Parents, Schools and Human Capital Differences across Countries*

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Online Appendix Here

Abstract

Results from international standardized 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 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 international standardized tests 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 calculate that parental influence accounts for a sizable part of the performance gap across countries.

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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 show a rather disappointing performance. An emerging strand of the growth literature argues that these scores capture differences in human capital that have great explanatory power for cross-country differences in economic performance (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 the role of country-specific factors such as access to public education, sectoral composition and skill premia in shaping 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 parental influence is relevant also at the country level. 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.

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. The analysis involves a set of 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

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

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.

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.[2] This holds true when controlling for parental education, socio-economic status and other characteristics of parents' countries of origin. We find a similar pattern for a different schooling outcome in a specific host country, which is grade repetition in the United States. 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.

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 for school performance of country-specific "cultural" traits,

[2]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, 78% of the target population can be classified as native, according to this definition. Students born in a country different from the one where they are taking the test are excluded from all the analyses that follow.

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. Time use data for immigrants in the US show that 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 less education and fewer years spent in the US.

This paper contributes to the debate on cross-country differences in human capital. Several papers study the importance of 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, in terms of both 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. 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 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.

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. Our empirical approach is 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).[3] 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.

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; Fernandez, 2011; Alesina et al., 2013). 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. Moreover, while most of the focus in this 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.[4]

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.

[3] 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. We discuss this and other channels through which immigrant parents' ethnic network might affect children's human capital accumulation in Appendix D.

[4] 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 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 measure of parental influence that we propose in this paper, based on school performance gaps across second-generation immigrants, 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.

An important qualification 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, 2017), as might do school quality if there are complementarities 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 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, labor 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.

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. We emphasize that this is a particularly 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. The test covers three subjects: reading comprehension, science and mathematics. 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.[5]

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.[6] 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

[5]The results are not presented as point estimates but rather as "plausible values": the OECD estimates for each student a probability distribution of 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, but measures of dispersion need to be adjusted to reflect the associated measurement error. 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). Appendix B explains in greater detail how standard errors are constructed, and shows that our results are robust to some possible alternatives.

[6]The PISA test in China is held in Shanghai only, and as such is not representative of the whole country; however in our sample second-generation immigrants from China might come from any part of the country. This mismatch is likely to work against our main finding, since Shanghai is one the wealthiest areas in China and Chinese second-generation immigrants in our sample will be negatively selected. See section 5 for a discussion on this issue.

European countries concentrate in the middle of the distribution, while all Latin American countries are below the average. The superior performance of Chinese and other 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.[7] The exact country of origin of the parents is, however, not available in all participating countries' questionnaires and for the 2000 wave.[8] In addition, for some countries and waves further information is available from the School Questionnaire and the Parent Questionnaire.

The final 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. 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 identify countries that belong to the "core sample". Even when imposing this restriction, our sample covers most of the score distribution, and includes countries from all regions.

Descriptive statistics for second-generation immigrants on the mother's side are provided in Panel A of Table I. 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

[7]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. As such, it provides a rough proxy for parental income.

[8]Individual countries 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 countries consistently defined over time. See Appendix A for the details.

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.

[Table I about here]

The second source of data is the Integrated Public Use Microdata Series (IPUMS) created by the US Census Bureau. 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, include the grade currently attended at school.[9] 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 common in the United States and is correlated with standard 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.[10] Following Oreopoulos 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. The final sample includes 53,081 second-generation immigrants on the mother's side and 46,410 on the father's side, from 61 different countries of origin. Descriptive statistics for second-generation immigrants on the mother's side are provided in Panel B of Table I.

In addition, 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.[11]

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.

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

[10]This grade-for-age measure will induce 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.

[11]We follow Aguiar and Hurst (2007) for the construction of these variables.

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 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. We present results for the PISA and the US Census samples in turn.

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 a 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 in principle 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:

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

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 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} svereal 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

[12]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).

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 given second-generation immigrant's performance and the average score of native students in country m.

Table II 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.[14] Standard errors are clustered at the level of the mother's country of origin, and inflated by the estimated measurement error in test scores.[15]

[Table II about here]

We proceed by progressively adding controls. Column 1 of Table II controls for students' baseline characteristics (gender and age in months), fathers' immigrant status and wave fixed effects only. The 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 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. The difference in the size of the coefficient between the first two specifications and column 3 is quite illuminating, since it suggests that, within the same host country, mothers from high PISA countries might send their children to better schools. We will discuss the implications of this pattern 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 θ_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,

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

[15]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.

