87	60.64	28.61	60.87
				(3.17)	(4.97)	(3.14)	(4.96)
Romania	-0.31	0.62	0.35	23.16	39.56	21.56	36.88
				(7.08)	(8.33)	(7.10)	(8.32)
Uruguay	-0.34	0.87	0.40	7.50	36.03	5.09	29.26
				(12.17)	(17.40)	(12.15)	(17.45)
Chile	-0.38	0.65	0.28	20.40	42.27	17.35	35.39
				(10.58)	(15.27)	(10.59)	(15.30)
Malaysia	-0.41	0.67	0.01	18.63	56.42	16.71	51.66
				(11.37)	(18.10)	(11.43)	(18.24)
Argentina	-0.63	0.85	0.47	7.45	26.78	5.96	22.39
				(8.54)	(12.06)	(8.53)	(12.08)
Jordan	-0.67	0.59	0.14	20.23	43.11	19.62	41.68
				(3.90)	(4.98)	(4.04)	(5.22)
Albania	-0.68	0.45	-0.02	27.19	50.65	24.64	44.71
				(3.15)	(4.38)	(3.15)	(4.42)
Brazil	-0.75	0.81	0.37	9.16	30.16	6.31	22.01
				(7.44)	(8.54)	(7.43)	(8.58)
India	-0.98	0.66	0.23	14.83	33.04	11.13	22.82
				(2.68)	(3.43)	(2.67)	(3.40)
Average	0.18	0.75	0.38	22.06	58.17	21.70	57.30
				(4.42)	(6.35)	(4.45)	(6.46)

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 using the provided replicate weights, and inflated by the estimated measurement error in test scores.

Table VII: 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 VIII: 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 of at most 18 years. $Parent$ refers to the interviewed parent, $Spouse$ to the other one; $Mother$ is 1 when the interviewed 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 IX: 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 × Mother ISEI	0.003***	0.003***	0.003***	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father Working × Father ISEI	0.003***	0.003***	0.003***	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log GDP Country *m*		-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. All specifications control for intercept, students' age (in months), wave fixed effect, a dummy for father's immigrant status and dummies for parents' employment status (full-time employed, part-time employed, not working). *Working* refers to either full-time or part-time employed. *Log GDP Country m*, *Avg Years Edu in m* and *Log Exp per Pupil in m* are respectively the wave-specific contemporaneous log real GDP per capita, the average years of schooling in 2005 of 35- to 45-year-old adults and the log expenditure in 2000 per pupil in secondary schools in the country of birth of the mother. 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%.

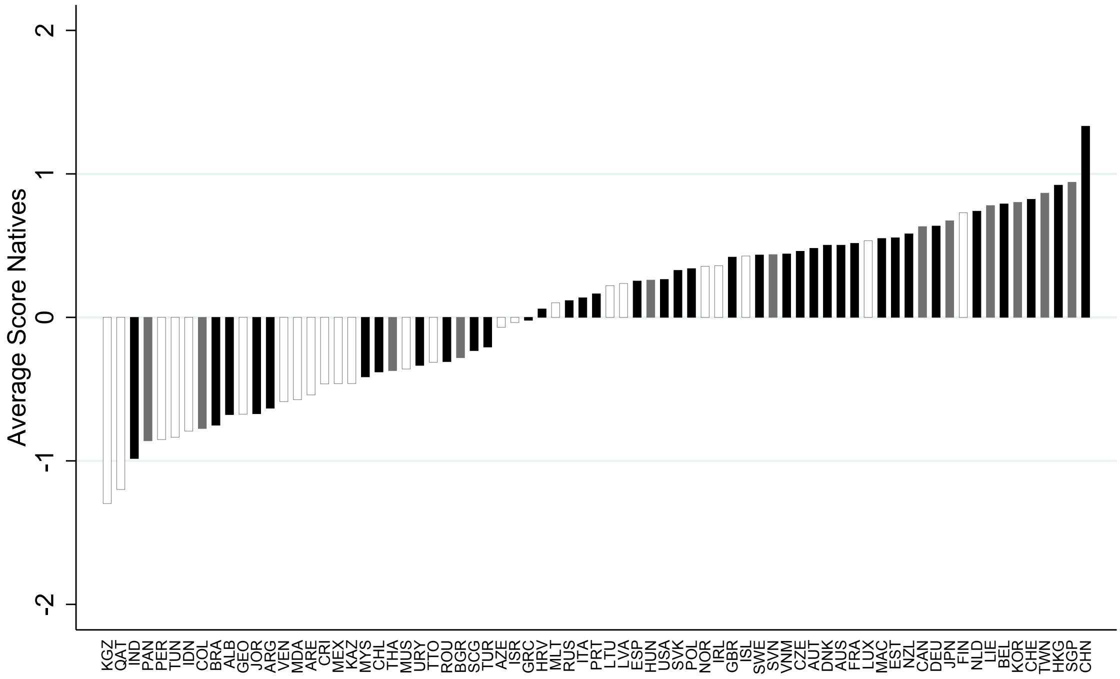
Table X: Country of Origin Characteristics - Cultural Traits

