Parents, Schools and Human Capital Differences across Countries*

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Abstract

This paper studies the contribution of parental influence in accounting for cross-country gaps in human capital achievements. We argue that the cross-country variation in unobserved parental characteristics is at least as important as the one in commonly used observable proxies of parental socio-economic background. We infer this through an indirect empirical approach, based on the comparison of the school performance of second-generation immigrants. We document that, within the same host country or even the same school, students whose parents come from high-scoring countries in standardized international tests (PISA) do better than their peers with similar socio-economic backgrounds. This finding is not driven by differential selection into emigration. We provide several pieces of evidence that support the transmission of cultural values as a leading channel behind the cross-country variation in the parental component. Unobserved parental characteristics account for about 15% of the cross-country variance in test scores, roughly doubling the overall contribution of parental influence.

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1 Introduction

Human capital varies greatly across countries, in terms of both years of schooling and results in international standardized tests. East Asian countries consistently position themselves at the top of international test rankings, while several Southern European and Latin American countries perform poorly. An emerging strand of the growth literature argues that human capital accounts for a substantial part of cross-country differences in economic performance (Schoellman, 2012; Jones, 2014; Lagakos et al., 2018), especially when measured by standardized tests (Hanushek and Woessmann, 2012).

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. Previous research analyzes the role of educational systems and parental socio-economic background for cross-country gaps in standardized test scores, finding that both aspects play some role. Such analyses, however, face the challenge that countries may differ in a range of factors, related to both the institutional setting and the cultural traits, preferences and skills transmitted by parents, which are difficult to fully capture and identify through the observable characteristics commonly available for cross-country comparisons.

This paper investigates the importance of parental influence for the cross-country variation in test scores. We start from a simple educational production function framework, along the lines of Woessmann (2016), relating individual-level educational performance to several observable characteristics of students, households, countries and schools. We show that, when the effect of proxies for parental socio-economic status is estimated exploiting within country (or within school) variation only, cross-country differences in those characteristics account for a relatively limited part of the cross-country variation in average performance. However, studies on skill formation at the individual level suggest that parents influence children's human capital through a number of channels not fully captured by socio-economic characteristics, including parenting styles (Cobb-Clark et al., 2019; Doepke and Zilibotti, 2017), features of the home environment (Todd and Wolpin, 2007; Almond and Currie, 2011) and the transmission of preferences and cultural traits (Bisin and Verdier, 2010; Figlio et al., 2019). A natural question then is whether the variation in these factors is also relevant at the country level.[1]

Motivated by this question, we propose an empirical strategy to infer the importance of cross-country gaps in unobserved parental characteristics. Our approach is based on the analysis of second-generation immigrant students. We compare the educational performance of students born in the same country and, for part of the analysis, educated in the same school, with a similar socio-economic background but with parents of different nationalities. In absence of differential selection into migration (which we discuss below), we propose to use performance gaps across parental nationalities for otherwise similar second-generation immigrants as proxies for cross-country gaps in an unobservable parental component. The logic is simple: these students are

[1] 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.

all exposed to the same (host country) educational system and institutional environment, but their parents plausibly embody some of the parental attitudes, practices and skills typical of their country of origin. To quantify the importance of this unobserved parental component, we augment the baseline educational production function specification with country-of-origin fixed effects, identified from the gaps in performance between second-generation immigrant students (observed in the same country or school), and we compare their cross-country variation with the overall cross-country variation in average performance.

Our results point towards a substantial role for unobserved parental characteristics. 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 in their parents' country of origin: 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 proxies of parents' socio-economic status and other characteristics of their countries of origin. We analyze patterns of migrants' selection on observable characteristics, and conclude that these findings do not appear to be driven by a differential selection into emigration. Moreover, we find a similar result for a different schooling outcome in a specific host country, which is grade repetition in the United States.

The inferred cross-country variation in parental influence is substantial. The estimated parental country-of-origin fixed effects account for about 15% of the cross-country variation in test performance, roughly doubling the overall contribution of parental influence. The unobserved parental component is a key driver of the high performance of East Asian countries, as well as of the relatively low performance of Southern European countries. Overall, a narrow focus on observable socio-economic characteristics substantially underestimates the importance of parents for cross-country gaps in human capital.

We then explore potential mechanisms behind the estimated gaps in this parental unobservable component, using US data. We show that the relationship between the performance of second-generation immigrants and the average score in the parents' country of origin is not stronger - if anything, somewhat weaker - for parents with more education in their home country. This suggests that our results are not driven by the intergenerational transmission of the quality of education parents were exposed to. Moreover, the relationship is weaker for parents that have spent more years in the host country, which is consistent with the importance of country-specific "cultural" traits, that are progressively lost by emigrants as they integrate in their new host country. Consistently with this interpretation, most of the variation in second-generation immigrants' performance is accounted for by differences across parental nationalities in proxies for cultural traits likely to be conducive to human capital investment, such as long-term orientation, locus of control and trust. Finally, we rely on time use data for US immigrants to document actual parental practices that might contribute to our results, and we show that

[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, natives represent 77% of the target population. Students born in a country different from the one where they are taking the test are excluded from the analysis.

parents from high PISA countries spend more time on various forms of child care.

This paper contributes to the debate on cross-country differences in human capital. Our analysis is similar in spirit to Woessmann (2016), which relates standardized test performances across countries to differences in observable characteristics of the educational systems and of students' family background. Specific evidence for the importance of heterogeneity in school quality is also provided, among others, by Singh (2019). More broadly, the literature on cross-country differences in educational attainment emphasizes country-specific factors, such as technology and relative prices, that shape the costs and expected benefits of human capital investments (Bils and Klenow, 2000; Manuelli and Seshadri, 2014). Our focus on parents is shared by Doepke and Zilibotti (2017), who model the choice of different parenting styles as a function of local economic conditions. We contribute to this literature by quantifying and characterizing the role of differences in observable and unobservable parental influence for children's school performance.

We also relate to a wide literature across economics and sociology on the school performance of first- and second-generation immigrant children (see Levels et al., 2008; Dustmann et al., 2012, for broad reviews). Differently from these papers, our objective is to understand gaps in performance between natives of different nationalities, and our focus on second-generation immigrants is mostly instrumental in that it provides us with an empirical strategy to discriminate between possible sources for these gaps. Some existing contributions focus on the performance of immigrants from specific nationalities; for example, Dustmann et al. (2012) on Turkish immigrants and Jerrim (2015) on East Asian immigrants. We add to these papers since we conduct our analysis on a broad sample of host and origin countries and we rely on several additional sources to provide evidence on the mechanisms underlying our results.[3]

Our paper shares the approach of a large literature that looks at first- and second-generation immigrants to identify the importance of "portable" cultural traits, for various outcomes (the so-called "epidemiological approach"; see among others Giuliano, 2007; Fernandez and Fogli, 2009; Fernandez, 2011). Differently from these papers, we study the school performance of the second generation, and use the results to quantify the importance of parents for cross-country differences in the same outcome. While most of the focus in this literature is on immigrants in the US, our sample includes a large set of both host and source countries, allowing us to exploit variation in both dimensions.

In contemporaneous and independent work, Figlio et al. (2019) use a similar methodology to document the association between the educational performance of first- and second-generation immigrants and a specific cultural trait in their parents' country of origin, namely long-term orientation. Compared to their paper, we adopt a broader object of interest - overall parental

[3]Like us, Levels et al. (2008) and Dronkers and de Heus (2016) compare the performance of (a combination of) first- and second-generation immigrants across countries of origin. However, they do not relate those to the performances of natives in the countries of origin, nor explore the implications in terms of cross-country gaps in performance. Yet another distinct strategy is the one in Borjas (1992), who relates the average educational attainment of ethnic groups residing in the US (what he calls "ethnic capital") to schooling and wages of the following generation. We discuss this and other channels through which immigrant parents' ethnic network might affect children's human capital accumulation in Online Appendix D.2.

influence, as opposed to a specific cultural trait - and we quantify its contribution to cross-country gaps in performance. Moreover, we consider several possible mechanisms behind the cross-country variation in parental influence. Consistently with Figlio et al. (2019), we find that the transmission of cultural traits - including, but not limited to, long-term orientation - is an important channel. While the strong correlation between several relevant dimensions of culture and the difficulty associated with their measurement make it hard to evaluate the relative importance of different traits, our approach yields a quantification of the overall importance of parental influence, which can directly inform future theoretical and quantitative work on cross-country differences in human capital accumulation.

The paper is structured as follows. Section 2 describes the data, while Section 3 quantifies the role of observable parental characteristics for cross-country gaps in performance. Section 4 introduces the idea of using second-generation immigrants to capture cross-country differences in unobserved parental characteristics, shows evidence on their performance and addresses selection into emigration. Section 5 augments the decomposition exercise of Section 3 with an explicit role for parental unobservables. Finally, Section 6 explores the mechanisms behind our results, and Section 7 concludes.

2 Data

Our main data come from the 2003, 2006, 2009, 2012 and 2015 waves of the PISA test. PISA is a triennial survey of the knowledge and skills of 15-year-old children, explicitly designed to allow comparisons across countries. The test covers three subjects: reading, mathematics and science. We standardize scores to have mean 0 and individual-level standard deviation 1 across all countries (pooled, equally weighted) participating in at least one wave of the test.[4]

Results for all subjects vary greatly across countries. Figure 1 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). Students in Shanghai score more than one (individual-level) standard deviation higher than the average, and almost three standard deviations better than the worst-performing countries.[5] These magnitudes are striking; according to OECD (2012a), a gap of 0.4 on this scale corresponds to what is learned in an average year of schooling. There is substantial geographical clustering: East Asian countries occupy the first positions of the ranking, followed by several Western European countries; Southern European countries concentrate in the middle of the distribution, while Latin American countries are below the

[4]The results are not presented as point estimates but rather as "plausible values": the OECD estimates for each student a probability distribution of scores, and randomly draws from it five values. Following OECD (2009), we compute variances of all functions of test scores (including regression coefficients) 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. In addition, we correct the standard errors of all regression coefficients for the estimated measurement error in test scores, based on the variance of the estimates across sets of plausible values. Online Appendix B discusses the details of this procedure.

[5]Within China, the PISA test was held in Shanghai only for the 2009 and 2012 waves, and in the provinces of Beijing, Shanghai, Jiangsu and Guangdong for the 2015 wave. In the rest of the paper we refer to "China" as the latter aggregation of provinces.

average. The superior performance of East Asian students is stronger in mathematics, but the ranking across regions is quite stable across subjects (see Table A.2.1 in the Online Appendix for the average scores in these and other broadly defined regions).

[Figure 1 about here]

A Student Questionnaire provides basic demographic and socio-economic information on students and parents, including their immigration status, education, language spoken at home, number of books at home, employment and the ISEI index of socio-economic occupational status (see Online Appendix A for more details on these variables). We refer as second-generation immigrants to students born in the country where they are taking the test and with foreign-born parents. Our analysis of second-generation immigrants focuses on 41 host countries where the questionnaire identifies the country of birth of both parents.[6] Across these host countries, we observe on average about 7 foreign parental nationalities. Overall, the PISA sample includes 49,097 second-generation immigrants on the mother's side and 48,834 on the father's side, from 59 and 58 different countries of origin and distributed across 41 host countries. Each country of origin is observed on average in about 3 foreign host countries (see Tables A.2.2 and A.2.3 in the Online Appendix for summary statistics by origin and host country). The sample size by parental country of origin varies greatly, and for some countries of origin we have only a few observations to work with. In light of 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 31 countries from which we have at least 100 emigrant mothers and fathers. Solid bars in Figure 1 correspond to countries for which we observe second-generation immigrants, and the black ones identify the "core sample". Descriptive statistics for second-generation immigrants on the mother's side are provided in Panel A of Table 3.

[Table 3 about here]

Our second data source is the US Census, which we use to explore the mechanisms behind our results. We use the 1% sample for 1970 and 5% sample for 1980. We follow Oreopoulos and Page (2006) in combining information on children's age and grade currently attended to construct an indicator of whether or not students have repeated any grade.[7] We focus on children between the ages of 8 and 15 and 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.[8] This outcome, while still related to school performance, captures quite a different dimension

[6] National educational authorities have flexibility on whether to ask for and how to classify parents' country of origin, and many of them group some or all nationalities in broader categories (such as continents), recording separately only those that are relatively frequent. We construct a set of countries consistently defined over time; see Online Appendix A for the details. Online Appendix B discusses both the potential issues of unreported countries of origin and misclassification in the parental immigration status reported by students.

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

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

compared to the PISA score, given that the variation here comes only from the bottom part of the distribution (more than 80% of the students in the sample has never repeated a grade) and from students aged 8-15 (while PISA is administered to 15-year-old students only). As for the PISA data, we identify second-generation immigrants based on children's and parents' country of birth. Our final sample includes 53,553 second-generation immigrants on the mother's side and 46,498 on the father's side, from 64 countries of origin. Descriptive statistics are provided in Panel B of Table 3.