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] Finally, the last column of Table II shows that results are not driven only by the particularly good 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, 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 I). On the other hand, while the PISA dataset contains only 15-year-old children, the US data allows us to look at students between 8 and 15 years of age. 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 in Table II. In an attempt to capture some of the differences across educational systems within the US, we control for Commuting Zone fixed effects.[17] 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 III shows our results. Once again, the coefficient on T^m is positive and significant through-

[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.

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

out. 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

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

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 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.

What type of selection should we worry about in this context? Figure III 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.

[Figure III about here]

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.

We now discuss which pattern of differential selection is likely to apply in our setting, using both insights from the existing migration literature and evidence from observable characteristics of emigrant and non-emigrant parents in the PISA sample. A similar analysis on the Census data is discussed in Appendix C.

5.1.1 Insights from the Migration Literature

The migration literature has extensively debated the country-level determinants of emigrants' self-selection in terms of observable and unobservable skills. 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 advocated as measuring direct determinants of selection. In Figure IV 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.[18]

[Figure IV about here]

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 IV show that on average emigrant parents from high PISA countries do emigrate to countries more unequal (as measured by

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

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.[19] However, this theory has received mixed support (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.[20]

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. Since the average PISA score is positively correlated with real GDP in 1985 (Panel d), 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.[21] China is an outlier in this dimension, since many Chinese parents 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 differential selection for the other countries.[22] 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.[23] This is relevant since geographical distance has been shown to be associated with negative selection

[19]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.

[20]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 thousands of 2000 US dollars) between the 80^{th} and 20^{th} percentiles of the income distribution in each country.

[21]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.

[22]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 over-performance 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.

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

(Grogger and Hanson, 2011; Belot and Hatton, 2012), most likely due to its effect on the cost of migrating.

Recent work by Albornoz et al. (2012) examines theoretically the determinants of selection in terms of parental motivation for their children's education, which might be only partially correlated with parents' skills. Among other channels, the authors stress the importance of the relative quality of the school systems in the host and source countries, since highly motivated parents are more likely to migrate to countries with better educational prospects for their children.[24] Under the presumption that high PISA countries have better schools on average, parents emigrating from these countries should be, ceteris paribus, relatively more negatively selected.

All in all, given the determinants of self-selection considered in the literature, we conclude that a pattern of (weakly) negative differential selection should be expected.

5.1.2 Evidence based on Selection on Observables

In this section we ask whether emigrant parents are differentially selected in terms of their own education. While the main threat to our approach is represented by 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.[25]

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.[26] Taking into

[24] Other determinants of selection considered in Albornoz et al. (2012) are the absolute skill premia in host and source countries and migration costs. As discussed above, the available evidence on these dimensions suggests that, if anything, we should expect parents emigrating from high PISA countries to be relatively negatively selected.

[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 their 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 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.

[26] 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).

account differences in the 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.[27]

Figure V 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 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). This suggests 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 III).[28]

[Figure V about here]

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. The pattern is rather similar for 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.

[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. Moreover, Hendricks and Schoellman

[27] 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.

[28] The fact that Chinese emigrant parents are negatively selected might appear in contrast with the 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 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. 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.

(2016) show that emigrants from poor countries are more positively selected in terms of pre-migration wages and occupations.

5.2 Selection into Host Countries and Schools

A distinct issue 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 II, suggesting that parents from high PISA countries might select educational environments more conducive to a good schooling performance. 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.

This pattern 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 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.[29] 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.

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, in our quantitative analysis we show results from both specifications, with the understanding that regressions with school fixed

[29] This would not necessarily be true in a world where parental and schooling inputs are complementary in the human capital production function. In Appendix E we investigate this possibility, and conclude that it is unlikely to be quantitatively important in our setting.

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.[30]

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 V explores this possibility. In column 2 we add to the baseline regression of column 1 a dummy variable that takes value 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.

[Table V about here]

In column 4 and 6 we add to the baseline specifications (reported in columns 3 and 5 respectively) controls for linguistic distance (constructed through the softwares provided by the Automated Similarity Judgment Program (Wichmann and Brown, 2016)) and cultural distance (from Spolaore and Wacziarg (2015)); 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.[31]

6 Decomposition

For our decomposition we introduce a more general model, which allows both maternal and paternal influence to differ across countries. Suppose that the test score in wave t of a second-generation

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

[31]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.

immigrant i, studying in school s and country c, whose mother and father were born in countries m and f is given by

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

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 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. 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.[32] 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.[33] 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 test takes 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

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

[32]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.

