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Parents, schools and human capital differences across countries

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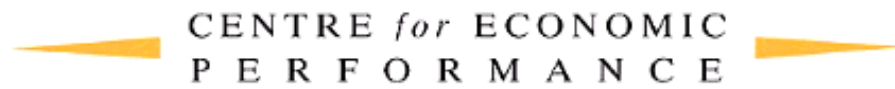
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Parents, Schools and Human Capital Differences across Countries

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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 the PISA test do better than their peers with similar socio-economic backgrounds. Differential selection into emigration does not explain this finding. The result is larger when parents have little education and have recently emigrated, suggesting the importance of country-specific cultural traits that parents progressively lose as they integrate in the new host country, rather than of an intergenerational transmission of education quality. 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., 2016), especially when measured by standardized tests (Hanushek and Woessmann, 2012a).

Given the role that gaps in human capital measures play in the academic and policy debates, it is important to understand where they come from. 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 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 student, household, country and school characteristics. 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., 2016; 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., 2016). A natural question then is whether the variation in these factors is relevant also 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

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[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 compare their cross-country variation with the overall 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 from the country of origin of their parents: the best performing second-generation immigrants are those whose parents come from countries where natives are particularly successful in standardized tests.[2] This holds true when controlling for 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 focus on the US data to explore potential mechanisms behind gaps in this parental unobservable component. We show that the relationship between the performance of second-generation immigrants and the average score in the parents' country of origin is strongest for parents with little or no formal education. This suggests that our results are not driven by the intergenerational transmission of the quality of education received by parents in their home country. 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, part 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 attitudes towards leisure. 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 parents from

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[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.

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 observable characteristics of the educational systems and students' family background. Specific evidence for the importance of international differences in school quality is provided by, among others, Singh (2017). 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 develop a model of preference transmission to explain the international variation in parenting styles as a function of local economic conditions.[3] We contribute to this literature by quantifying and characterizing cross-country differences in observable and unobservable parental influence.

We also relate to a wide literature across economics and sociology on the school performance of first- and second-generation immigrant children (see Levels et al., 2008; Dustmann et al., 2012, for broad reviews). Differently from these papers, our objective is to understand gaps in performance between natives of different nationalities, and our focus on second-generation immigrants is mostly instrumental in that it provides us with an empirical strategy to discriminate between possible sources for these gaps.[4] In addition, we conduct our analysis on a broad sample of host and origin countries (while, for example, Dustmann et al. (2012) focus on Turkish immigrants, and Jerrim (2015) on East Asian immigrants), and we rely on several additional sources to provide evidence on the mechanisms underlying our results.

Our paper shares the approach of a large literature that looks at first- and second-generation immigrants to identify the importance of "portable" cultural traits for various outcomes (the so-called "epidemiological approach"; see among others Giuliano, 2007; Fernandez and Fogli, 2009; Fernandez, 2011). Differently from these papers, we study the school performance of the second generation, and use the results to quantify the importance of parents for cross-country differences in the same outcome. While most of the focus in this literature is on immigrants in the US, our sample includes a large set of both host and source countries, allowing us to exploit variation in both dimensions. In more recent and independent work, Figlio et al. (2016) adopt a similar methodology to document the relevance of long-term orientation for educational performance. Compared to their paper, our aim is to study and quantify the overall importance of observable and unobservable parental characteristics for the cross-country variation in human

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[3]As mentioned above, the focus on parents is motivated by a growing micro-level literature emphasizing the importance of various types of parental inputs for skill formation (see Heckman and Mosso (2014) for an extensive review).

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

capital achievements, without restricting attention to a specific cultural trait.[5]

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.[6]

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.[7] These magnitudes are striking; according to OECD (2012a), a gap of 0.4 on this scale corresponds to what is learned in an average year of schooling. There is substantial geographical clustering: East Asian countries occupy the first positions of the ranking, followed by several Western European countries; Southern European countries concentrate in the middle of the distribution, while Latin American countries are below the average. The superior performance of East Asian students is stronger in mathematics, but the ranking across regions is quite stable across subjects (see Table A.1 in the Appendix for the average scores in these and other broadly defined regions).

A Student Questionnaire provides basic demographic and socio-economic information on students and parents, including their country of birth, education, language spoken at home, number of books at home, employment and the ISEI index of socioeconomic status.[8]

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[5]In Section 6 we do look explicitly at long-term orientation, among other cultural traits, and confirm the Figlio et al. (2016)'s result that it affects students' performance, even though it cannot account for the whole cross-country variation in parental influence.