Finally, we rely on several other data sources to construct controls at the host country, school, and parents' country of origin level. We discuss the details below as we introduce these variables in the analysis.

3 The Role of Parental Observable Characteristics

This section presents a simple decomposition to quantify the role of parents' observable characteristics for cross-country gaps in PISA performance. We rely on an international education production function, a regression model that relates individual-level test performance across several countries to various relevant factors. Similar specifications have been widely employed in the literature - for a recent review, see Woessmann (2016). We will discuss the role of unobservable parental characteristics in the following sections.

Let T_{icst} be the test score in wave t of student i, born in country c and educated in school s. We distinguish between two factors driving test scores: the effect of characteristics of parents and the home environment on one hand, $Parents_{icst}$, and the effect of the resources and institutional features of the educational system on the other, $EduSystem_{cst}$. Moreover, we control for a vector of basic student demographic characteristics, D_{icst}, which includes age (in months) and gender. We assume the linear relationship

$$T_{icst} = Parents_{icst} + EduSystem_{cst} + \beta' D_{icst} + \alpha_t + \varepsilon_{icst} \tag{1}$$

where α_t is a wave fixed effect, and ε_{icst} a mean zero idyosincratic term (non-linear extensions are discussed in Online Appendix E).

We experiment with different approaches to capture $EduSystem_{cst}$. First, we control for a vector of observable characteristics of schools and countries' educational environments, based on Woessmann (2016). This vector includes both proxies for the amount of available resources, such as expenditure per student and school-level indicators on the shortage of instructional material, and institutional features of the educational system, such as various indicators for the degrees of accountability, monitoring and autonomy in schools (see Online Appendix A for a full list of the included variables and their sources). These observables are available for a sample of 37 countries. Second, we control for (wave-specific) country or school fixed effects. This allows to control flexibly for any relevant difference in educational quality and in the institutional context, and to extend the analysis to countries for which the observables described above are not available.

School fixed effects (and, to some extent, school observable characteristics) absorb the within country variation in school quality. In fact, part of this variation is likely to be driven by parental characteristics: parents play an important role in school selection, and one might want to ascribe an higher "demand" for better schools to the parental factor. However, if parents are not completely free to choose schools, or if the supply of school quality is to some extent fixed, a higher average demand for good schools would not by itself raise the average performance. We display results from both country and school fixed effects specifications, with the understanding that controlling for school fixed effects provides us with a lower bound for the importance of parental influence for cross-country gaps in performance.[9]

The parental term is given by the sum of the effects of observable socio-economic characteristics, collected in the vector X_{icst}, and an unobservable term, u_{icst}

$$Parents_{icst} = \rho' X_{icst} + u_{icst}$$

We include in X_{icst} controls for parents' education, employment and occupational status, as well as for the number of books at home and a dummy identifying households where the primary spoken language is not the one of the test.[10] This selection follows closely previous work on educational production functions estimated on PISA data. In Online Appendix B (Table B.1.8) we show that the results are robust to alternative controls for socio-economic status available in the PISA dataset. For now, we treat u_{icst} as a residual, implying that part of its effect might be absorbed by other regressors. In particular, any systematic cross-country variation in the average of any relevant unobservable would be absorbed by country or school fixed effects, if included in the regressions. In the following sections, we propose an approach to separately identify this variation.

We estimate equation 1 using the micro-level data from the math PISA assessment. Table 1 shows the individual-level regression results. Column 1 only includes parental and demographic characteristics, while column 2 introduces observable controls for features of schools and the educational system. Columns 3 and 4 control for country fixed effects, and columns 5 and 6 for school fixed effects. As mentioned above, the fixed effects specifications allow us to extend the analysis to a wider sample (79 countries); the corresponding results are shown in columns 4 and 6.

[Table 1 about here]

Across specifications, several parental and home background characteristics are statistically significant predictors of students' performance in the expected direction. While the number of books at home and occupational status are significant throughout, for several parental characteristics the inclusion of country and, especially, school fixed effects causes a reduction in the

[9] Moreover, parents may also shape the characteristics and the quality of the educational system itself. What we estimate in our analysis is the part of the parental component independent of potential impacts that parents might have on the education system. If anything, this likely implies that we are underestimating the role of cross-country differences in parental influence.

[10] 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.

magnitude of the associated coefficients. This points to the fact that parental observables are correlated with relevant country and school characteristics.[11]

Our ultimate object of interest is the cross-country variation in average performance. The average score (across all available waves) of students in country c can be written as

$$T_c = \rho' X_c + u_c + EduSystem_c + \beta' D_c + \alpha_c \tag{2}$$

where X_c, u_c, $EduSystem_c$, D_c and α_c are country-level averages of the corresponding variables (pooled across waves).[12] Let's denote the estimated effect of parental observables as

$$\widehat{ParentsObs}_c = \widehat{\rho}' X_c$$

where $\widehat{\rho}$ is estimated according to the different individual-level specifications displayed in Table 1.

The cross-country variance of T_c can be additively decomposed in the contributions of the covariances between T_c and all terms on the right hand side of equation 2. We quantify the contribution of parental observables by computing

$$\frac{\mathrm{Cov}(\widehat{ParentsObs}_c, T_c)}{\mathrm{Var}(T_c)}$$

Table 2 shows the decomposition results. Each column corresponds to the specification estimated in the respective column of Table 1. When no other controls are included, parental observable characteristics account for about 43% of the overall cross country variation (column 1), while once educational quality is controlled for through observables this share of variance almost halves (similarly to what is reported in Woessmann (2016)). Country and, especially, school fixed effects further reduce the contribution of parental observables, to 25% and 13% respectively when using the same sample of 37 countries for which all the educational system controls are available, and to 17% and 9% when using the full sample.[13]

[Table 2 about here]

Overall, while the exact magnitudes depend on the sample of countries under consideration, parental observable characteristics account for a minority share of the cross-country variation in performance. However, these observables might fail to capture relevant channels through which

[11]The coefficients on school and country observable characteristics included in the specification in column 2 are roughly comparable to what has been found in previous work (for a smaller set of countries and waves). The main exceptions are that we do not find a positive impact for various indicators of accountability and monitoring that emerge as important in Woessmann (2016). The discrepancy is mostly due to the different sample coverage in terms of countries and waves. Given that the rest of the paper focuses on the fixed effects specifications, we leave more detailed comparisons of these results for future work.

[12]The average of the wave fixed effects is country-specific as different countries participated in different waves. The variation in this term plays virtually no role for the overall cross-country variation in T_c.

[13]The difference across samples is driven by the fact that the average PISA score has a larger variance and a smaller covariance with $\widehat{ParentsObs}_c$ in the full sample. The smaller covariance is in turn explained by a smaller variability in average parental characteristics in the full sample, while the difference across samples in the associated coefficients has a negligible impact.

parents affect human capital accumulation, and as a result they might lead to underestimate the overall importance of parental influence for cross-country gaps. We investigate this possibility in the rest of the paper.

4 Second Generation Immigrants: Motivating Evidence

We argue that second-generation immigrants represent an interesting laboratory to study cross-country differences in parental influence. This is based on two premises. First, students born and raised in the same country, educated in the same school and with parents with similar socio-economic characteristics are subject to similiar conditions in terms of the educational system and any other country-specific relevant factor. Second, part of any systematic difference across countries in parental practices and (unobservable) parental characteristics should be preserved across countries of origin of immigrant parents, and therefore be reflected in the educational performance of second-generation immigrants.[14]

These two points are subject to some caveats. Emigrant parents might be systematically different from non-emigrant parents, and differences in performance across parental nationalities might be due to differences in the degree of emigrants' selection. Moreover, immigrant parents might face frictions in terms of cultural assimilation, language and various types of discrimination, and once again the severity of those frictions might vary depending on countries of origin, even for otherwise observationally equivalent parents. We acknowledge these possibilities and discuss their empirical relevance for our results in Section 4.3.

Concerns on selection notwithstanding, if unobserved parental factors are important drivers of cross-country differences in test performance, then we should expect second-generation immigrants from high-scoring countries to do better than those from low-scoring countries, controlling for host-country and school fixed effects as well as for parental socio-economic characteristics. This is the hypothesis we test in the next two subsections. Using both PISA and US Census data, we relate the educational performance of second-generation immigrant students to the average PISA performance in their parents' country of origin, conditional on controls for socio-economic status and school or educational system characteristics.

We focus here on second-generation immigrants on the mother's side only. This is only to simplify the exposition, and in Online Appendix B (Tables B.1.1 and B.1.2) we show that 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.

[14] Of course parental choices are likely to be partially driven by *context-specific* incentives: for example, higher expected returns to skills in the labour market might induce parents to stress the importance of education and hard work (Doepke and Zilibotti, 2017). Immigrant parents in our sample arguably 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. Comparing second-generation immigrants instead isolates the role of factors that are embedded into parents, independently of the context-specific incentives they face. We discuss and attempt to discriminate between some of these factors in Section 6.

4.1 Evidence Using PISA Data

Figure 2 displays in the left panel the average score of second-generation immigrants against the average score of natives in the countries of origin of their mothers, pooled across all available waves. The relationship is positive and tight. While the cross-country variation in natives' performance reflects a combination of school quality, economic, cultural and institutional factors, the fact that these gaps are largely preserved across second-generation students in other countries suggests that parents might play an important role. Of course, this pattern might be driven by factors unrelated to systematic differences in parental influence across countries. We investigate several potential confounders in our regression analysis.

[Figure 2 about here]

We amend the notation to take into account the heterogeneity in terms of mothers' countries of origin. 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. We estimate variants of the following specification:

$$T^m_{icst} = \theta_0 + \theta_1 T^m + \theta_2' X_{icst} + \theta_3' D_{icst} + \theta_4 NatFath_{icst} + \theta_{cst} + \varepsilon^m_{icst} \tag{3}$$

where T^m is the average score of native students in the mother's country of origin, X_{icst} and D_{icst} include the same socio-economic and demographic characteristics considered above, $NatFath_{icst}$ is a dummy identifying students whose father is a native of country c, θ_{cst} is a wave times host-country (or wave times school, depending on the specification) fixed effect and ε^m_{icst} is an error term. As before, specifications with host country fixed effects control for any difference in the host country's institutional setting, while specifications with school fixed effects further control for the quality of the school attended by each student (and implicitly, since host country fixed effects are nested in school fixed effects, also for any difference in the host country's institutional context). The main coefficient of interest is θ_1, which captures the relationship between a second-generation immigrant's performance and the average score of native students in country m, after having accounted for observable parental characteristics and for the quality of the host country's educational system.[15]

Table 4 shows our results for second-generation immigrants on the mother's side. Standard errors are clustered at the level of the mother's country of origin, and inflated by the estimated measurement error in test scores.[16]

[Table 4 about here]

[15] We focus on the average score pooled across waves, T^m, because cross-country gaps in performance are quite stable over time, and the parental factors we investigate are also unlikely to vary dramatically from one wave to the other. Using the average score of countrym m in wave t as a regressor leads to very similar results, though we lose all the observations corresponding to second-generation immigrants tested in waves where the countries of origin of their mothers did not participate to PISA.

[16] 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 inflated by the estimated imputation variance, which is proportional to the variance of the estimated coefficients across sets of plausible values. See Online Appendix B for the details.

We proceed by progressively adding controls. Column 1 controls for students' demographic characteristics (gender and age in months), fathers' immigrant status and wave fixed effects only. The correlation of interest is strong and highly significant: a gap of one (individual-level) standard deviation in the average score in the mother's country of origin is reflected in a gap of 76% of a standard deviation among second-generation immigrants.

The coefficient shrinks when we introduce controls for parental observable characteristics (column 2) and, especially, host-country (column 3) and school (column 4) fixed effects, but is still positive and significant. A comparison between the first two specifications and columns 3 and 4 suggests that children of immigrant mothers from high PISA countries are located in countries and schools with conditions more conducive to positive performances. However, a substantial part of the gap across mothers' countries of origin persists even conditional on host-country and school characteristics. The last column of Table 4 shows that results are not driven exclusively by the performances of students with East Asian origins, since the coefficient is robust to the exclusion of East Asian mothers.

The right panel of Figure 2 displays the main result of this section. The relationship between the performance of second-generation immigrants and natives in the mother's country of origin, after having controlled for the effect of all observable characteristics, including school fixed effects, weakens but is still positive and significant.