[33]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.

where $NatMoth_{ist}^{mf}$ 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. 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 second-generation immigrants (see footnote 35 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.[34] 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.[35]

In order to do that, 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 $\widehat{\gamma}^c$, $\widehat{\delta}^c$ and $\widehat{\beta}$ are our estimated parameters from equation (4). As discussed, we focus on two different specifications, one that includes school fixed effects and another with host country fixed effects only.

[34]The constant α absorbs the average of the wave fixed effects.

[35]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.

Figure VI 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).[36] 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.

[Figure VI 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[37]

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

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.[38]

Table VI 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

[36] Table VII displays $Parents^c$ for all countries.

[37] 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.

[38] 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.

20% when we do not clean it from the variation in school quality within countries. Most of the international 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 VI).

[Table VI 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 the parental component 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 VII shows that the parental component 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 large gap between the results from the school and country fixed effect specifications suggests that school choice is a particularly important factor that sets Chinese parents apart. The role of parental education and socio-economic background is negligible, as 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 (Spain, Portugal, Italy, Croatia, Greece and Turkey in particular), but not so pronounced for the worst performers.

[Table VII about here]

In terms of the geographic variation, 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, it is interesting to notice the relatively limited role that parental influence plays for Latin American countries, whose poor performance in standardized test has been object of recent study (Hanushek and Woessmann, 2012b).[39]

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 several possible drivers of cross-country differences in parental influence: the educational system, 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 some observable practices that might help to explain their children's better performance at school. Finally, we test whether proxies for economic development, educational attainment or culture can explain our correlation of interest.

7.1 Interactions

Cross-country differences in parental influence might be driven by a number of sources. One possibility is that the outstanding performance of second-generation immigrants from high PISA countries reflects the higher quality of the education received by parents 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 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

[39] In Appendix F we show in a standard development accounting framework how the relative variation in the parental component 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.

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.[40] 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.[41] Moreover, there is some evidence that highly educated immigrants have an easier time integrating in their host country (Schoen and Wooldredge, 1989; 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

[40]According to this view, 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.

[41]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.

and the average score of natives in the same country. A mechanism 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 once again restrict attention to second-generation immigrants on the mother's side in the main text. 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, in intervals of approximately 5 years. We impute the exact year 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.

Table VIII 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 VII 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.[42]

[Table VIII and Figure VII 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 VIII, the correlation between T^m and children's school performance is weaker for mothers that have emigrated many years ago.[43]

[42]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.

[43]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 date of immigration is not available in the PISA data.

As shown in Figure VIII, 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; Nielsen and Schindler Rangvid, 2012).

[Figure VIII 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 VIII 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 are supportive of an interpretation based on country-specific cultural environments, given that our correlation of interest is attenuated by both parental education and integration in the United States. While we cannot entirely rule out a role for genetic traits, the fact that gaps in performance disappear when focusing on highly educated and more 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.

Table IX 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.

[Table IX about here]

To parallel the analysis above on the Census data, Figures IX and X 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 IX, while the coefficient for primary school educated parents is estimated 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 the college-educated. This is once again inconsistent with an important role for educational quality in parents' country of origin. Figure X mimics qualitatively the pattern obtained in Figure VIII 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.

[Figures IX and X about here]

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 are driving the results found in the previous sections.

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 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 X 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; 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.[44]

[Table X about here]

Table XI controls for proxies for 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 labor supply and predisposition to effort in different context: tastes for leisure, locus of control and long-term orientation.[45,46]

[Table XI about here]

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

[44] 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.

[45] Among others, Mocan and Pogorelova (2015) and Moriconi and Peri (2015) study country-specific preferences for leisure and labor supply choices, Coleman and DeLeire (2003) and Cebi (2007) estimate the effect of the locus of control on educational and labor 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.

[46] Tastes for leisure are measured from a question asking *how important leisure time is in your life*, whose 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 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 et al., 2010); it ranges from 0 to 1.

of origin, which retains its statistical significance and drops by one third compared to the baseline specification without cultural proxies (reported in column 5).

Overall, the results in Table XI imply that observable 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. In this paper 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 in favor of 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.

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.

Further research is also needed to identify the specific activities, attributes or skills responsible for the cross-country variation in parental influence.