[6]The results are not presented as point estimates but rather as "plausible values": the OECD estimates for each student a probability distribution of scores, and randomly draws from it five values. Following OECD (2009), we compute variances of all functions of test scores as the average of the 5 variances estimated with each set of plausible values, and standard deviations as the square root of the corresponding quantities.

[7]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.

[8]The ISEI index, developed by Ganzeboom et al. (1992), is a measure of occupational status that assigns

Our second 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.[9] We classify a child as a repeater if his or her educational attainment is below the mode for the corresponding state, age, quarter of birth, and census year cell.[10] We focus on children between the ages of 8 and 15.

We use the 2002 to 2015 waves of the ATUS-US Time Use Survey to analyze how parents spend their time. The survey is administered to one person per household, chosen randomly among all individuals at least 15 years old. We compute the total time (in minutes) spent on child care on the previous day, and, following Aguiar and Hurst (2007), three subcategories that split total child care in educational, recreational and basic activities.

Finally, we rely on several other sources to construct controls at the host country, school, and parents' country of origin level. We discuss the details below as we introduce these variables to 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 students' demographic characteristics, D_{icst}, which includes age (in months) and gender. We assume the linear relationship[11]

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

where α_t is a wave fixed effect, and ε_{icst} a mean zero idyosincratic term.

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,

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to each occupation a score from 16 to 90 combining information on average income and education of full-time employed men across several countries.

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

[10]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.

[11]Non-linear extensions are discussed in Appendix E. We find no evidence for significant interaction effects.

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 proxies for the degrees of accountability, monitoring and autonomy in schools.[12] 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. Of course, 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.[13]

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.[14] This selection follows closely previous work on educational production functions estimated on PISA data.[15] 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 PISA assessment; we focus on the math test in the main body of the paper, and illustrate the (similar) results for reading and science in the Appendix. 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, the fixed effects

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[12]See Appendix A for a full list of the included variables and their sources.

[13]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.

[14]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.

[15]In Appendix B we show that the results are robust to alternative controls for socio-economic status available in the PISA dataset.

specifications allow us to extend the analysis to a wider sample (79 countries); the corresponding results are shown in Column 4 and 6.

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 magnitude of the associated coefficients. This points to the fact that parental observables are correlated with relevant country and school characteristics.[16]

The average score (across all available waves) of students in country c is

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

where X_c, u_c, $EduSystem_c$, D_c and α_c are country-level averages of the corresponding variables (pooled across waves).[17] 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

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

Table 2 shows the decomposition results. Each column corresponds to the specification estimated in the corresponding 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 reported in Woessmann (2016)). Country and, especially, school fixed effects further reduce the contribution of parental observables, to 25% and 13% when using the same sample of 37 countries with all educational system controls available, and to 16% and 9% when using the full sample.[18]

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[16]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 detailled comparisons of these results for future work.

[17]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.

[18]The difference across samples is driven by the fact that the average PISA score has a larger variance and

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 parents affect human capital accumulation, and as a result might 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.[19]

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, controlling for host-country and school fixed effects as well as for parental socio-economic characteristics, second generation immigrants from high-scoring countries to do better than those from low-scoring countries, exactly because of the unobserved parental component u_c postulated above. 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

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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 sample in the associated coefficients has a negligible impact.

[19]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.

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performance in 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 Appendix B 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.

4.1 Evidence Using PISA Data

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 39 host countries.[20] Sample sizes vary greatly, and for some countries of origin we have only a few parents to work with (see Tables A.2 and A.3 in the Appendix for summary statistics by origin and host country). To account for this, we weight countries of origin by the number of second-generation immigrants in the sample when considering cross-country patterns, and we present country-specific estimates for a "core sample" of 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.

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.

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

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[20]National educational authorities have flexibility on how to classify parents' country of origin, and most of them only record separately those parental nationalities that are relatively frequent (grouping the others in broader categories). We construct a set of countries consistently defined over time; see Appendix A for the details. Appendix B discusses both the potential issues of unreported countries of origin and misclassification in the parental immigration status reported by students.

$$T_{icst}^m = \theta_0 + \theta_1 T^m + \theta_2' X_{icst} + \theta_3' D_{icst} + \theta_4 NatFath_{icst} + \theta_{cst} + \varepsilon_{icst}^m \qquad (3)$$

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 school, depending on the specification) fixed effect and ε_{icst}^m is an error term. As before, by introducing host-country (or school) fixed effects we control for differences in the characteristics of the institutional context (or specific school) students are exposed to. The main coefficient of interest is θ_1, which captures the relationship between a second-generation immigrant's performance and the average score of native students in country m, after having accounted for observable parental characteristics and the quality of the host country's educational system.[22]

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.[23]

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

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

[22]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 country 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.