	Dependent variable: Math Test Score					
	[1]	[2]	[3]	[4]	[5]	[6]
Score Country *m*					0.251***	0.158***
					(0.071)	(0.060)
Female	-0.200***	-0.202***	-0.200***	-0.198***	-0.201***	-0.198***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.022)	(0.023)
Father Sec Edu	0.013	0.010	0.012	0.011	0.016	0.014
	(0.023)	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)
Father Ter Edu	0.043	0.044	0.041	0.040	0.047	0.043
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Mother Sec Edu	-0.003	-0.009	-0.007	-0.019	-0.014	-0.020
	(0.041)	(0.040)	(0.040)	(0.035)	(0.038)	(0.034)
Mother Ter Edu	0.002	-0.007	-0.007	-0.021	-0.010	-0.020
	(0.043)	(0.045)	(0.042)	(0.042)	(0.043)	(0.043)
Mother Working $\times$ Mother ISEI	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father Working $\times$ Father ISEI	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Leisure Important in *m*	-0.258***			-0.232***		-0.247***
	(0.088)			(0.057)		(0.070)
Locus of Control in *m*		0.308**		0.440***		0.266**
		(0.140)		(0.087)		(0.112)
Long Term Orientation in *m*			0.445***	0.421***		0.237*
			(0.153)	(0.115)		(0.125)
N	39882	39882	39882	39882	39882	39882
# Country *m*	46	46	46	46	46	46
R Squared	0.67	0.67	0.67	0.68	0.67	0.68
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. *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, a dummy for father's immigrant status and dummies for parents' employment status (full-time employed, part-time employed, not working). *Working* refers to either full-time or part-time employed. *Leisure Important in m* and *Locus of Control in m* are constructed from answers of natives in the country of birth of the mother to the corresponding questions in the World Value Survey (described in the main text), and are standardized to take mean 0 and standard deviation 1 in the WVS sample. *Long Term Orientation in m* is constructed in Hofstede et al. (2010) and ranges from 0 to 1. 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%.