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 policies aimed at replicating school practices successful in other countries 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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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 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 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 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 III: Main results - US CENSUS

	Dependent variable: 1 = Never repeated a grade					
	[1]	[2]	[3] All	[4]	[5]	[6] 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 for columns (1) and (2) and emigrant fathers 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 V: 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 $\times$ 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 $\times$ 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		-0.063**				
		(0.028)				
Mother Linguistic Distance				-0.001		
				(0.013)		
Father Linguistic Distance				0.012		
				(0.009)		
Mother Cultural Distance						0.070
						(0.075)
Father Cultural Distance						-0.053
						(0.082)
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, 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. *Linguistic Distance* and *Cultural Distance* vary at the country-pair level, and are standardized to take mean 0 and standard deviation 1 across all country pairs in the sample (sources are discussed in the main text). 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 VI: 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 VII: Decomposition Results - Countries

Country	PISA Score	$Parents^c$ School FE	$Parents^c$ Country FE	$S_{Parents}(c, \text{CHINA})$ (%) School FE	$S_{Parents}(c, \text{CHINA})$ (%) Country FE	$S_{FE}(c, \text{CHINA})$ (%) School FE	$S_{FE}(c, \text{CHINA})$ (%) 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)
Greece	-0.02	0.46	0.01	39.88	73.52	39.65	72.61
				(10.17)	(11.39)	(10.18)	(11.44)

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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
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 VIII: 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 IX: 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 X: 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 $\times$ Mother ISEI	0.003***	0.003***	0.003***	0.003**	0.003**
	(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**
	(0.001)	(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%.

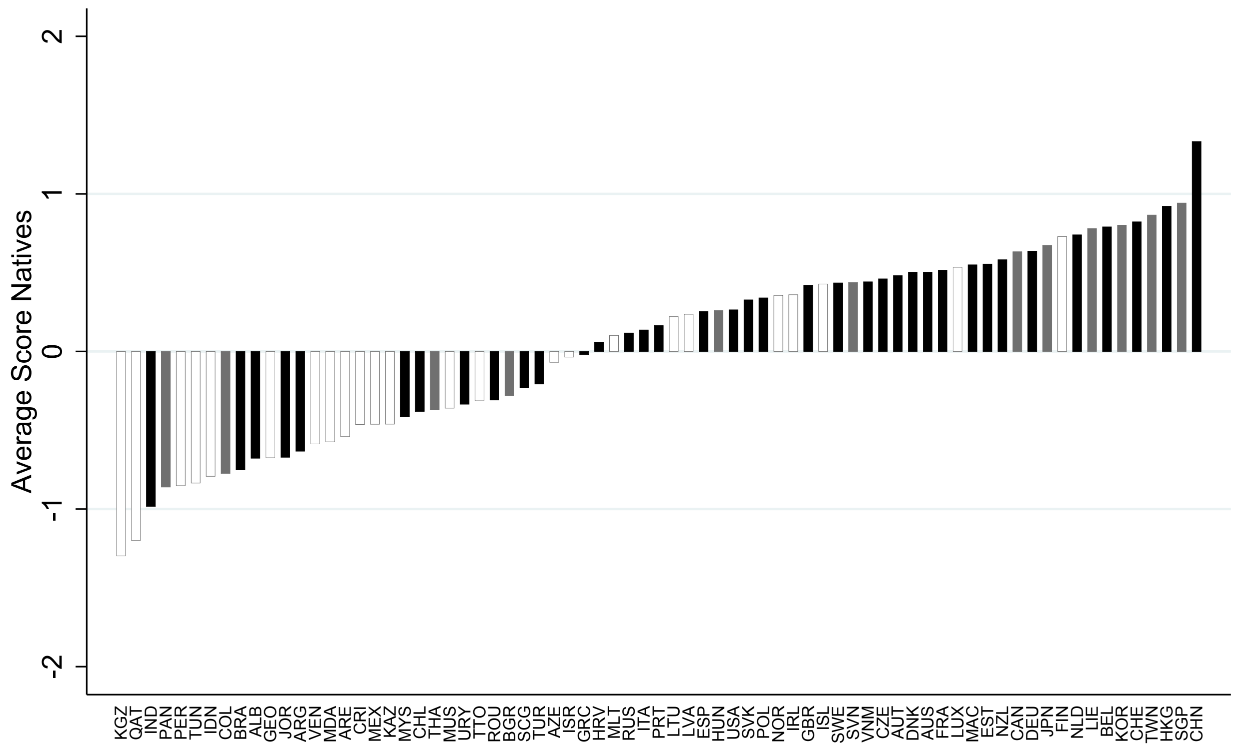
Table XI: Country of Origin Characteristics - Cultural Traits