[23]As recommended in OECD (2009), each regression is estimated separately for each set of plausible values, and the sampling variance is computed from the average estimated variance-covariance across these specifications. In addition, standard errors are corrected for the imputation variance, which is proportional to the variance of the estimated coefficients across sets of plausible values. In Appendix B we discuss the details of this procedure, and show that the statistical significance of our results is robust to alternative ways to construct the standard errors.

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.[24]

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.

4.2 Evidence Using US Census Data

We apply a similar specification as in equation (3) to the US Census data. The dependent variable is a dummy which takes value one if a child has never repeated any grade. This outcome, while still related to school performance, captures quite a different dimension compared to the PISA score, given that the variation here comes only from the bottom part of the distribution (more than 80% of the students in the sample has never repeated a grade, as shown in Table 3) and from students aged 8-15 (while PISA is administered to 15-year-old students only).

The US Census does not include any information on the school children are attending. To capture some of the differences across educational systems within the US, we control for Commuting Zone fixed effects.[25] Compared to the PISA sample, we can control here 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.

Our final sample includes 53,553 second-generation immigrants on the mother's side and 46,310 on the father's side, from 64 countries of origin. Descriptive statistics are provided in Panel B of Table 3.

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).

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 random sample of the population, and might be selected

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[24]In Appendix B we show that the estimated relationship is not driven by any single host or origin country. 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.

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

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 (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.[26] 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.[27]

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). However, 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 country (columns 1 and 3) and school (columns 2 and 4) fixed effects. For both mothers and fathers, the point estimates are negative and not

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[26]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 Appendix C). Moreover, this potential "contamination" of our proxy for unobservable parental skills is problematic for our purposes only to the extent that is differential across countries of origin.

[27]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 Appendix C we show 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.

statistically significant, suggesting that the type of differential selection that would invalidate our results is not present neither within host countries nor within schools.

These results are broadly consistent with the patterns of selection reported in the development accounting literature. Schoellman (2012) documents that, among migrants (not necessarily parents of school-age children) residing in the US, the education gap compared to non-migrants is higher for poor origin countries. Hendricks and Schoellman (2018) show that emigrants from poor countries are more positively selected in terms of pre-migration wages and occupations.[28]

An additional concern is that immigrant parents from high PISA countries may be systematically selecting host countries where, because of idiosyncratic factors, it is easier for them and their children to integrate and perform well. We check whether immigrants from high PISA countries are located in countries which are, according to reasonable proxies, culturally closer to their country of origin. Table 7 explores this possibility. In column 2 and 4 we add to the baseline specifications (reported in columns 1 and 3 respectively) controls for linguistic distance (constructed through the softwares provided by the Automated Similarity Judgment Program Wichmann and Brown, 2016) and cultural distance (from Spolaore and Wacziarg, 2015); both measures are standardized to have mean 0 and standard deviation 1 across all country pairs in the sample. Column 6 includes both proxies simultaneously.

In all cases, our coefficient of interest increases marginally when measures of bilateral distance are included. The point estimates on these controls are generally positive, and marginally significant for linguistic distance. One possible interpretation is that linguistic and cultural distance 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.

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.[29]

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

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

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

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

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 effect of socio-economic and unobservable characteristics. Crucially, we write the latter as the sum of two parental country of origin specific unobserved components, γ^m and δ^f, and a residual, $\tilde{u}_{icst}^{mf}$,

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

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

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

$$T_c = \xi' X_c + \gamma^c + \delta^c + \tilde{u}_c + \widehat{EduSystem_c} + \zeta' D_c + \theta^c + \zeta^c + \alpha_c \qquad (5)$$

We estimate the contribution of unobservable parental characteristics as

$$\widehat{ParentsU}nobs_c = \widehat{\gamma}^c + \widehat{\delta}^c$$

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

$$\frac{\mathrm{Cov}(\widehat{ParentsU}nobs_c, T_c)}{\mathrm{Var}(T_c)}$$

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.