Online Appendix B performs a number of additional robustness tests. We show that the results are similar for the reading and science tests (Tables B.1.3 and B.1.4) and that the estimated relationship is not driven by any single host or origin country (Figures B.1.1 and B.1.2). Moreover, we document that the results are virtually identical when we restrict the sample to host countries with nearly universal secondary school enrollment, ruling out any important role for early school dropouts in driving our relationship of interest (Table B.1.5). Finally, we show that our inference is robust to the implementation of several alternative ways to construct standard errors, including the Balanced Repeated Replication method recommended in OECD (2009), the wild cluster boostrap proposed in Cameron et al. (2008) and two-way clustering on schools and countries of origin (Tables B.1.6 and B.1.7).

4.2 Evidence Using US Census Data

We apply a similar specification as in equation (3) to the US Census data. The US Census does not include any information on the school children are attending. To capture some of the differences across educational systems within the US, we control for Commuting Zone (constructed following Autor and Dorn (2013)) fixed effects. Importantly, compared to the PISA sample, in the US data we can control for a richer set of family characteristics, such as number of siblings, parents' age and family income, as well as for the number of years passed since the mother has migrated to the US.

Table 5 shows our results. Once again, the coefficient on T^m is positive and significant throughout. Commuting zones fixed effects and controls for parental education, mother's years since migration and family income explain about two thirds of the raw gap in performance between second-generation immigrants from high and low PISA countries. According to column 4, 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 2.9 percentage points (3% over the average). As for the PISA specification, the result is robust to the exclusion of East Asian mothers (column 5). Online Appendix B.2 performs robustness checks similar to those proposed for the PISA data.

[Table 5 about here]

4.3 Selection

As our analysis relies on emigrant parents to make inference on all parents of a given nationality, a concern is that emigrants are not a representative 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? Our quantity of interest is the hypothetical gap in performance between second-generation immigrants whose parents come from low- and high-scoring countries, in a world where emigrant parents were randomly selected from their country of origin's population. A common degree of selection into emigration across countries of origin with different PISA scores would not bias our estimate of this object: the effect of such form of selection would be picked up by the intercept θ_0 in equation (3) (or by the host-country or school fixed effects, if the degree of selection varies across host countries or schools), leaving the coefficient θ_1 unaffected. Patterns of differential selection correlated with the home country's PISA score would instead lead to a biased estimate of our coefficient of interest. In particular, our findings can be rationalized if parents emigrated from countries with high PISA scores are more positively selected than parents emigrated from countries with low PISA scores.

To understand which case is empirically relevant in our setting, we look at differential selection in terms of parental education. While the main threat to our approach is differential selection on unobservables, it seems plausible that several unobservable parental traits that positively affect children's school performance (such as skills and attitudes towards schooling) are positively correlated with parents' own educational achievements. We can therefore alleviate the concerns on differential selection if we can show that the relative "quality" of emigrants compared to stayers is not higher for high PISA countries.[17] 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.[18]

[17] Ideally, we would like to perform such an exercise with a measure of quality pre-determined with respect to migration. Parental education, as any other socio-economic control available in the PISA dataset, does not satisfy this condition, since parents might have acquired part of their education in their host countries, or have based their educational choices in their countries of origin anticipating their future relocation. In the Census data, where information on year of arrival is available, we find similar patterns of selection for those parents that are more likely to have completed their education in the country of origin (see Online Appendix C).

[18] 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). In Online Appendix C.1.1 we show

Figure 3 plots the average of this measure across mothers' countries of origin against the average score of native students in those countries. For a majority of countries of origin, emigrant mothers are positively selected (that is, our measure is greater than 0), a finding consistent with most of the recent literature (for example, Feliciano, 2005 documents that US immigrants from most nationalities are positively selected on education). Importantly, the relationship between the degree of selection and the average PISA score is flat. In Table 6 we further test this result by regressing the individual-level measure of selection of emigrant parents on the average PISA score in their country of origin, controlling for host country (columns 1 and 3) and school (columns 2 and 4) fixed effects. A positive coefficient in these regressions would imply that emigrants from high scoring countries are more positively selected than those from low scoring countries. For both mothers and fathers, the point estimates are small and not statistically significant, suggesting that the type of differential selection that would invalidate our results is not present, either within host countries or within schools.

[Figure 3 and Table 6 about here]

The absence of a positive correlation between the degree of selection and the PISA score is broadly consistent with the findings in the development accounting literature. Schoellman (2012) documents that, among migrants residing in the US (not necessarily parents of school-age children), the education gap compared to non-migrants is higher for poor origin countries, which on average have lower PISA scores. Similarly, Hendricks and Schoellman (2018) show that emigrants from poor countries are more positively selected in terms of pre-migration wages and occupations. More broadly, our results are consistent with a large literature studying the determinants of emigrants' self-selection, such as income inequality, migration costs, social networks, geography and school quality (see Online Appendix C.1.3 for a detailed discussion).

In addition, Online Appendix C.2 implements methods to explicitly correct our estimates for any differential selection into migration. First, we introduce various individual-level measures of selection on observable characteristics as additional controls in specification (3): to the extent that selection on these characteristics is correlated with the average score in the parental country of origin, controlling for it might affect the magnitude of our coefficient of interest. Second, we propose an application of inverse probability weighting (Horvitz and Thompson, 1952), which consists in re-weighting observations in order to make the subsamples of migrant parents from each country of origin as representative as possible of the corresponding populations of non-migrant parents. In both cases, the results are very similar to our benchmarks in Table 4.

A distinct concern is differential selection in terms of quality of the "match" between the parental country of origin and the host country, i.e. the possibility that immigrant parents from high PISA countries may be systematically selecting host countries where it is easier for them and their children to integrate and perform well. Table 7 explores this issue by adding to

that using either the ratio or the difference between migrant and non-migrant parents' years of education as alternative proxies for selection leads to equivalent conclusions. Moreover, in Online Appendix C.1.2 we document that selection patterns in terms of other observable characteristics (number of books at home, time use and wages) are consistent with those reported here.

specification (3) controls at the bilateral level. Columns 2, 4 and 6 add to the baseline specifications (reported in columns 1, 3 and 5) controls for linguistic, cultural and geographical distance between the host country and the parents' countries of origin.[19] The relationship of interest is robust across all specifications, and controlling for all distance measures simultaneously makes it somewhat stronger (column 8). The point estimates on these controls are generally positive, and marginally significant for linguistic distance. One possible interpretation is that linguistic differences increase migration costs, and, consistently with the mechanism in Albornoz et al. (2018a) and the evidence in Albornoz et al. (2018b), generate a more positive selection of emigrant parents. Column 9 controls instead for interactions between host country and parental continent of origin fixed effect, which absorb the effect of any host country-specific factor that shapes the performance of second-generation immigrants from a given continent. The result is robust in this specification as well.

[Table 7 about here]

5 The Role of Parental Unobservable Characteristics

This section quantifies the role of the unobserved component of parental influence in accounting for cross-country differences in average test scores. For this purpose, we build on the specification proposed in Section 3, incorporating second-generation immigrants as well as natives across all countries.

The test score in wave t of student i, educated in school s and country c, whose mother and father were born in countries m and f is given by

$$T_{icst}^{mf} = Parents_{icst}^{mf} + EduSystem_{cst} + \mu' D_{icst} + \theta^m NatMoth_{icst}^m + \zeta^f NatFath_{icst}^f + \varepsilon_{icst}^{mf} \quad (4)$$

where $NatMoth_{icst}^m$ and $NatFath_{icst}^f$ are dummies identifying native parents (mothers and fathers, respectively), and D_{icst} is the same vector of students' demographic characteristics used in (1) and (3). As before, we control for $EduSystem_{cst}$ through either wave times country or wave times school fixed effects.

The $Parents_{icst}^{mf}$ term is once again the combination of the effects of socio-economic and unobservable characteristics. Crucially, we write the latter as the sum of two country of origin specific unobserved components, γ^m and δ^f, and a residual, $\tilde{u}_{icst}^{mf}$,

$$Parents_{icst}^{mf} = \xi' X_{icst} + \gamma^m + \delta^f + \tilde{u}_{icst}^{mf} \quad (5)$$

We interpret γ^m and δ^f as the average unobservable contributions of, respectively, mothers

[19] Linguistic distance is computed using the programs provided by the Automated Similarity Judgment Program (Wichmann, Søren, Eric W. Holman, and Cecil H. Brown, 2016), cultural distance is taken from Spolaore and Wacziarg, 2015, and geographic distance (simple distance between the most populated cities, expressed in kilometers) from the CEPII's GeoDist dataset (Mayer and Zignago, 2011). Linguistic and cultural distance are standardized to have mean 0 and standard deviation 1 across all country pairs in the sample. For native fathers, the distance measures are normalized to a constant (the value of which is irrelevant, as it is captured by the coefficient on the native father dummy).

born in country m and fathers born in country f. When second-generation immigrants are included, these components can be separately identified from $EduSystem_{cst}$ through mothers' and fathers' country-of-origin fixed effects (γ^m and δ^f).[20]

The coefficient θ^m (and ζ^f), in the spirit of a difference in differences, captures the extent to which the relative performance of students whose mother is from country m, compared to second-generation immigrant students from another country, is larger or smaller in country m (where the mother is native) as opposed to a different host country. We allow the "native advantage" to be country-specific for both mothers and fathers: a failure to do so would imply that this kind of variation would be absorbed by the country-of-origin fixed effects.

The average performance of native students in country c (pooled across waves) is

$$T_c = \xi' X_c + \gamma^c + \delta^c + \tilde{u}_c + EduSystem_c + \zeta' D_c + \theta^c + \zeta^c + \alpha_c \tag{6}$$

We estimate the contribution of unobservable parental characteristics as

$$\widehat{ParentsUnobs}_c = \widehat{\gamma}^c + \widehat{\delta}^c$$

and quantify its importance for cross-country gaps in average performance through

$$\frac{\text{Cov}(\widehat{ParentsUnobs}_c, T_c)}{\text{Var}(T_c)}$$

which we benchmark against the corresponding quantity for $\widehat{ParentsObs}_c = \widehat{\xi} X_c$.

Table 8 displays the decomposition results. We show results for two specifications, one where educational quality is controlled for by host-country fixed effects, and one by school fixed effects. The contribution of parental unobservables is substantial, ranging between 12% and 16%, and roughly doubles the overall contribution of parental influence to cross-country differences in performance.

[Table 8 about here]

To better understand the cross-country variation, Table 9 displays estimates for all countries in the core sample. In particular, columns 3 and 4 show the difference between $\widehat{ParentsObs}_c$ and the cross-country mean, while columns 5 and 6 display the corresponding quantities for $\widehat{ParentsUnobs}_c$. These figures should be benchmarked against the gap in PISA performance with respect to the cross-country mean, reported in column 2. For several of the top performing East Asian countries, unobserved parental characteristics play an important role. For example, unobservables account for between a quarter and 60% of the gap between the performance of Hong Kong students and the cross-country average, and for between half and all of China's out-performance. A low value of $\widehat{ParentsUnobs}_c$ is also a key driver of the low scores in several

[20] A necessary condition for the identification of all fixed effects is that parental nationalities are part of a connected set, as in Abowd et al. (2002). This is not very restrictive in our context, as native parents (which can be found in most schools) can also be used to "connect" nationalities that never overlap in the same school. Indeed, the condition is satisfied in our sample, even when we control for school fixed effects.

Southern European countries. Instead, unobserved parental influence does not contribute to explain the low scores in Brazil and India, the two worst performing countries in the core sample.[21]

[Table 9 about here]

6 Mechanism

What are the unobserved attributes and practices of parents from high PISA countries that drive the superior school performance of their children? This section presents several pieces of evidence that shed some light on the mechanisms behind our results.

We distinguish between three broad interpretations of the parental country of origin effect. First, the outstanding performance of second-generation immigrants from high PISA countries might reflect the higher quality of the education received by parents in their country of origin (the "intergenerational transmission of educational quality" interpretation). Under this interpretation, our results would reinforce the rationale for policies aiming to replicate the schooling practices adopted in the most successful countries, since the benefit of doing so would extend to the following generations. Second, parents might transmit a set of values, preferences and beliefs on education typical of their country-of-origin's cultural context (the "cultural" interpretation). This variation in cultural traits might have its roots in factors deeply entrenched in a country's history and traditions, 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 might be systematically endowed with different genetic traits that shape their human capital investment (the "genetic" interpretation). This view would leave little room for policies to affect achievement gaps.

This section makes progress by proceeding in three steps. First, we explore the heterogeneity of our baseline results with respect to various parental characteristics, and we discuss how this evidence can shed light on the relative merit of the three interpretations discussed above. Second, we augment our baseline specification with controls for country-of-origin-level proxies for educational resources and economic development on one hand and cultural traits on the other, to examine their explanatory power for our country-of-origin effect. Finally, we turn to time use surveys to see whether immigrant parents from high PISA countries differ in practices that might help explain their children's better performance at school.