	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

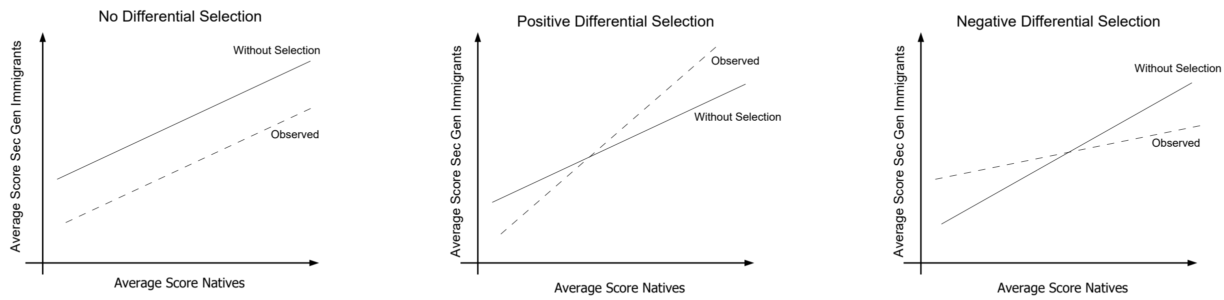


Notes: The height of the bar represents the average PISA score in mathematics for native students. Scores are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) 73 countries participating to at least one wave of the test. Black bars refer to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

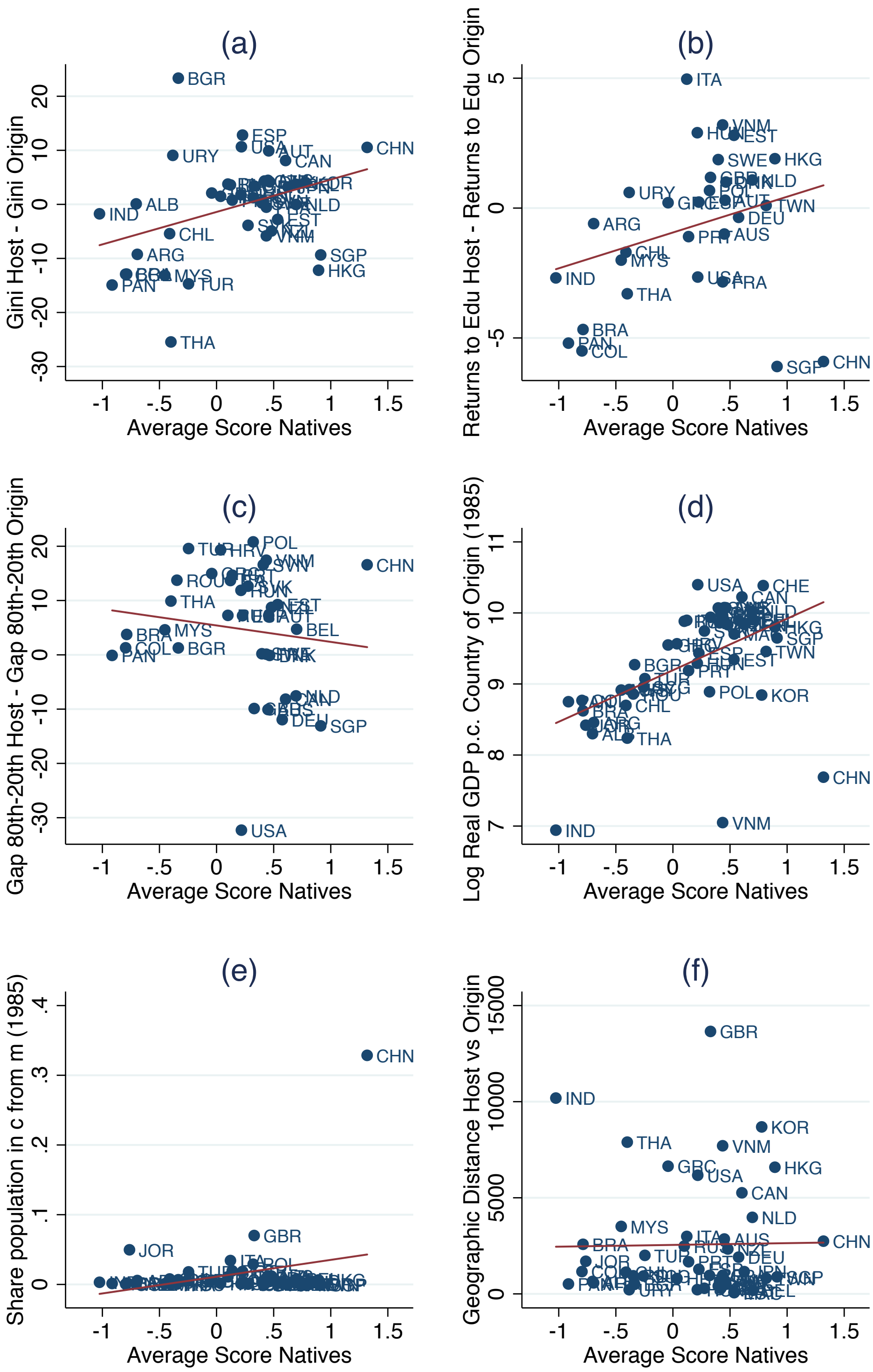
Notes: The left panel plots the average PISA score of second generation immigrants whose mother is from country m against the average math PISA score of natives in country m, for all countries with at least 100 second generation immigrants on the mother's side in the sample. The right panel plots the 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