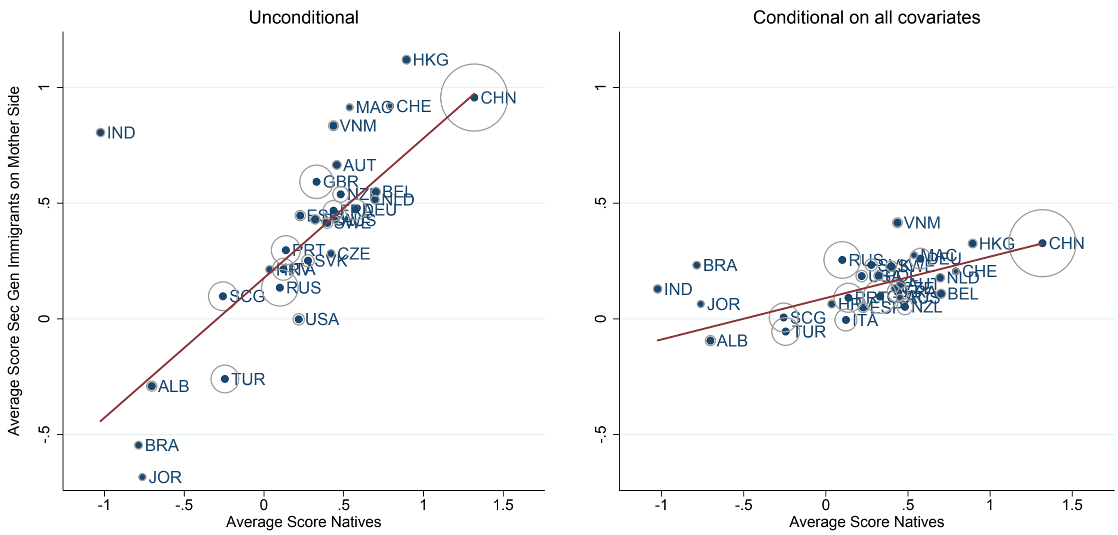
Figures

Figure I: Performance of Native Students across Countries



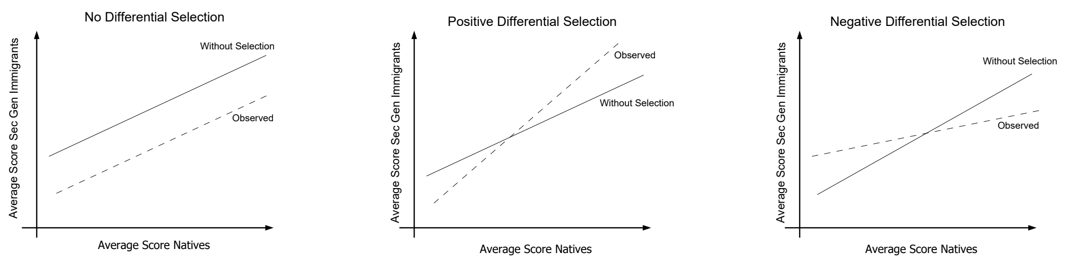
Notes: The height of the bar represents the average PISA score in mathematics for native students. Scores are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) 73 countries participating to at least one wave of the test. Black bars refer to 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 II: Performance of Second Generation Immigrants and Natives



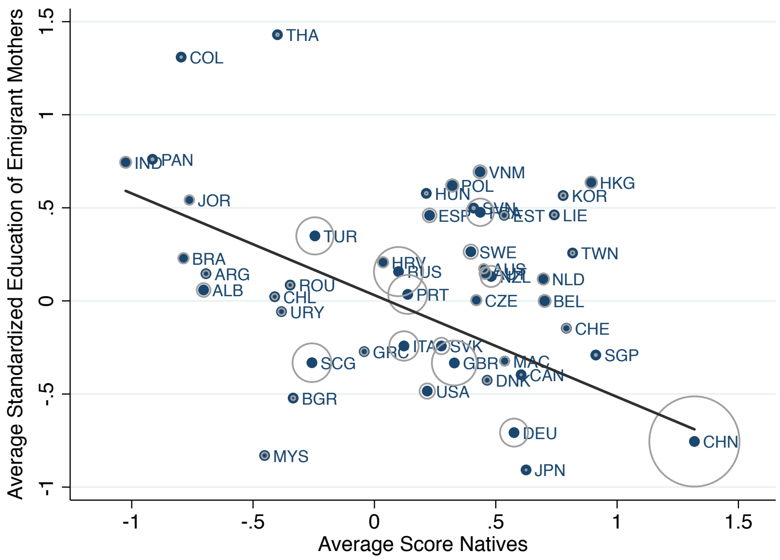
Notes: The left panel plots the average PISA score of second generation immigrants whose mother is from country m against the average math PISA score of natives in country m, for all countries with at least 100 second generation immigrants on the mother's side in the sample. The right panel plots the 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's side. The size of the circles is proportional to the number of second generation immigrants on the mother's side in the sample. The line shows the best (weighted) linear fit.

Figure III: Different Types of Selection



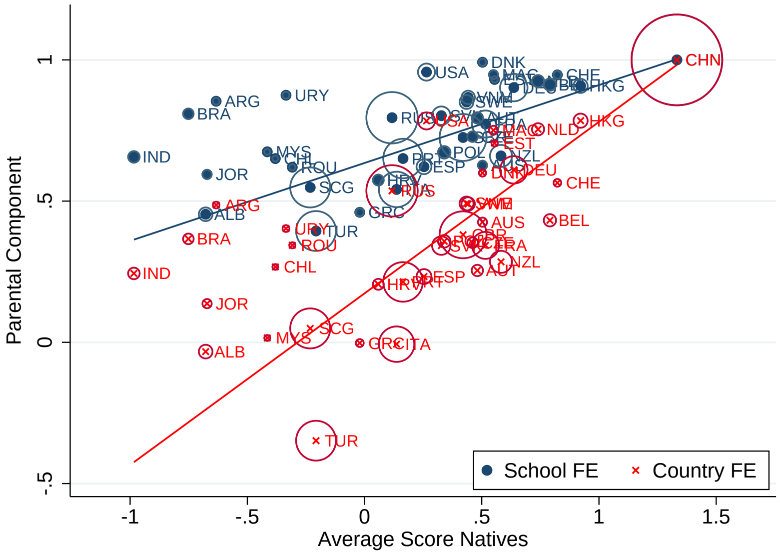
Notes: The Figure represents three possible patterns of emigrant parents' selection on unobservables. The first panel refers to the case where emigrant parents are selected to the same extent across all countries of origin. The second (third) panel refers to the case where emigrant parents from high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