[21] In Online Appendix F we discuss how the cross-country variation in the unobserved parental component affects the relationship between average PISA scores and GDP per capita. We show that that a high parental component is an important driver of the out-performance of the poorest countries in our sample (China, India and Vietnam) compared to what one would predict based on their level of development. In a standard development accounting exercise, the unobservable parental component accounts for a slightly negative share of the cross-country dispersion in GDP when all countries are considered, and for a slightly positive share when these 3 countries are excluded.

6.1 Heterogeneity

The interpretations discussed above have different implications in terms of which parental characteristics should amplify or weaken the transmission of country-specific parental influences. Under the "intergenerational transmission of educational quality" interpretation, we expect the correlation between school performance and the PISA score in the parents' country of origin to be stronger for students whose parents acquired more education in their home country, and were therefore more exposed to the home country's educational system. At the extreme, parents with no education cannot transmit the quality of their home country's school system at all.

On the other hand, under the "cultural" interpretation 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 emigrated many years ago.[22] Moreover, there is evidence that highly educated immigrants have an easier time integrating in their host country (Lichter and Qian, 2001; Meng and Gregory, 2005); therefore, under the "cultural" interpretation, parental years of schooling might 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 various sources of differences in parental influence. The intergenerational transmission of educational quality mechanism would imply a positive interaction term between parental years of schooling acquired in the home country and the average score of natives in the same country. A story 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 would not predict differential effects in either dimension.

We now turn to the US Census data to put these predictions to empirical scrutiny. We compute mothers' years of schooling both in their home and in their host countries based on information on year of immigration and age at the end of education (imputed from the educational level).[23]

Table 10 shows the results. We add to the baseline specification in column 1 an interaction term between T^m and mother's years of schooling, finding a negative and significant coefficient (column 2). When we break down years of schooling between those acquired in the US and those acquired in country m (column 3), we find that the interaction term is negative in both cases, with coefficients of similar magnitudes. Figure 4 plots the coefficient on T^m for different

[22] There is widespread evidence that years since migration correlate positively with immigrants' assimilation (Chiswick, 1978). Children of parents that have spent more time in the US fare better in terms of years of schooling, earnings (Abramitzky et al., 2020) and school performance (Nielsen and Schindler Rangvid, 2012), a result that we confirm in our setting (with the caveat that the impact of years since migration is heterogeneous depending on the country of origin). Online Appendix D.1 shows that results are similar when we focus on alternative measures on immigrants' assimilation.

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

levels of mothers' educational attainment: most of the gap is driven by mothers with either no education or primary schooling only, and disappears when we focus on mothers with college education. As shown in Table D.3.1 in Online Appendix D, the corresponding regression on the PISA data yields similar conclusions: the interaction between T^m and overall mother's years of education is negative, though in that case not significantly different from zero. These results are inconsistent with the "intergenerational transmission of educational quality" interpretation.[24]

[Table 10 and Figure 4 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 10, the correlation between T^m and children's school performance is weaker for mothers that emigrated many years ago.[25] As shown in Figure 5, 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 persists when we absorb the effect of T^m as well as any other country-of-origin-specific characteristic through country of origin fixed effects (with the interaction between years of schooling and T^m turning marginally insignificant in this specification).

[Figure 5 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 10 shows results for a sub-sample of mothers entirely educated in their country of origin. The interaction between T^m and mother's years of schooling is negative and significant, and so is the one between T^m and years since migration. The magnitudes of the estimated coefficients are virtually identical to the ones obtained with the full sample.

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

6.2 Country-of-Origin-Level Characteristics

In this subsection we augment specification (3) with a series of controls at the level of the mother's country of origin. The objective is to understand which country-level characteristics

[24] 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.

[25] This result provides an additional reason why our decomposition exercise in Section 5 might understate the importance of parental influence. If immigrant parents from different countries progressively become more similar to each other as they integrate in their host country, we would find a larger role for parental influence by focusing on those who have just emigrated, which are still very comparable to non-emigrants in their country of origin. Unfortunately, date of immigration is not available in the PISA data.

drive, at least in part, the difference in performance between second-generation immigrants from high- and low-scoring countries. We consider two sets of controls: one relative to characteristics of the educational system and the overall level of economic development, and another capturing cultural traits.

Table 11 includes controls for educational resources and overall economic development in country m.[26] If the "intergenerational transmission of educational quality" interpretation is correct, we expect rich schooling enviroments in the parents' country of origin to be reflected in the performance of second-generation immigrants and to explain away some of our correlation of interest.[27] The results in Table 11 do not support this view. Columns 2 and 3 include averages across all available waves of two of the measures of educational inputs that emerge as important in Table 1, i.e. cumulative expenditure per student and a proxy for shortages of instructional materials (results for all other educational controls included in Table 1 are reported in Table D.4.1 in Online Appendix D); the signs of their coefficients are mostly inconsistent with the "intergenerational transmission of educational quality" interpretation, and the coefficent on T^m is either unaffected or larger compared to the baseline specification in column 1. Column 4 includes the average pupil to teacher ratio in the mother's country of origin, which once again does not affect the correlation of interest. Columns 5 and 6 consider broad measures of average educational attainment and economic development in country m; while the former does not have any impact, real GDP per capita enters with a negative sign, and controlling for it raises the coefficient on T^m.[28] The conclusions are similar when all these controls are introduced simultaneously (column 7): accounting for the educational and economic resources in the parents' country of origin does not explain away (and, if anything, increases) the performance gap between second-generation immigrants from high- and low-scoring countries.

[Table 11 about here]

We now turn to proxies for various cultural traits of the mother's country of origin. While in principle many cultural traits might be relevant in this context, we focus on five measures that

[26] We use variables from the following sources: (i) cumulative expenditure per pupil in secondary schools and indicators of shortages of instructional materials from the PISA School Questionnaire and other sources described in Online Appendix A; (ii) the average pupil to teacher ratio in the 2003-2015 period in secondary (or, if unavailable, lower secondary) schools from the World Bank EdStats database (original source: UNESCO Institute of Statistics); (iii) average years of schooling for 35- to 45-year-old adults in 2010 from Barro and Lee (2013); (iv) real GDP per capita from the Penn Word Tables 9.0 (Feenstra et al., 2015) (the 2015 observation, whenever missing, is imputed using the most recent available observation and the average growth rate after 2010).

[27] In principle, one would want to test this prediction using information on educational system characteristics at the time when parents where in school. This is not feasible, as the coverage for most of the variables used in Table 11 and for most countries starts from more recent periods. However, we notice that over the available period there is strong persistence in the cross-country differences in institutional features of the educational system.

[28] The negative correlation (conditional on other covariates) between GDP in country m and the performance of second-generation immigrants whose mothers come from m is somewhat surprising. One should keep in mind that the regression controls for T^m, strongly correlated with GDP in country m, so that the estimated coefficient quantifies the effect of that part of GDP in country m not already reflected in the PISA score in country m (if we drop T^m from the specification, the coefficient on GDP becomes small and not significantly different from zero). A possible interpretation is that this might be driven by differential selection into migration: if a lower GDP per capita implies higher migration costs, then parents migrating from poorer countries should be more positively selected (once again, consistently with the mechanism in Albornoz et al., 2018a and the evidence in Albornoz et al., 2018b).

the literature has explicitly associated with human capital accumulation: long-term orientation, beliefs on the importance of hard work, locus of control, trust, and secular values.

First, long-term orientation, defined by Hofstede (1991) as the "fostering of virtues oriented toward future rewards, perseverance, and thrift", has been argued to be related to differences across countries in average years of schooling (Galor and Ömer Özak, 2016) and across immigrants' nationalities in school performance (Figlio et al., 2019). Second, a long tradition dating back to Weber (1930) emphasizes the importance attributed to hard work as a key factor behind socio-economic success. Third, the skills formation literature finds evidence for an important role of the locus of control, i.e. the extent to which individuals believe that their actions can influence their future outcomes, on educational attainment, early-childhood cognitive achievements and parental investments on children (Coleman and DeLeire, 2003; Lekfuangfu et al., 2018). Fourth, a large literature documents that trust is associated to favourable socio-economic outcomes (see Guiso et al., 2006; Algan and Cahuc, 2014, for broad reviews) including various measures of educational attainment (Coleman, 1988; Rafael La Porta and Vishny, 1997; Bjørnskov, 2009). Finally, Ek (2018) develops a country-specific measure of human capital based on immigrants' labor productivity, and finds that the strongest correlate of this measure is a proxy constructed by Inglehart and Welzel (2005) for the prevalence of secular and rational values (such as independence, autonomy and determination, as opposed to religion, authority and obedience).

We construct country-level proxies for these cultural traits from the World Value Survey, using the same questions and methodology as in the previous work discussed above (the details can be found in Online Appendix A). Columns 2 to 6 of Table 12 introduce these traits one by one as additional controls to our baseline specification, reported in column 1 (regressions without T^m as control are reported in Table D.5.1 of Online Appendix D). All coefficients have the expected sign, though only those of trust and locus of control are statistically significant.[29] The introduction of trust has a sizable effect on the coefficient of the PISA performance in the mother's country of origin, which roughly halves; locus of control, secular values and long-term orientation account for a more limited part of the correlation of interest. Column 7 shows that the five cultural traits, when introduced simultaneously, completely explain away the correlation between the performance of second-generation immigrants and the one of natives in their mother's country of origin; in this specification, long-term orientation and locus of control emerge as the strongest predictors. Column 8 documents that the inclusion of these two traits in isolation is sufficient to reduce substantially the correlation of interest, which becomes

[29] The coefficient on long-term orientation in column 2 is smaller compared to the corresponding estimate in Figlio et al. (2019), which reports a coefficient of 0.745 for the PISA math test (Table 18, column 1). There are several differences between the two specifications: (i) we additionally control for the average score in the mother's country of origin; (ii) we control for school fixed effects, as opposed to host country fixed effects (iii); we use a slightly different sample, which includes the 2003-2015 waves as opposed to 2003-2012, but excludes countries of origin where the PISA test is not administered; (iv) we control for a broader set of parental socio-economic characteristics. The results in Table D.5.1 of Online Appendix D show that the coefficient roughly doubles when the average score in the mother's country of origin is excluded; moreover, we find a coefficient of 0.553 when, in addition, we replace school fixed effects with host country fixed effects (results not shown). Most of the difference between the two estimates is therefore explained by (i) and (ii).

statistically insignificant.

[Table 12 about here]

As an additional check on the role of parental cultural traits in accounting for cross-country gaps in performance, we extend the decomposition exercise of Section 5 as follows. Let Z^c be a vector of relevant parental cultural traits prevailing in country c, and suppose that the parental term defined in (5) can be written as

$$Parents^{mf}_{icst} = \xi' X_{icst} + \eta' Z^m + \lambda' Z^f + \tilde{u}^{mf}_{icst}$$

Compared to (5), this expression replaces the country of origin fixed effects with the cultural controls. The coefficients η and λ can be identified from an individual-level regression which includes second-generation immigrants (while for natives, the effect of Z^c is absorbed by country or school fixed effects, depending on the specification). With these coefficients at hand, we compute the contribution of parental cultural traits as

$$\widehat{ParentsCulture}_c = \widehat{\eta}' Z^c + \widehat{\lambda}' Z^c$$

and quantify its importance for cross-country gaps in average performance through

$$\frac{\mathrm{Cov}(\widehat{ParentsCulture}_c, T_c)}{\mathrm{Var}(T_c)}$$

Table 13 displays the results. We focus on the three cultural traits that emerge as the most relevant from Table 12 - long-term orientation, trust and locus of control - and show results for both host country and school fixed effects specifications. When considered in isolation, trust can account for between 14% and 25% of the cross-country variation in average performace, while the contribution of long-term orientation and locus of control is smaller. When all three cultural traits are included in Z^c, they explain between 13% and 24% of the cross-country variance. These magnitudes are comparable to the overall contribution of parental unobservables (identified through country of origin fixed effects) documented in Table 8, giving further credence to the hypothesis that culture is an important driver of the cross-country variation in parental influence.

[Table 13 about here]

The interpretation of the results in Tables 12 and 13 is subject to a number of caveats. Several of the cultural traits considered here are strongly correlated with each other, making it difficult to discern their relative importance in driving the performance of second-generation immigrant students (we display the cross-correlations between the cultural traits considered and the PISA score in Table D.5.2 of Online Appendix D). Moreover, the WVS-based measures are at best imperfect proxies of the underlying cultural traits, and it is possible that their coefficients might pick up the effect of other unmeasured factors. For these reasons, we view the country of origin fixed effects strategy considered in Section 5 as preferable for the purpose of quantifying the overall role of parental influence for cross-country gaps in educational performance. Nevertheless, the results displayed in this Section support the "cultural" interpretation of the parental unobservable characteristics we identify as important in Section 5.