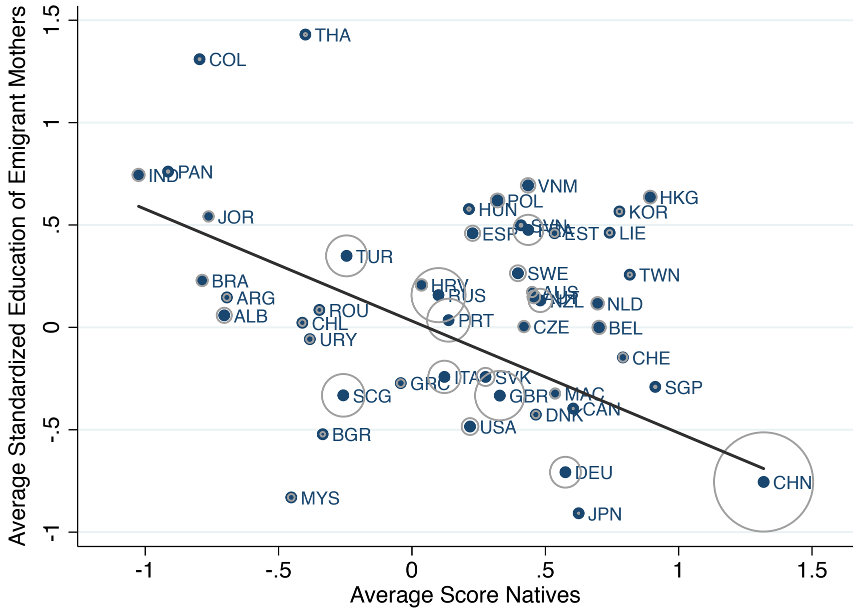
Notes: The Figure represents three possible patterns of emigrant parents' selection on unobservables. The first panel refers to the case where emigrant parents are selected to the same extent across all countries of origin. The second (third) panel refers to the case where emigrant parents from high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

Figure IV: Possible Determinants of Emigrants' Selection



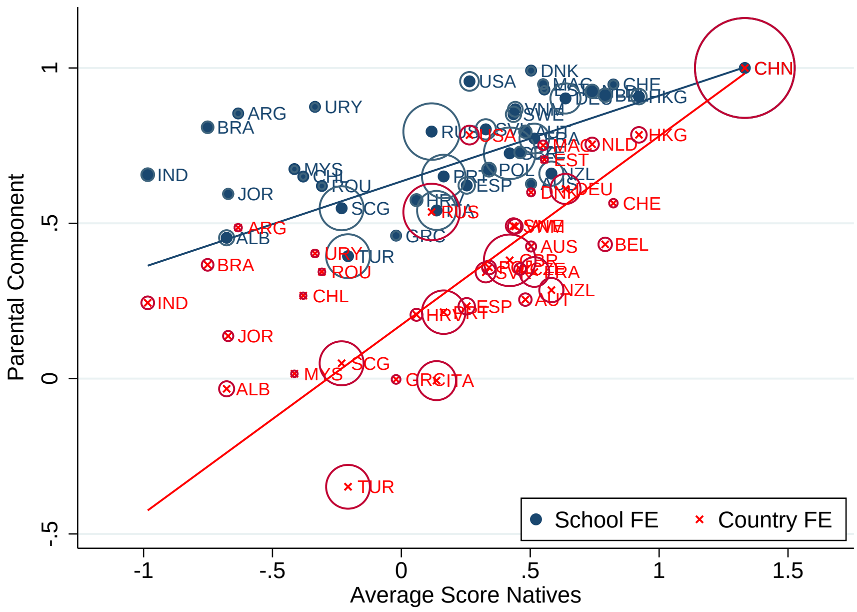
Notes: Each Panel plots the relationship between the average score among natives and a possible determinat of emigrants' selection. Panel (a) plots the difference between the average Gini Index faced by emigrants from country m in their respective host countries and the Gini Index in country m. Similarly, Panels (b) and (c) plot the difference between the average value faced by emigrants from country m and country m's value for the estimated return to education and the absolute income gap between the 80^{th} and the 20^{th} percentiles (in thousands of 2000 US dollars). Panel (d) plots the log real GDP per capita in 1985. Panel (e) and (f) plot the average across emigrants from m of the share of host country population born in country m and of the geographic distance between the host country and country m (in kilometers). The lines show the best linear fits.