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 the Chinese outperformance. A low value of $\widehat{ParentsUnobs}_c$ is also a key driver of the low scores in several Southern European countries. Unobserved parental influence instead does not contribute to explain the low scores in Brazil and India, the two worst performing countries in the core sample.[30]

6 Mechanism

We now study possible mechanisms behind the results. What is it about parents from high PISA countries that drives the superior school performance of their children? While answering this question precisely is difficult, we make progress by proceeding in three steps. First, we 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 importance of several possible drivers of cross-country differences in parental influence: the educational system to which parents were exposed, the country-specific cultural context and the genetic transmission of relevant traits. Then we turn to time use surveys to see whether immigrant parents from high PISA countries differ in practices that might help to explain their children's better performance at school. Finally, we test whether country-level proxies for economic development, educational attainment or culture can explain the parental country-of-origin effect.

6.1 Heterogeneity

The documented country-of-origin effect might in principle be driven by a number of sources. First, the outstanding performance of second-generation immigrants from high PISA countries might reflect the higher quality of the education received by parents in their country of origin. This would imply an intergenerational multiplier effect of educational quality, therefore providing an even stronger rationale for policies aiming to replicate the best practices in this domain.

An alternative is that the country-of-origin's cultural context, defined as a shared set of beliefs and preferences within a given country, might have shaped parents' attitudes and beliefs

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[30]In 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.

towards education. 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 are systematically endowed with different genetic traits that shape their human capital investment. This interpretation would leave little room for policies to affect achievement gaps.

To discriminate between these views, we explore the heterogeneity of country-specific parental influences with respect to parental characteristics. If the intergenerational transmission of educational quality is important, we expect the correlation between school performance and the PISA score in the parents' country of origin to be particularly strong for students whose parents acquired more education in their home country, and were therefore more exposed to the home country's educational system.[31] At the extreme, parents with no education cannot transmit the quality of their home country's school system at all.

On the other hand, if what matters is the cultural context in the source country, we expect the country-of-origin effect to be smaller among parents that are more integrated in their host country and have at least in part converged to its cultural norms. As cultural assimilation takes time, the correlation between children's performance and the average test score in the country of origin should be weaker for parents that have emigrated many years ago.[32] 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 two sources of differences in parental influence. The intergenerational transmission of educational quality mechanism would imply a positive interaction term between parental years of schooling acquired in the home country and the average score of natives in the same country. A story based on differences in cultural environments would instead involve a negative interaction between the average test score and parents' years since migration, as well as parents' years of schooling. A purely genetic view, instead, would not have any obvious implication in terms of differential effects.

We now turn to the US Census data to put these predictions to empirical scrutiny.[33] We

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

[32] There is widespread evidence that years since migration correlate positively with immigrants' assimilation (Chiswick, 1978). Children of parents that have spent more time in the US fare better in terms of years of schooling, earnings (Abramitzky et al., 2016) and school performance (Nielsen and Schindler Rangvid, 2011), a result that we confirm in our setting (with the caveat that the impact of years since migration is heterogeneous depending on the country of origin). Appendix D shows that results are similar when we focus on alternative measures on immigrants' assimilation.

[33] We focus on the US Census data because in the PISA sample we do not have information on parents' year of immigration, which we need both to compute years since migration and to split parents' years of schooling in those accumulated in the home and in the host countries. We report the PISA results on the heterogeneity with respect to overall parental education in Appendix D.

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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).[34]

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 levels of mothers' educational attainment: most of the gap is driven by mothers with either no education or primary schooling only, and disappears when we focus on mothers with college education. These results are inconsistent with strong intergenerational effects of educational quality.[35]

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 have emigrated many years ago.[36] 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 (as well as the results on education discussed above) is unaffected by the inclusion of controls for age at migration, which has also been shown to be important for the assimilation of immigrants (Bleakley and Chin, 2010).

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 still 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.

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[34]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.

[35]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.

[36]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.

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

6.2 Time Use

In this section we investigate whether immigrant parents from high PISA countries allocate more time to activities that might plausibly stimulate their children's human capital accumulation. The analysis complements and extends the work of Ramey (2011), who compares time use practices across ethnic groups.

Table 11 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.[37]

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

6.3 Country-Level Characteristics

We now augment specification (3) with a series of controls at the mother's country-of-origin-level. The objective is to understand which country-level characteristics drive, at least in part, the difference in performance between second generation immigrants from high- and low-scoring countries.