6.3 Time Use

The evidence discussed so far is informative on the importance of various possible sources of the cross-country variation in parental influence. In this subsection, we investigate whether this variation is reflected into different observable parental practices. To do so, we turn to US time use data and study whether immigrant parents from high PISA countries allocate more time to activities that might plausibly stimulate their children's human capital accumulation. The analysis complements and extends the work of Ramey (2011), who compares time use practices across ethnic groups.

We use the 2002 to 2015 waves of the American Time Use Survey (ATUS). The survey is administered to one person per household, chosen randomly among all individuals at least 15 years old. We compute the total time (in minutes) spent on child care on the previous day, and, following Aguiar and Hurst (2007), three subcategories that split total child care in educational, recreational and basic activities. We identify second-generation immigrants based on the children's and interviewed parents' country of birth.

Table 14 shows our results. Columns 1 to 3 refer to total child care, while columns 4 to 6 break down the time spent with children in the educational, recreative and basic categories. 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 84 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. Online Appendix D.4 shows that the effect is once again mostly concentrated among low educated parents and those more recently emigrated (Figures D.4.1 and D.4.2).

[Table 14 about here]

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

7 Conclusions

This paper shows that the importance of parents in explaining cross-country achievement gaps goes well beyond what could be inferred by only considering observable parental socio-economic characteristics. We show that a relevant share of the international variation in test scores is accounted for by parental factors beyond education, income and labour market status. We reach this conclusion through an indirect empirical approach, based on the comparison of the school performance of second-generation immigrants, studying in the same country or even in the same school, with parents of different nationalities.

Cross-country differences in unobserved parental characteristics, inferred from achievement gaps between second-generation immigrants, account for about 15% of the cross-country variance in test scores, roughly doubling the overall contribution of parental influence. For what concerns the sources of this result, we do not find evidence for a mechanism of intergenerational transmission of school quality, as parental education appears to attenuate rather than reinforce the magnitude of the inferred unobserved component. Our results support instead the importance of cultural factors, varying across countries, that shape parents' attitudes towards their children's education. Moreover, differences in parental influence across nationalities are reflected in observable time use practices.

These results have implications for the study of human capital from a cross-country perspective. Models of human capital accumulation should be consistent with an important role for parents in the transmission of knowledge, beyond what can be inferred from the empirical effect of socio-economic characteristics. Moreover, parental influence potentially represents a competing mechanism to gaps in TFP and local economic conditions for generating human capital and output gaps across countries. A systematic quantitative analysis of the interaction between these factors is a promising avenue for future work.

Our conclusions also naturally lead to interesting questions on cross-country differences in parental attitudes towards education. If those attitudes are important determinants of human capital achievement, it is crucial to understand how they form and evolve, and why they do so differently across time and space. Historical circumstances experienced in different countries might have played an important role, and social interactions between people of various origins (brought about by migration or trade linkages) might have shaped the diffusion of different cultural traits.

Finally, our results are relevant for policy-makers aiming to raise students' performance in standardized tests. Cross-country gaps go beyond differences in school quality and parents' socio-economic background; therefore, policies aimed at simply replicating school practices successful in other countries might have smaller-than-expected effects.

References

Abowd, John M., Robert H. Creecy, and Francis Kramarz, "Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data," Longitudinal Employer-Household Dynamics Technical Papers 2002-06, Center for Economic Studies, U.S. Census Bureau March 2002.

Abramitzky, Ran, Leah Boustan, and Katherine Eriksson, "Do Immigrants Assimilate More Slowly Today Than in the Past?," *American Economic Review: Insights*, March 2020, *2* (1), 125–41.

Aguiar, Mark and Erik Hurst, "Measuring Trends in Leisure: The Allocation of Time over Five Decades," *Quarterly Journal of Economics*, August 2007, *122* (3), 969–1006.

Albornoz, Facundo, Antonio Cabrales, and Esther Hauk, "Immigration and the school system," *Economic Theory*, June 2018, *65* (4), 855–890.

_ , _ , Paula Calvo, and Esther Hauk, "Immigrant children's school performance and immigration costs: Evidence from Spain," *Economics Letters*, 2018, *170* (C), 27–30.

Algan, Yann and Pierre Cahuc, "Trust, Growth, and Well-Being: New Evidence and Policy Implications," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 2 of *Handbook of Economic Growth*, Elsevier, 2014, chapter 2, pp. 49–120.

Almond, Douglas and Janet Currie, "Human Capital Development before Age Five," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Vol. 4 of *Handbook of Labor Economics*, Elsevier, 2011, chapter 15, pp. 1315–1486.

Autor, David H. and David Dorn, "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, August 2013, *103* (5), 1553–97.

Barro, Robert J. and Jong Wha Lee, "A New Data Set of Educational Attainment in the World, 1950-2010," *Journal of Development Economics*, 2013, *104* (C), 184–198.

Bils, Mark and Peter J. Klenow, "Does Schooling Cause Growth?," *American Economic Review*, December 2000, *90* (5), 1160–1183.

Bisin, Alberto and Thierry Verdier, "The Economics of Cultural Transmission and Socialization," in Matt Jackson Jess Benhabib, Alberto Bisin, ed., *Handbook of Social Economics*, Vol. 2 of *Handbook of Social Economics*, Elsevier, 2010, chapter 9, pp. 339–416.

Bjørnskov, Christian, "Social trust and the growth of schooling," *Economics of Education Review*, 2009, *28* (2), 249 – 257.

Borjas, George J, "Ethnic Capital and Intergenerational Mobility," *Quarterly Journal of Economics*, February 1992, *107* (1), 123–50.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, "Bootstrap-based improvements for inference with clustered errors," *The Review of Economics and Statistics*, 2008, *90* (3), 414–427.

Cascio, Elizabeth U., "School Progression and the Grade Distribution of Students: Evidence from the Current Population Survey," IZA Discussion Papers 1747, Institute for the Study of Labor September 2005.

Chiswick, Barry R, "The Effect of Americanization on the Earnings of Foreign-born Men," *Journal of Political Economy*, October 1978, *86* (5), 897–921.

Chua, Amy, *Battle Hymn of the Tiger Mother*, The Penguin Press, 2011.

Cobb-Clark, Deborah A., Nicolas Salamanca, and Anna Zhu, "Parenting Style as an Investment in Human Development," *Journal of Population Economics*, 2019, *32*, 1315 – 52.

Coleman, James S., "Social Capital in the Creation of Human Capital," *American Journal of Sociology*, 1988, *94*, S95–S120.

Coleman, Margo and Thomas DeLeire, "An Economic Model of Locus of Control and the Human Capital Investment Decision," *Journal of Human Resources*, 2003, *38* (3), 701–721.

de Silanes, Andrei Shleifer Rafael La Porta Florencio Lopez and Robert W. Vishny, "Trust in Large Organizations," *American Economic Review*, May 1997, *87* (2), 333–338.

Doepke, Matthias and Fabrizio Zilibotti, "Parenting With Style: Altruism and Paternalism in Intergenerational Preference Transmission," *Econometrica*, September 2017, *85*, 1331–1371.

Dronkers, Jaap and Manon de Heus, "Educational Performance of the Children of Immigrants in Sixteen OECD Countries," in D. J. Besharov and M. H. Lopez, eds., *Adjusting to a World in Motion: Trends in Global Migration and Migration Policy*, Adjusting to a World in Motion: Trends in Global Migration and Migration Policy, Oxford University Press, 2016, pp. 264–290.

Dustmann, Christian, Tommaso Frattini, and Gianandrea Lanzara, "Educational Achievement of Second-generation Immigrants: an International Comparison," *Economic Policy*, January 2012, *27* (69), 143–185.

Ek, Andreas, "Cultural Values and Productivity," Working Paper, Lund University December 2018.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer, "The Next Generation of the Penn World Table," *American Economic Review*, 2015, *105* (10), 3150–3182.

Feliciano, Cynthia, "Educational selectivity in U.S. Immigration: How do immigrants compare to those left behind?," *Demography*, 2005, *42* (1), 131–152.

Fernandez, Raquel, "Does Culture Matter?," in Mattew O. Jackson Jess Benhabib and Alberto Bisin, eds., *Handbook of Social Economics*, Elsevier, 2011, chapter 11, pp. 481–510.

_ **and Alessandra Fogli**, "Culture: An Empirical Investigation of Beliefs, Work, and Fertility," *American Economic Journal: Macroeconomics*, January 2009, *1* (1), 146–77.

Figlio, David, Paola Giuliano, Umut Özek, and Paola Sapienza, "Long-Term Orientation and Educational Performance," *American Economic Journal: Economic Policy*, November 2019, *11* (4), 272–309.

Galor, Oded and Ömer Özak, "The Agricultural Origins of Time Preference," *American Economic Review*, October 2016, *106* (10), 3064–3103.

Giuliano, Paola, "Living Arrangements in Western Europe: Does Cultural Origin Matter?," *Journal of the European Economic Association*, September 2007, *5* (5), 927–952.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, "Does Culture Affect Economic Outcomes?," *Journal of Economic Perspectives*, Spring 2006, *20* (2), 23–48.

Hanushek, Eric A. and Ludger Woessmann, "Do Better Schools lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation," *Journal of Economic Growth*, December 2012, *17* (4), 267–321.

Hendricks, Lutz and Todd Schoellman, "Human Capital and Development Accounting: New Evidence from Wage Gains at Migration," *The Quarterly Journal of Economics*, 2018, *133* (2), 665–700.

Hofstede, Geert, *Cultures and organizations: software of the mind*, McGraw-Hill, 1991.

_ **, Gert Jan Hofstede, and Michael Minkov**, *Cultures and organizations: software of the mind: intercultural cooperation and its importance for survival*, McGraw-Hill, 2010.

Horvitz, Daniel G. and Donovan J. Thompson, "A Generalization of Sampling Without Replacement From a Finite Universe," *Journal of the American Statistical Association*, 1952, *47* (260), 663–685.

Inglehart, Ronald and Christian Welzel, *Modernization, Cultural Change, and Democracy: The Human Development Sequence*, Cambridge University Press, 2005.

Jerrim, John, "Why do East Asian children perform so well in PISA? An investigation of Western-born children of East Asian descent," *Oxford Review of Education*, 2015, *41* (3), 310–333.

Jones, Benjamin F., "The Human Capital Stock: A Generalized Approach," *American Economic Review*, November 2014, *104* (11), 3752–3777.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Life-Cycle Human Capital Accumulation across Countries: Lessons from US Immigrants," *Journal of Human Capital*, 2018, *12* (2), 305–342.

Lekfuangfu, Warn N., Nattavudh Powdthavee, Nele Warrinnier, and Francesca Cornaglia, "Locus of Control and its Intergenerational Implications for Early Childhood Skill Formation," *Economic Journal*, February 2018, *128* (608), 298–329.

Levels, Mark, Jaap Dronkers, and Gerbert Kraaykamp, "Immigrant Children's Educational Achievement in Western Countries: Origin, Destination, and Community Effects on Mathematical Performance," *American Sociological Review*, 2008, *73* (5), 835–853.

Lichter, Daniel T. and Zhenchao Qian, "Measuring Marital Assimilation: Intermarriage Among Natives and Immigrants," *Social Science Research*, 2001, *30*, 289–312.

Manuelli, Rodolfo E. and Ananth Seshadri, "Human Capital and the Wealth of Nations," *American Economic Review*, 2014, *104* (9), 2736–62.

Mayer, Thierry and Soledad Zignago, "Notes on CEPII's distances measures: The GeoDist database," Working Papers 2011-25, CEPII Research Center December 2011.

Meng, Xin and Robert G. Gregory, "Intermarriage and the Economic Assimilation of Immigrants," *Journal of Labor Economics*, January 2005, *23* (1), 135–176.

Nielsen, Helena Skyt and Beatrice Schindler Rangvid, "The Impact of Parents' Years since Migration on Children's Academic Achievement," *IZA Journal of Migration*, 2012, *1* (6).

OECD, "PISA Data Analysis Manual: SPSS," Technical Report 2009.

_ , "PISA 2012 Results: What Students Know and Can Do," Technical Report 2012.

_ , "PISA 2012 Technical Report," Technical Report 2012.

Oreopoulos, Philip and Marianne E. Page, "The Intergenerational Effects of Compulsory Schooling," *Journal of Labor Economics*, October 2006, *24* (4), 729–760.

Ramey, Valerie, "Is there a "Tiger Mother" Effect? Time Use Across Ethnic Groups," *Economics in Action*, 2011, *4.*

Schoellman, Todd, "Education Quality and Development Accounting," *Review of Economic Studies*, 2012, *79* (1), 388–417.

Singh, Abhijeet, "Learning More with Every Year: School Year Productivity and International Learning Divergence," *Journal of the European Economic Association*, June 2019, *00* (0).