Figure V: Selection on Parental Education



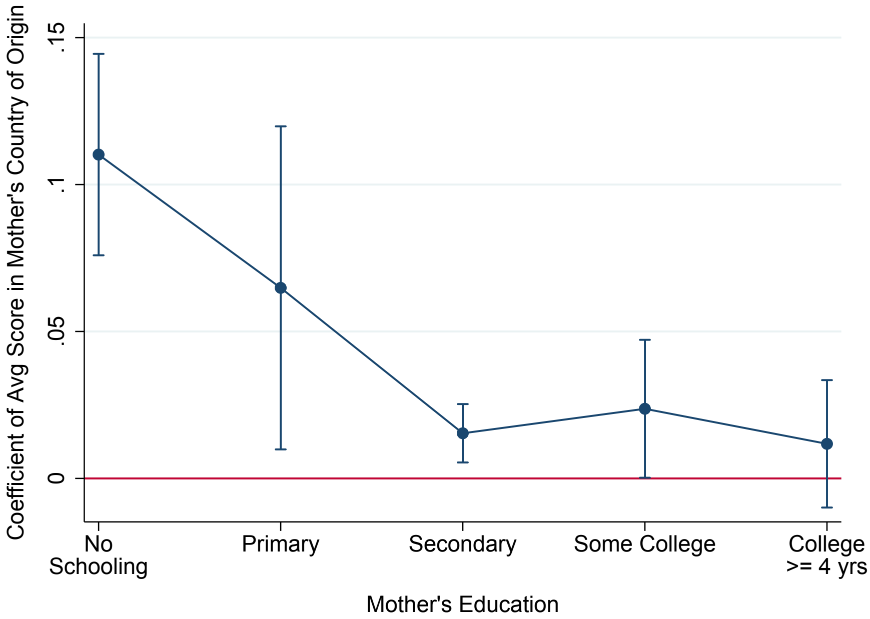
Notes: The Figure plots the average years of schooling of emigrant mothers from country m standardized by the average and the standard deviation of years of schooling of non-emigrant mothers in country m (y-axis) against the average PISA score of native students in country m (x-axis). The sizes of the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

Figure VI: Parental Component



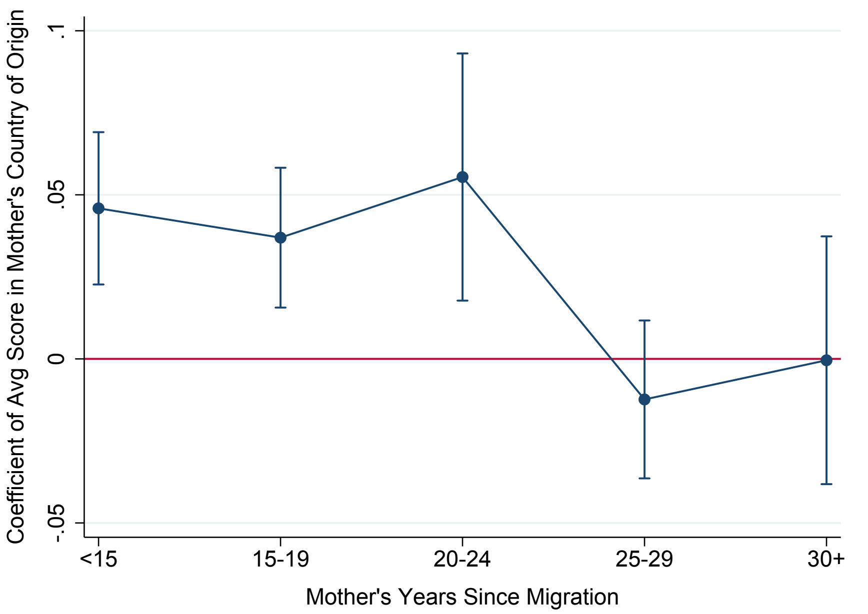
Notes: The Figure plots the estimated parental component ($Parents^c$ as defined in Section 6), normalized such that it takes value 1 for China (y-axis) against the average PISA score of natives (x-axis). Only countries with at least 100 emigrant parents in the sample are included. The sizes of the circles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