Table 12 includes controls related to economic development and schooling in country m.[38] As high-scoring countries in the PISA test are richer and have more educated populations, we want to check whether this gives to second-generation immigrants from those countries some direct advantage which might explain their superior performance. In column 2 we add to the

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

[38]We use real GDP per capita from the Penn Word Tables 8.0, average years of schooling for 35- to 45-year-old adults in 2010 from Barro and Lee (2013), and cumulative expenditure per pupil in secondary schools from various sources described in Appendix A.

baseline specification in column 1 log real GDP per capita in the mother's country of origin; the coefficient is actually negative and statistically significant. Average years of schooling in the mother's country of origin, included in column 3, is not related to the performance of second generation immigrants. Column 4 further controls for the cumulative expenditure per pupil in secondary schools. While the coefficient is negative, this is driven by the correlation between expenditure and GDP per capita; indeed, in a specification that includes all these controls simultaneously (column 5), expenditure is positively related to second generation immigrants' performance, while GDP has a stronger negative effect.

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). Whatever the underlying mechanism, Table 12 suggests that controlling for more proxies for economic and educational development of country m does not weaken the association between second generation immigrants' performance and the PISA score in country m; if anything, it makes it stronger.

Table 13 controls for proxies for various cultural traits from the World Value Survey. While, to our knowledge, a direct measure of attitudes towards education is not available, we focus on three proxies that have been studied elsewhere as determinants of labor supply and effort: tastes for leisure, locus of control and long-term orientation.[39,40]

Columns 1 to 3 introduce our cultural proxies in regressions controlling for the usual parental characteristics and school fixed effects. All three coefficients are of the expected sign; second-generation immigrants from countries where leisure is considered less important, where people believe to have control on events in their life and are oriented towards the future score better

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

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

than their peers, even if school quality is controlled for. A similar message emerges when the cultural proxies are included simultaneously (column 4). In column 6 we further control for the average performance of native students in the mother's country of origin, which retains its statistical significance and drops somewhat compared to the baseline specification without cultural proxies (reported in column 5).

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

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 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 arrive to 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 seem to 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 partially reflected in observable time use practices.

These results have implications for the study of human capital in a cross-country perspective. Models of human capital accumulation should be consistent with an important role for parents in the transmission of knowledge, beyond what can be inferred by 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 moreover 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 their students' performance in standardized tests. Cross-country gaps go beyond differences in school quality and parents' socio-economic background, and policies aimed at simply replicating school practices successful in other countries might have smaller-than-expected effects.

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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	0.045***					
	(0.006)					
Avg Share Gov Funding	-0.518***					
	(0.195)					
Share Private	0.154					
	(0.192)					
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					
	(0.055)					
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 host 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	16.18	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	Yes	Yes
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

	[1]	[2]	[3]	[4]	[5]
	Dependent variable: 1 = Never repeated a grade				
			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 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	-0.003	-0.083		
	(0.217)	(0.197)		
Score Country f			0.017	-0.135
			(0.204)	(0.164)
N	49097	49097	48834	48834
R Squared	0.07	0.61	0.07	0.59
Host Country × Wave FE	Yes	Yes	Yes	Yes
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: Linguistic and Cultural Distance