Spolaore, Enrico and Romain Wacziarg, "Ancestry, Language and Culture," in Victor Ginsburgh and Shlomo Weber, eds., *The Palgrave Handbook of Economics and Language*, London: Palgrave Macmillan, 2015, chapter 7, pp. 174–211.

Todd, Petra E. and Kenneth I. Wolpin, "The Production of Cognitive Achievement in Children: Home, School, and Racial Test Score Gaps," *Journal of Human Capital*, 2007, *1* (1), 91–136.

Weber, Max, *The Protestant Ethic and the Spirit of Capitalism*, Allen & Unwin, 1930.

Wichmann, Søren, Eric W. Holman, and Cecil H. Brown, "The ASJP Database (version 17)," Technical Report 2016.

Woessmann, Ludger, "The Importance of School Systems: Evidence from International Differences in Student Achievement," *Journal of Economic Perspectives*, 2016, *30* (3), 3–32.

Tables

Table 1: Educational Production Function Estimation - PISA

	Dependent Variable: Math Test Score					
	[1]	[2]	[3]	[4]	[5]	[6]
	Parental Socio-Economic Background					
Father Sec Edu	0.151***	0.033**	0.053***	0.086***	0.012	0.017**
	(0.038)	(0.014)	(0.010)	(0.011)	(0.011)	(0.007)
Father Ter Edu	0.211***	0.106***	0.113***	0.139***	0.017	0.020**
	(0.045)	(0.023)	(0.020)	(0.011)	(0.017)	(0.010)
Mother Sec Edu	0.198***	0.034	0.059***	0.090***	-0.001	0.002
	(0.045)	(0.021)	(0.011)	(0.011)	(0.013)	(0.013)
Mother Ter Edu	0.244***	0.069**	0.097***	0.119***	0.000	-0.003
	(0.052)	(0.030)	(0.016)	(0.011)	(0.012)	(0.010)
Mother Working × Mother ISEI	0.004***	0.003***	0.004***	0.005***	0.003***	0.003***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Father Working × Father ISEI	0.006***	0.006***	0.006***	0.006***	0.003***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Different Lang at Home	-0.289***	-0.132*	-0.005	-0.024	0.027	0.019
	(0.066)	(0.072)	(0.052)	(0.044)	(0.036)	(0.037)
11-25 Books	0.105*	0.082**	0.093**	0.090***	0.047	0.041*
	(0.059)	(0.041)	(0.037)	(0.027)	(0.032)	(0.022)
26-100 Books	0.423***	0.286***	0.278***	0.286***	0.158***	0.157***
	(0.086)	(0.058)	(0.051)	(0.032)	(0.048)	(0.030)
101-200 Books	0.626***	0.419***	0.409***	0.416***	0.242***	0.239***
	(0.095)	(0.069)	(0.062)	(0.044)	(0.059)	(0.044)
201-500 Books	0.863***	0.610***	0.591***	0.593***	0.386***	0.371***
	(0.101)	(0.071)	(0.067)	(0.051)	(0.071)	(0.054)
500+ Books	0.836***	0.597***	0.585***	0.565***	0.403***	0.362***
	(0.120)	(0.096)	(0.091)	(0.067)	(0.084)	(0.063)
	Educational System Resources & Institutions					
Expenditure per Student		0.046***				
		(0.006)				
Avg Share Gov Funding		-0.520***				
		(0.195)				
Share Private		0.153				
		(0.191)				
External Exit Exams		0.220***				
		(0.062)				
Some Shortage Material		-0.093***				
		(0.014)				
Large Shortage Material		-0.163***				
		(0.024)				
Assessment for Retention		0.025				
		(0.026)				
Assessment to Group Students		-0.024				
		(0.021)				
Assessment for School Comparison		-0.012				
		(0.028)				
Share Certified Teachers (F.T.)		0.024				
		(0.054)				
Share Certified Teachers (P.T.)		0.033				
		(0.024)				
Teacher Monitor - Principal		-0.024				
		(0.035)				
Teacher Monitor - Inspector		-0.053*				
		(0.028)				
Autonomy - Hiring		0.060				
		(0.037)				

Autonomy - Salary		-0.102***				
		(0.031)				
Autonomy - Budget		0.036				
		(0.027)				
Autonomy - Content		-0.008				
		(0.026)				
N	411213	411213	411213	1381823	411213	1381823
# Country	37	37	37	79	37	79
R Squared	0.35	0.44	0.47	0.45	0.62	0.62
Host Country × Wave FE	No	No	Yes	Yes	No	No
School × Wave FE	No	No	No	No	Yes	Yes
Sample	Edu Obs	Edu Obs	Edu Obs	All	Edu Obs	All

Notes: The Table shows results for native students. All specifications control for intercept, students' age (in months), gender, wave fixed effect and dummies for parents' employment status (full-time employed, part-time employed, not working). *Working* refers to either full-time or part-time employed. *Sample* indicates the sample inclusion criteria: *Edu Obs* refers to countries where the educational system controls displayed in column 2 are available, while *All* refers to all countries. Observations are weighted according to the provided sample weights. Standard errors are clustered by country, and inflated by the estimated measurement error in test scores. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 2: Baseline Decomposition Results

	[1]	[2]	[3]	[4]	[5]	[6]
$\frac{\text{Cov}(\widehat{ParentsObs_c}, T_c)}{\text{Var}(T_c)}$	42.62	26.36	25.10	17.42	12.70	8.89
# Country	37	37	37	79	37	79
School Controls	No	Yes	No	No	No	No
Host Country × Wave FE	No	No	Yes	Yes	No	No
School × Wave FE	No	No	No	No	Yes	Yes
Sample	Edu Obs	Edu Obs	Edu Obs	All	Edu Obs	All

Notes: The Table shows decomposition results for native students. $\widehat{ParentsObs_c}$ is the effect of observable parental characteristics estimated from the corresponding specification in Table 1. *Sample* indicates the sample inclusion criteria: *Edu Obs* refers to countries where the educational system controls displayed in column 2 of Table 1 are available, while *All* refers to all countries.

Table 3: 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	0.39	0.88	0.22	0.84	0.76	0.87
Score Country m	0.24	0.38	0.05	0.32	0.64	0.11
Mother Sec Edu	0.51	0.50	0.50	0.50	0.54	0.50
Mother Ter Edu	0.33	0.47	0.37	0.48	0.26	0.44
Father Sec Edu	0.51	0.50	0.49	0.50	0.54	0.50
Father Ter Edu	0.36	0.48	0.40	0.49	0.28	0.45
Mother Working	0.71	0.45	0.73	0.45	0.67	0.47
Working Mother ISEI	42.29	19.94	42.18	20.28	42.56	19.10
Father Working	0.90	0.30	0.90	0.30	0.90	0.29
Working Father ISEI	42.03	18.69	41.96	18.70	42.18	18.65
Different Lang at Home	0.24	0.43	0.28	0.45	0.15	0.36
Books at Home	139.19	194.28	140.72	195.96	135.83	190.51
Immigrant Father	0.62	0.49	0.64	0.48	0.56	0.50
Observations	49097		24581		24516	

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	0.77	0.42	0.85	0.35
Score Country m	0.20	0.48	-0.14	0.40	0.60	0.11
Mother Sec Edu	0.48	0.50	0.40	0.49	0.58	0.49
Mother Ter Edu	0.21	0.40	0.15	0.36	0.27	0.44
Father Sec Edu	0.39	0.49	0.35	0.48	0.44	0.50
Father Ter Edu	0.33	0.47	0.26	0.44	0.42	0.49
Log Family Income	10.84	0.70	10.71	0.73	10.98	0.63
Father Immigrant	0.46	0.50	0.56	0.50	0.35	0.48
Yrs Since Migr Mother	20.06	8.74	19.26	8.74	20.97	8.65
Student Age	11.34	2.29	11.23	2.28	11.47	2.29
Observations	53553		30814		22739	

Notes: The Table shows descriptive statistics for second generation immigrants on the mother's side in the PISA (Panel A) and US Census (Panel B) samples. Only cases where both parents report a country of origin and the country of origin of the mother participates to PISA are included. Scores are from the math test and are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) countries participating to the test. *Books at Home* is constructed imputing the middle value of the available categorical variables (and 750 for the 500+ category). Observations weighted according to the provided sample weights.

Table 4: Reduced Form Results on Second Generation Immigrants - PISA

	Dependent Variable: Math Test Score				
	[1]	[2]	[3]	[4]	[5]
		All			No East Asia
Score Country m	0.755***	0.628***	0.271**	0.225***	0.174**
	(0.208)	(0.223)	(0.119)	(0.072)	(0.082)
Female	-0.116***	-0.145***	-0.155***	-0.200***	-0.186***
	(0.034)	(0.029)	(0.024)	(0.022)	(0.024)
Father Sec Edu		0.015	0.027	0.028	0.053
		(0.045)	(0.027)	(0.021)	(0.037)
Father Ter Edu		-0.044	0.051	0.019	0.034
		(0.055)	(0.038)	(0.028)	(0.046)
Mother Sec Edu		0.033	0.064*	-0.038	-0.007
		(0.058)	(0.037)	(0.032)	(0.065)
Mother Ter Edu		-0.071	0.081**	-0.035	-0.012
		(0.076)	(0.039)	(0.033)	(0.064)
Mother Working × Mother ISEI		0.003***	0.004***	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Father Working × Father ISEI		0.006***	0.005***	0.002***	0.002**
		(0.001)	(0.001)	(0.000)	(0.001)
Different Lang at Home		-0.131**	-0.081*	-0.066**	-0.056**
		(0.066)	(0.045)	(0.029)	(0.028)
11-25 Books		0.124**	0.139***	0.092***	0.116***
		(0.051)	(0.033)	(0.027)	(0.028)
26-100 Books		0.398***	0.359***	0.201***	0.242***
		(0.050)	(0.036)	(0.037)	(0.038)
101-200 Books		0.519***	0.487***	0.260***	0.302***
		(0.061)	(0.039)	(0.044)	(0.048)
201-500 Books		0.726***	0.661***	0.392***	0.453***
		(0.080)	(0.059)	(0.063)	(0.069)
500+ Books		0.677***	0.613***	0.404***	0.465***
		(0.077)	(0.046)	(0.072)	(0.075)
N	49097	49097	49097	49097	31347
# Country m	59	59	59	59	52
R Squared	0.10	0.23	0.34	0.66	0.62
Host Country × Wave FE	No	No	Yes	No	No
School × Wave FE	No	No	No	Yes	Yes

Notes: The Table shows results for second generation immigrants on the mother's side. The sample includes only cases where both parents report a country of origin and the country of origin of the mother participates to PISA. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. All specifications control for intercept, students' age (in months), wave fixed effect and a dummy for father's immigrant status; specifications 2-5 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 5: Reduced Form Results on Second Generation Immigrants - US CENSUS

	Dependent variable: 1 = Never repeated a grade				
	[1]	[2]	[3]	[4]	[5]
			All		No East Asia
Score Country m	0.094***	0.050***	0.032***	0.029***	0.023**
	(0.031)	(0.014)	(0.010)	(0.010)	(0.010)
Female	0.069***	0.069***	0.068***	0.068***	0.071***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mother Sec Edu		0.055***	0.047***	0.044***	0.042***
		(0.012)	(0.012)	(0.011)	(0.012)
Mother Ter Edu		0.060***	0.053***	0.050***	0.045***
		(0.011)	(0.009)	(0.010)	(0.010)
Father Sec Edu		0.045***	0.039***	0.040***	0.045***
		(0.014)	(0.010)	(0.010)	(0.009)
Father Ter Edu		0.063***	0.062***	0.063***	0.068***
		(0.015)	(0.012)	(0.011)	(0.011)
Log Family Income		0.043***	0.036***	0.034***	0.035***
		(0.010)	(0.008)	(0.008)	(0.008)
N	53553	53553	53553	53553	49634
# Country m	64	64	64	64	57
R Squared	0.06	0.08	0.11	0.12	0.12
Comm Zone × Year FE	No	No	Yes	Yes	Yes
Years Since Migr Mother	No	No	No	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 6: Selection

	Dependent Variable: Standardized Years of Education			
	[1]	[2]	[3]	[4]
	Mothers		Fathers	
Score Country m	0.005	-0.083		
	(0.222)	(0.197)		
Score Country f			0.019	-0.135
			(0.210)	(0.164)
N	49097	49097	48834	48834
R Squared	0.07	0.61	0.07	0.59
Host Country × Wave FE	Yes	No	Yes	No
School × Wave FE	No	Yes	No	Yes