Figure IV: Selection on Parental Education



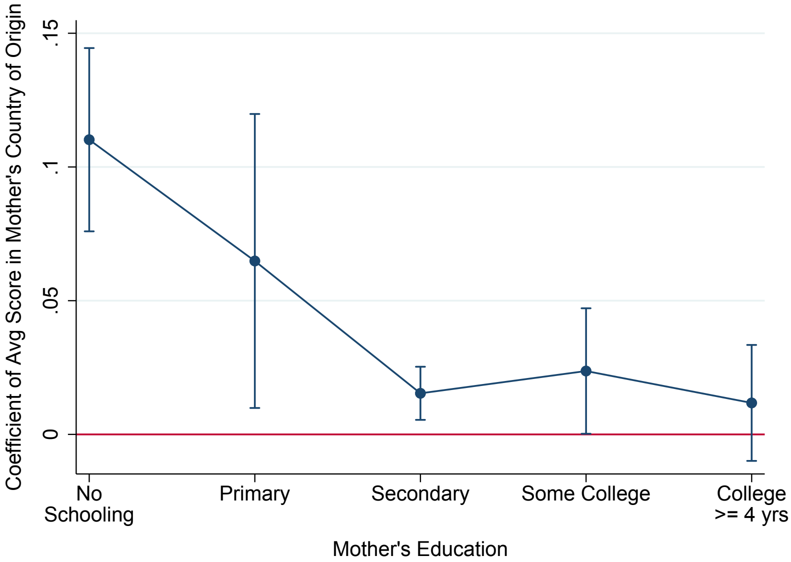
Notes: The Figure plots the average years of schooling of emigrant mothers from country m standardized by the average and the standard deviation of years of schooling of non-emigrant mothers in country m (y-axis) against the average PISA score of native students in country m (x-axis). The sizes of the circles are proportional to the number of emigrant mothers in the sample. The line shows the best (weighted) linear fit.

Figure V: Parental Component



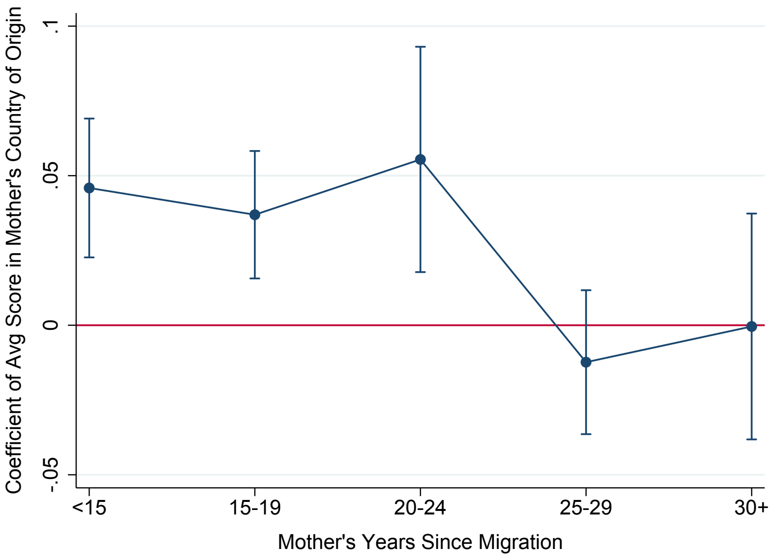
Notes: The Figure plots the estimated parental component ($Parents^c$ as defined in Section 6), normalized such that it takes value 1 for China (y-axis) against the average PISA score of natives (x-axis). Only countries with at least 100 emigrant parents in the sample are included. The sizes of the circles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

Figure VI: 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 column 5 of Table III. Standard errors are clustered by mother's country of origin.

Figure VII: 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 column 5 of Table III. Standard errors are clustered by mother's country of origin.