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



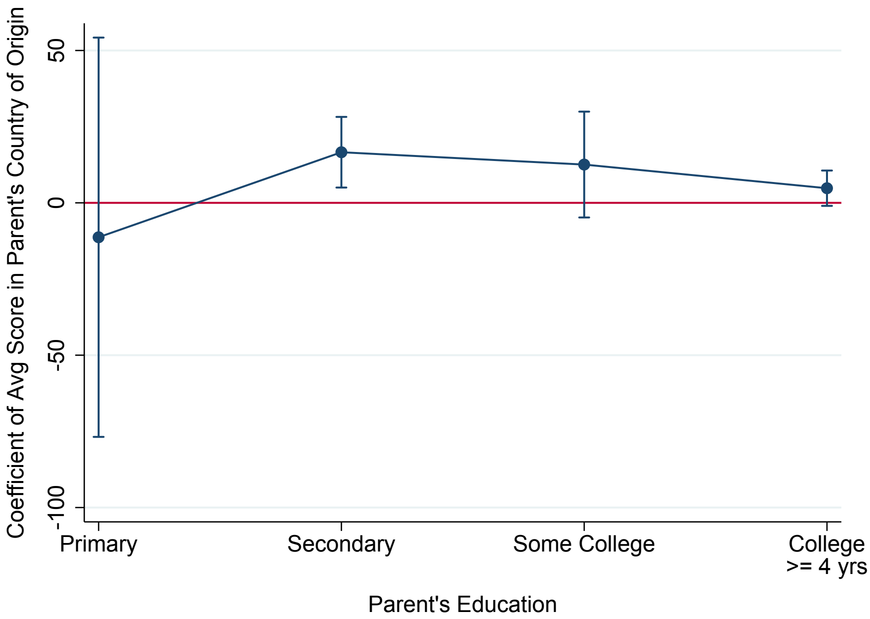
Notes: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in mother's country of origin and dummies corresponding to mother's educational achievement, with the dependent variable and other controls being the same as in column 5 of Table III. Standard errors are clustered by mother's country of origin.

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



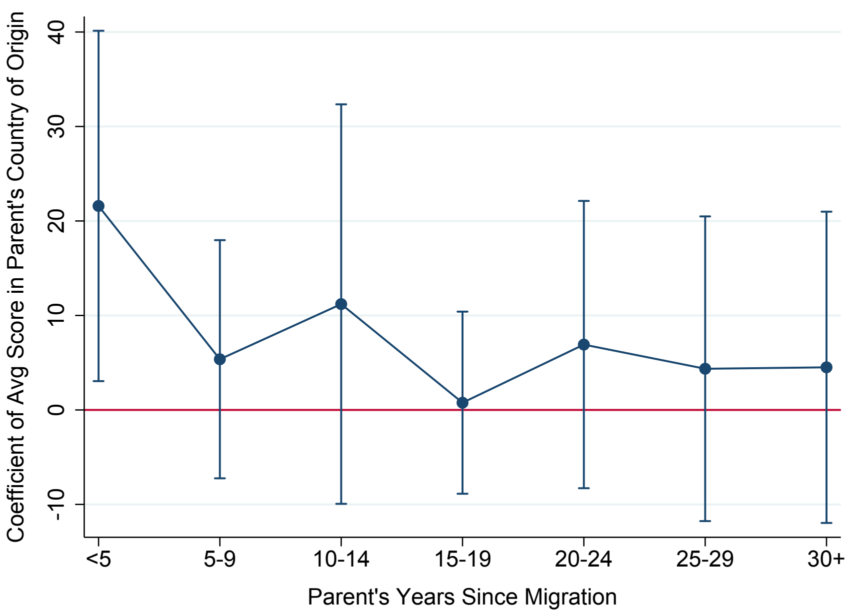
Notes: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in mother's country of origin and dummies corresponding to mother's years since migration, with the dependent variable and other controls being the same as in column 5 of Table III. Standard errors are clustered by mother's country of origin.

Figure IX: 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 IX. Standard errors are clustered by mother's country of origin.

Figure X: 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 IX. Standard errors are clustered by mother's country of origin.