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

Table 7: Bilateral Controls

	Dependent Variable: Math Test Score								
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Score Country m	0.247***	0.277***	0.229**	0.287***	0.233***	0.227***	0.249**	0.295***	0.216***
	(0.075)	(0.071)	(0.096)	(0.103)	(0.073)	(0.072)	(0.099)	(0.100)	(0.048)
Mother Linguistic Dist		0.018*						0.003	
		(0.009)						(0.017)	
Father Linguistic Dist		0.017*						0.030*	
		(0.009)						(0.017)	
Mother Cultural Dist				0.035				0.039	
				(0.024)				(0.033)	
Father Cultural Dist				0.009				-0.019	
				(0.026)				(0.032)	
Mother Log Geo Dist						-0.013		-0.020	
						(0.016)		(0.027)	
Father Log Geo Dist						0.019		0.020	
						(0.017)		(0.019)	
N	46896	46896	23513	23513	47278	47278	23331	23331	49097
# Country m	57	57	42	42	59	59	41	41	59
R Squared	0.78	0.78	0.81	0.81	0.78	0.78	0.81	0.81	0.79
Socio-Econ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host C × Cont m × Wave FE	No	No	No	No	No	No	No	No	Yes
Host C × Cont f × Wave FE	No	No	No	No	No	No	No	No	Yes

Notes: The Table shows results for second generation immigrants on the mother's side, augmented for bilateral controls. Sample includes only cases where both parents report a country of origin and the country of origin of the mother participates to PISA. 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 Dist*, *Cultural Dist* and *Log Geo Dist* vary at the country-pair level. *Linguistic Dist*, *Cultural Dist* are standardized to take mean 0 and standard deviation 1 across all pairs in the sample. Host C × Cont i × Wave FE control for the interaction between host country, continent of the country of origin of parent $i = \{m, f\}$ and wave fixed effects. 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 8: Decomposition Results with Parental Unobservables

	[1]	[2]
$\frac{\text{Cov}(\widehat{ParentsObs_c}, T_c)}{\text{Var}(T_c)}$	21.21	10.64
$\frac{\text{Cov}(\widehat{ParentsUnobs_c}, T_c)}{\text{Var}(T_c)}$	15.86	11.57
# Country	31	31
Host Country × Wave FE	Yes	No
School × Wave FE	No	Yes
Sample	Sec Gen	Sec Gen

Notes: The Table shows decomposition results for native students, using second generation immigrants to estimate parental unobservables. Only countries with at least 100 emigrant mothers and 100 emigrant fathers in the sample are included in the computation. $\widehat{ParentsObs_c}$ and $\widehat{ParentsUnbs_c}$ are the effects of observable and unobservable parental characteristics. *Sample* indicates the sample inclusion criteria: *Sec Gen* refers to countries from which we observe emigrant parents.

Table 9: Decomposition Results - Countries

			$\widehat{ParentsObs_c}$ Gap		$\widehat{ParentsUnobs_c}$ Gap	
Country	PISA Score	PISA Gap	School FE	Country FE	School FE	Country FE
Hong Kong	1.00	0.72	0.00	0.00	0.19	0.43
			(0.00)	(0.01)	(0.15)	(0.15)
Belgium	0.85	0.57	0.05	0.13	-0.02	-0.12
			(0.00)	(0.00)	(0.33)	(0.30)
China	0.82	0.54	-0.04	-0.09	0.25	0.62
			(0.01)	(0.01)	(0.04)	(0.05)
Netherlands	0.79	0.51	0.05	0.12	0.05	0.12
			(0.00)	(0.00)	(0.08)	(0.11)
Germany	0.72	0.44	0.09	0.17	0.10	0.11
			(0.00)	(0.00)	(0.06)	(0.07)
Macao	0.65	0.37	-0.04	-0.10	0.19	0.47
			(0.00)	(0.01)	(0.08)	(0.10)
New Zealand	0.63	0.35	0.08	0.15	-0.12	-0.19
			(0.00)	(0.00)	(0.04)	(0.04)
Denmark	0.59	0.31	0.06	0.14	0.22	0.07
			(0.00)	(0.00)	(0.15)	(0.14)
France	0.59	0.31	0.05	0.11	-0.06	-0.23
			(0.00)	(0.01)	(0.05)	(0.06)
Austria	0.57	0.29	0.05	0.12	0.04	-0.07
			(0.00)	(0.00)	(0.12)	(0.12)
Australia	0.54	0.26	0.09	0.17	-0.19	-0.17
			(0.00)	(0.00)	(0.15)	(0.14)
Czech Republic	0.53	0.25	0.06	0.11	0.01	-0.02
			(0.00)	(0.00)	(0.11)	(0.12)
Sweden	0.52	0.24	0.10	0.21	0.08	-0.04
			(0.00)	(0.00)	(0.07)	(0.07)
United Kingdom	0.49	0.21	0.06	0.12	-0.05	-0.12
			(0.00)	(0.00)	(0.02)	(0.03)
Vietnam	0.44	0.16	-0.14	-0.31	0.29	0.49
			(0.01)	(0.01)	(0.05)	(0.06)
Poland	0.42	0.14	0.00	0.00	0.04	0.10
			(0.00)	(0.00)	(0.07)	(0.08)
Slovakia	0.37	0.09	0.01	0.02	0.07	-0.08
			(0.00)	(0.00)	(0.08)	(0.09)
United States	0.35	0.07	0.05	0.12	0.13	0.12
			(0.00)	(0.01)	(0.10)	(0.12)
Spain	0.33	0.05	0.04	0.04	-0.07	-0.11
			(0.00)	(0.00)	(0.08)	(0.08)
Italy	0.27	-0.01	0.03	0.05	-0.18	-0.33
			(0.00)	(0.00)	(0.09)	(0.08)
Portugal	0.27	-0.01	-0.03	-0.11	-0.02	0.01
			(0.00)	(0.01)	(0.07)	(0.06)
Russia	0.22	-0.06	0.05	0.11	0.05	0.08
			(0.00)	(0.00)	(0.03)	(0.04)
Croatia	0.13	-0.15	-0.04	-0.05	-0.09	-0.04
			(0.00)	(0.00)	(0.13)	(0.12)
Greece	0.06	-0.22	0.02	0.05	-0.30	-0.30
			(0.00)	(0.01)	(0.16)	(0.16)
Serbia-Mont.	-0.15	-0.43	-0.04	-0.04	-0.11	-0.14
			(0.00)	(0.00)	(0.06)	(0.06)
Turkey	-0.17	-0.45	-0.10	-0.25	-0.22	-0.35
			(0.01)	(0.01)	(0.06)	(0.08)
Lebanon	-0.38	-0.66	0.01	0.00	-0.31	-0.42
			(0.01)	(0.02)	(0.10)	(0.09)
Albania	-0.61	-0.89	-0.12	-0.22	-0.09	-0.07

			(0.00)	(0.01)	(0.05)	(0.06)
Jordan	-0.62	-0.90	-0.09	-0.15	-0.10	-0.18
			(0.00)	(0.01)	(0.07)	(0.08)
Brazil	-0.65	-0.93	-0.13	-0.26	0.17	0.28
			(0.00)	(0.00)	(0.14)	(0.13)
India	-0.89	-1.17	-0.17	-0.36	0.05	0.10
			(0.01)	(0.01)	(0.10)	(0.11)

Notes: The Table shows the decomposition results across countries. Only countries with at least 100 emigrant mothers and 100 emigrant fathers in the sample are shown. *PISA Gap*, $\widehat{ParentsObs}_c$ *Gap* and $\widehat{ParentsUnobs}_c$ *Gap* are the differences between the country-specific value and the cross-country average of the average PISA score for the native students included in the decomposition exercise, the estimated effect of observable parental characteristics and the estimated effect of unobservable parental characteristics. Standard errors (in parentheses) are computed using the provided replicate weights, and inflated by the estimated measurement error in test scores (see Appendix B for the details).

Table 10: Interactions - US CENSUS

	Dependent variable: 1 = Never repeated a grade					
	[1]	[2]	[3]	[4]	[5]	[6]
			All			Mothers Educated in m
Score Country m	0.032***	0.101***	0.138***	0.200***		
	(0.008)	(0.030)	(0.046)	(0.050)		
Female	0.068***	0.067***	0.067***	0.067***	0.067***	0.067***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Yrs Schooling Father	0.006***	0.006***	0.006***	0.006***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Yrs Schooling Mother	0.006***	0.006***				
	(0.001)	(0.001)				
Score Country m × Yrs Schooling Mother		-0.006***				
		(0.002)				
Score Country m × Yrs Schooling Moth in US			-0.007***	-0.002	-0.001	
			(0.002)	(0.002)	(0.002)	
Score Country m × Yrs Schooling Moth in m			-0.006**	-0.007***	-0.005	-0.006*
			(0.002)	(0.002)	(0.003)	(0.003)
Yrs Schooling Moth in US			0.007***	0.002	0.003*	
			(0.001)	(0.002)	(0.001)	
Yrs Schooling Moth in m			0.006***	0.007***	0.007***	0.006***
			(0.001)	(0.001)	(0.001)	(0.001)
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)
N	53553	53553	53553	53553	53553	30300
# Country m	64	64	64	64	64	64
R Squared	0.11	0.12	0.12	0.12	0.12	0.15
Comm Zone × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country m FE	No	No	No	No	Yes	Yes
Country f FE	No	No	No	No	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 11: Country of Origin Characteristics - Educational and Economic Development

	Dependent variable: Math Test Score						
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Score Country m	0.234***	0.291***	0.228***	0.254***	0.230***	0.332***	0.351***
	(0.073)	(0.077)	(0.085)	(0.073)	(0.082)	(0.067)	(0.070)
Expenditure per Student in m		-0.007**					0.002
		(0.003)					(0.009)
Some Shortage Material in m			0.406**				0.254
			(0.189)				(0.264)
Large Shortage Material in m			-0.241				-0.431
			(0.224)				(0.464)
Pupil/Teacher Ratio in m				0.003			0.014***
				(0.007)			(0.005)
Avg Years Edu in m					0.001		0.017
					(0.012)		(0.013)
Log GDP in m						-0.114***	-0.144*
						(0.034)	(0.083)
N	48338	48338	48338	48338	48338	48338	48338
# Country m	49	49	49	49	49	49	49
R Squared	0.67	0.67	0.67	0.67	0.67	0.67	0.67
Socio-Econ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School × Wave FE	Yes	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) as well as all other parental socio-economic characteristics included in columns 2-5 of Table 4. *Expenditure per Student in m*, *Some Shortage Material in m* and *Large Shortage Material in m* are averages across all available waves of the corresponding variables used in Table 1 (see Appendix A for a detailed description) in the country of birth of the mother. *Pupil/Teacher Ratio in m* is the average pupil to teacher ratio in secondary schools between 2003 and 2015 in the country of birth of the mother. *Log GDP in m* and *Avg Years Edu in m* are respectively the wave-specific contemporaneous log real GDP per capita and the average years of schooling in 2010 of 35- to 45-year-old adults 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 12: Country of Origin Characteristics - Cultural Traits

	Dependent variable: Math Test Score							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Score Country m	0.223***	0.202***	0.236***	0.120*	0.175**	0.184**	0.038	0.111
	(0.073)	(0.075)	(0.074)	(0.066)	(0.073)	(0.077)	(0.082)	(0.081)
Long Term Orientation		0.141					0.464**	0.264*
		(0.124)					(0.215)	(0.137)
Hard Work			0.063				-0.091	
			(0.123)				(0.124)	
Trust				0.257**			0.193	
				(0.120)			(0.148)	
Locus of Control					0.198*		0.372**	0.305***
					(0.115)		(0.162)	(0.106)
Secular-Rational Values						0.044	-0.078	
						(0.033)	(0.060)	
N	48398	48398	48398	48398	48398	48398	48398	48398
# Country m	52	52	52	52	52	52	52	52
R Squared	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67
Socio-Econ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School $\times$ Wave FE	Yes	Yes	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, dummies for parents' employment status (full-time employed, part-time employed, not working) as well as all other parental socio-economic characteristics included in columns 2-5 of Table 4. *Hard Work*, *Trust* and *Locus of Control* are constructed from answers of natives in the mother's country of birth to the corresponding questions in the World Value Survey (described in the text), and are standardized to take mean 0 and standard deviation 1 in the WVS sample. *Long Term Orientation* is from Hofstede et al. (2010) and ranges from 0 to 1. *Secular-Rational Values* is constructed as the first principal component of the average answers to 10 questions in the World Value Survey, following Inglehart and Welzel (2005). 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 13: Decomposition Results with Parental Cultural Traits

$\frac{\text{Cov}(\widehat{ParentsCulture_c}, T_c)}{\text{Var}(T_c)}$	[1]	[2]
Long Term Orientation	10.49	6.08
Trust	24.75	13.71
Locus of Control	4.12	3.01
All	23.69	12.77
# Country	30	30
Host Country × Wave FE	Yes	No
School × Wave FE	No	Yes
Sample	Sec Gen	Sec Gen

Notes: The Table shows decomposition results for native students, using second generation immigrants to estimate the contribution of observable parental cultural traits. Only countries with at least 100 emigrant mothers and 100 emigrant fathers in the sample are included in the computation. $\widehat{ParentsCulture_c}$ represents the effect of observable cultural traits.

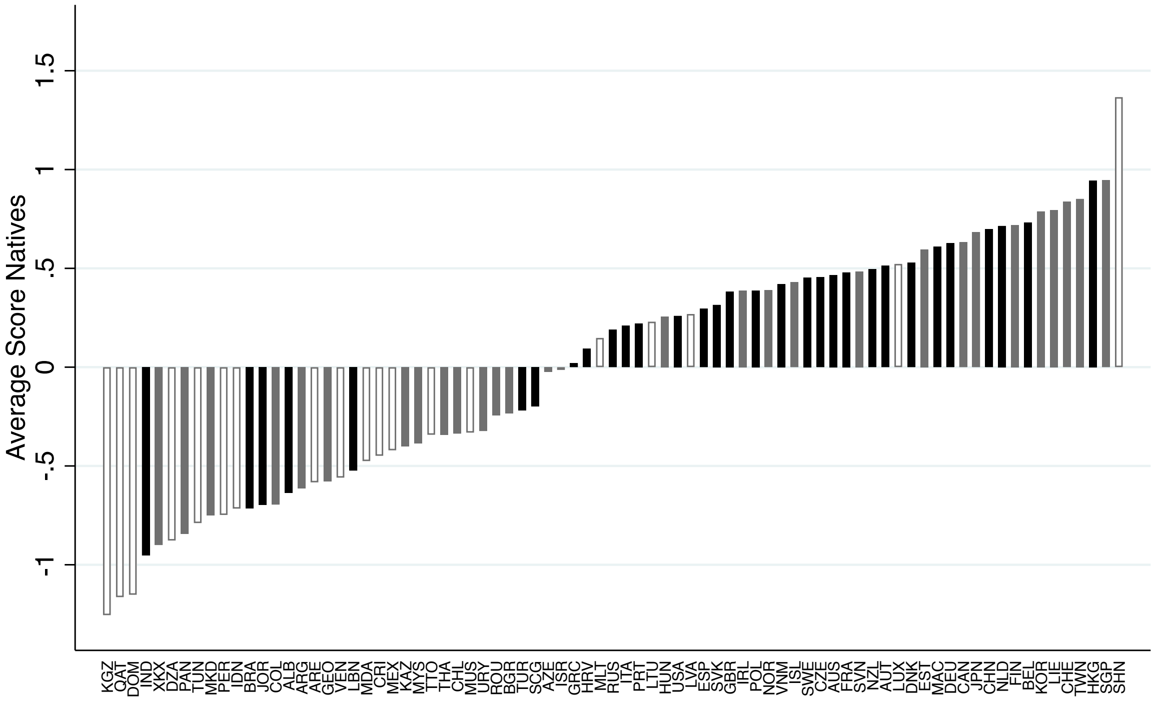
Table 14: Time Use of Parents

	Total	Total	Total	Educational	Recreational	Basic
	[1]	[2]	[3]	[4]	[5]	[6]
Score Country p	17.557*	17.009**	11.966***	3.118**	5.866**	2.982
	(10.070)	(8.342)	(4.258)	(1.333)	(2.271)	(2.046)
Mother			66.230***	8.480***	1.090	56.660***
			(3.854)	(0.870)	(3.192)	(2.434)
Parent Sec Edu			-1.702	4.631***	-2.945	-3.389
			(6.002)	(0.764)	(3.170)	(2.638)
Parent Ter Edu			4.220	4.100***	-1.999	2.119
			(3.586)	(1.297)	(2.288)	(1.850)
Spouse Sec Edu			3.242	-1.869**	6.188**	-1.077
			(2.912)	(0.813)	(2.832)	(1.225)
Spouse Ter Edu			12.816***	2.022	6.736**	4.059
			(3.388)	(1.517)	(2.655)	(3.016)
Log Family Income			5.731**	0.706	-1.356	6.381***
			(2.248)	(0.639)	(0.974)	(1.349)
Age Parent			0.229	0.105	0.085	0.039
			(0.361)	(0.071)	(0.337)	(0.196)
Age Spouse			0.388	0.152*	0.003	0.232
			(0.249)	(0.091)	(0.196)	(0.269)
Number of Children			20.089***	3.473**	1.071	15.545***
			(2.738)	(1.363)	(0.664)	(1.558)
Avg Age Children			-8.908***	-0.276*	-3.311***	-5.322***
			(1.029)	(0.139)	(0.413)	(0.570)
Number of Male Children			-1.178	0.821	-0.916	-1.083
			(1.631)	(0.533)	(1.034)	(1.002)
Yrs Since Migration			-0.184	-0.139***	-0.125	0.080
			(0.201)	(0.035)	(0.131)	(0.101)
N	5812	5812	5812	5812	5812	5812
# Country p	64	64	64	64	64	64
Mean Dep. Var.	89.33	89.33	89.33	10.54	22.03	56.75
St. Dev. Dep. Var.	119.61	119.61	119.61	32.25	57.91	88.36
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%.

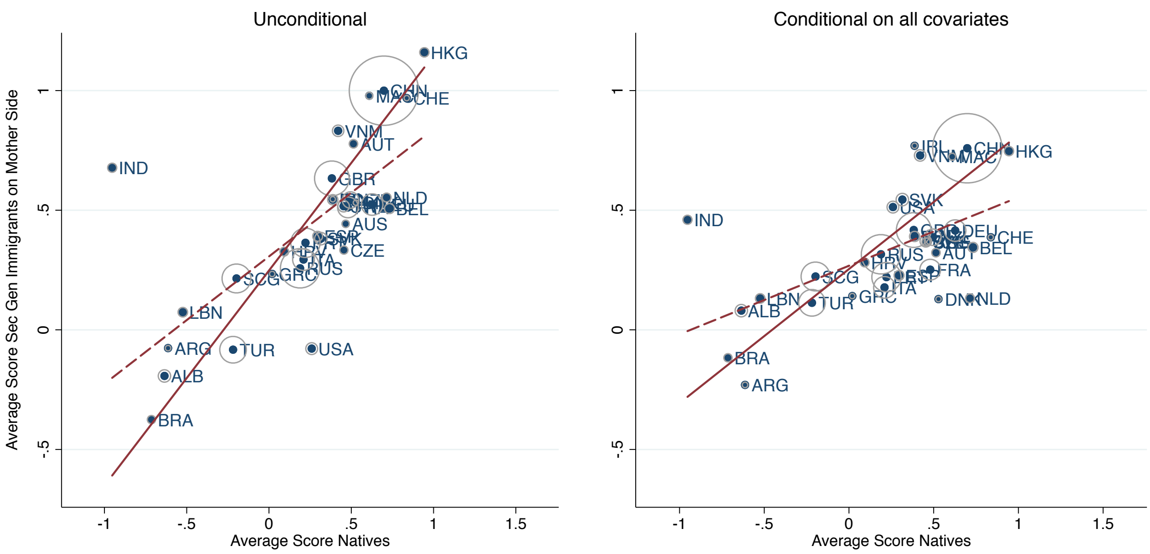
Figures

Figure 1: Performance of Native Students across Countries



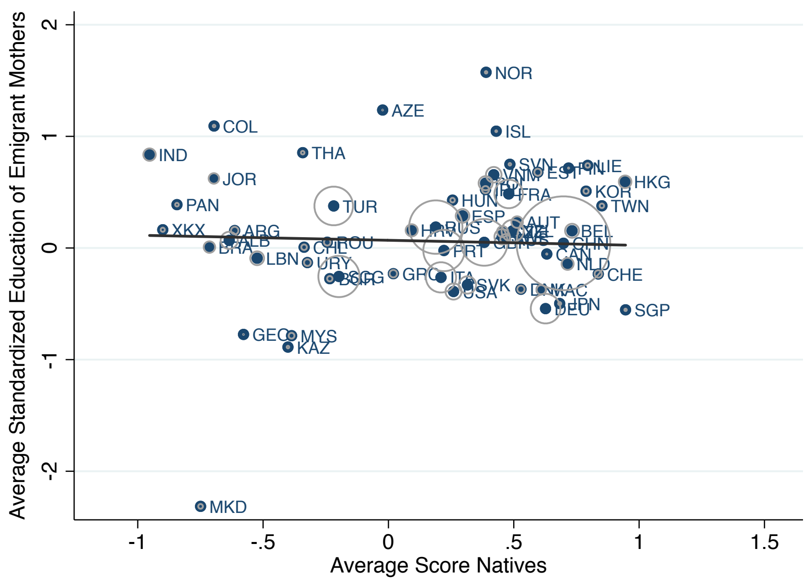
Notes: The height of the bar represents the average PISA score in mathematics for native students. Scores are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) countries participating to at least one wave of the test. Black bars refer to countries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

Figure 2: Performance of Second Generation Immigrants and Natives



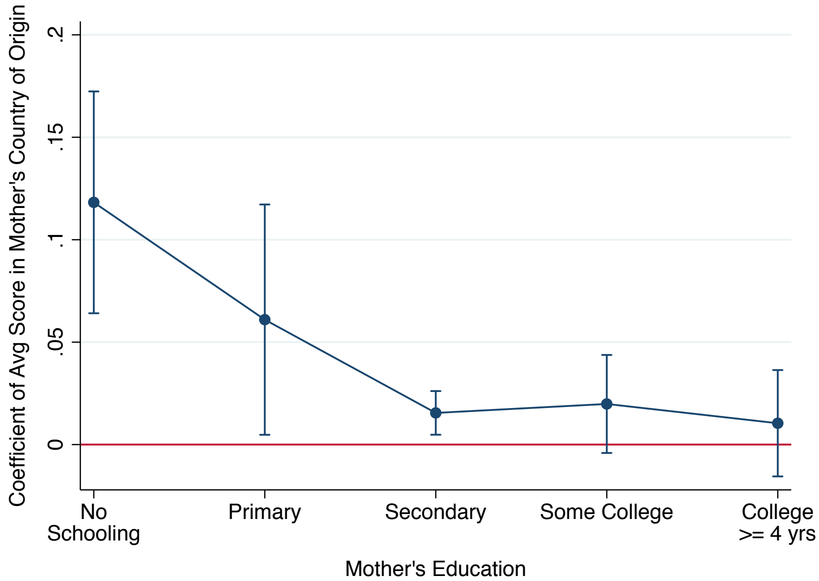
Notes: The left panel plots the average PISA score of second generation immigrants whose mother is from country m against the average math PISA score of natives in country m, for all countries with at least 100 second generation immigrants on the mother's side in the sample. The right panel plots the predicted scores from a regression with individual math scores as dependent variable and fixed effects for mother's country of origin, school fixed effects and all the other controls included in column 4 of Table 4, 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 solid (dashed) line shows the best weighted (unweighted) linear fit.

Figure 3: Selection on Parental Education



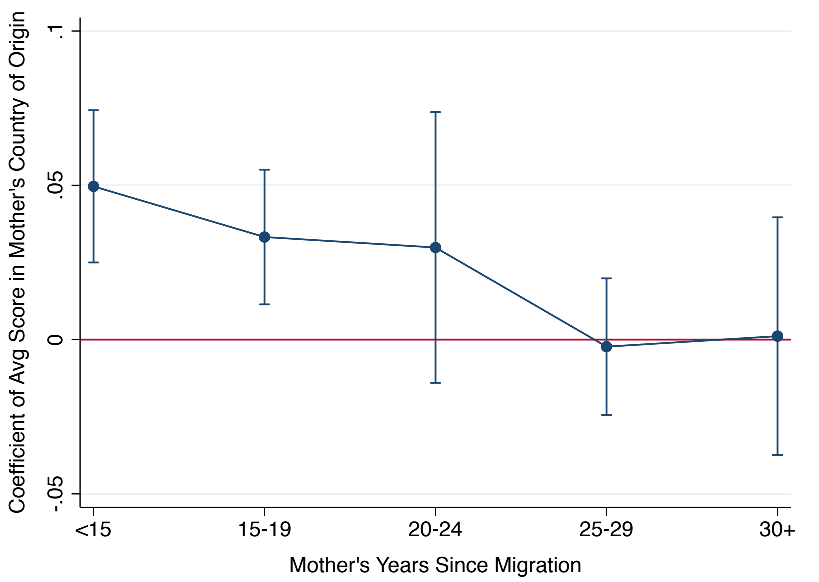
Notes: The Figure plots the average years of schooling of emigrant mothers from country m standardized by the average and the standard deviation of years of schooling of non-emigrant mothers in country m (y-axis) against the average PISA score of native students in country m (x-axis). The sizes of the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

Figure 4: 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 4 of Table 5. Standard errors are clustered by mother's country of origin.

Figure 5: 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 4 of Table 5. Standard errors are clustered by mother's country of origin.