	[1]	[2]	[3]	[4]	[5]	[6]
			Dependent Variable: Math Test Score			
Score Country m	0.247***	0.277***	0.229**	0.287***	0.249**	0.309***
	(0.075)	(0.071)	(0.096)	(0.103)	(0.099)	(0.101)
Female	-0.198***	-0.197***	-0.192***	-0.192***	-0.193***	-0.193***
	(0.023)	(0.023)	(0.026)	(0.026)	(0.027)	(0.027)
Father Sec Edu	0.024	0.025	0.051	0.052	0.042	0.043
	(0.021)	(0.021)	(0.040)	(0.041)	(0.040)	(0.041)
Father Ter Edu	0.014	0.014	0.017	0.014	0.009	0.006
	(0.028)	(0.028)	(0.050)	(0.051)	(0.051)	(0.052)
Mother Sec Edu	-0.034	-0.034	-0.031	-0.026	-0.023	-0.018
	(0.035)	(0.036)	(0.064)	(0.068)	(0.066)	(0.071)
Mother Ter Edu	-0.032	-0.030	-0.045	-0.037	-0.036	-0.028
	(0.033)	(0.033)	(0.061)	(0.066)	(0.064)	(0.069)
Mother Working × Mother ISEI	0.001	0.001	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father Working × Father ISEI	0.002**	0.002**	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Different Lang at Home	-0.070**	-0.082***	-0.073**	-0.085***	-0.077**	-0.096***
	(0.028)	(0.028)	(0.034)	(0.027)	(0.033)	(0.025)
11-25 Books	0.093***	0.093***	0.122***	0.121***	0.134***	0.132***
	(0.026)	(0.026)	(0.037)	(0.037)	(0.034)	(0.035)
26-100 Books	0.201***	0.201***	0.226***	0.224***	0.233***	0.232***
	(0.038)	(0.038)	(0.050)	(0.049)	(0.051)	(0.051)
101-200 Books	0.262***	0.263***	0.283***	0.282***	0.294***	0.295***
	(0.044)	(0.044)	(0.054)	(0.054)	(0.053)	(0.053)
201-500 Books	0.387***	0.390***	0.447***	0.448***	0.454***	0.460***
	(0.064)	(0.065)	(0.078)	(0.079)	(0.079)	(0.080)
500+ Books	0.404***	0.411***	0.441***	0.444***	0.450***	0.458***
	(0.074)	(0.075)	(0.091)	(0.094)	(0.091)	(0.094)
Mother Linguistic Distance		0.018*				0.005
		(0.009)				(0.018)
Father Linguistic Distance		0.017*				0.025
		(0.009)				(0.016)
Mother Cultural Distance				0.035		0.039
				(0.024)		(0.033)
Father Cultural Distance				0.009		-0.016
				(0.026)		(0.032)
N	46896	46896	23513	23513	23331	23331
# Country m	57	57	42	42	41	41
R Squared	0.66	0.66	0.64	0.64	0.64	0.64
Host Country × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
School × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The Table shows results for second generation immigrants on the mother's side, augmented for controls for linguistic and cultural distance. Sample includes only cases where both parents report a country of origin and the country of origin of the mother 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 Distance* and *Cultural Distance* vary at the country-pair level, and are standardized to take mean 0 and standard deviation 1 across all pairs in the sample. 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]
$\frac{\mathrm{Cov}(\widehat{ParentsObs_c},T_c)}{\mathrm{Var}(T_c)}$	21.21	10.64
$\frac{\mathrm{Cov}(\widehat{ParentsUnobs_c},T_c)}{\mathrm{Var}(T_c)}$	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

Country	PISA Score	PISA Gap	$\widehat{ParentsObs_c}$ Gap		$\widehat{ParentsUnobs_c}$ Gap	
			School FE	Country FE	School FE	Country FE
Hong Kong	1	0.72	0.00	0.00	0.19	0.43
			(0.00)	(0.03)	(0.15)	(0.16)
Belgium	0.85	0.57	0.05	0.13	-0.02	-0.12
			(0.00)	(0.03)	(0.33)	(0.29)
China	0.82	0.54	-0.04	-0.09	0.25	0.62
			(0.01)	(0.03)	(0.04)	(0.06)
Netherlands	0.79	0.51	0.05	0.12	0.05	0.12
			(0.00)	(0.03)	(0.08)	(0.11)
Germany	0.72	0.44	0.09	0.17	0.10	0.11
			(0.00)	(0.03)	(0.06)	(0.08)
Macao	0.65	0.37	-0.04	-0.10	0.19	0.47
			(0.00)	(0.03)	(0.08)	(0.11)
New Zealand	0.63	0.35	0.08	0.15	-0.12	-0.19
			(0.00)	(0.03)	(0.04)	(0.05)
Denmark	0.59	0.31	0.06	0.14	0.22	0.07
			(0.00)	(0.03)	(0.15)	(0.14)
France	0.59	0.31	0.05	0.11	-0.06	-0.23
			(0.00)	(0.03)	(0.05)	(0.07)
Austria	0.57	0.29	0.05	0.12	0.04	-0.07
			(0.00)	(0.03)	(0.12)	(0.12)
Australia	0.54	0.26	0.09	0.17	-0.19	-0.17
			(0.00)	(0.03)	(0.15)	(0.13)
Czech Republic	0.53	0.25	0.06	0.11	0.01	-0.02
			(0.00)	(0.03)	(0.11)	(0.12)
Sweden	0.52	0.24	0.10	0.21	0.08	-0.04
			(0.00)	(0.03)	(0.07)	(0.07)
United Kingdom	0.49	0.21	0.06	0.12	-0.05	-0.12
			(0.00)	(0.03)	(0.02)	(0.04)
Vietnam	0.44	0.16	-0.14	-0.31	0.29	0.49
			(0.01)	(0.03)	(0.05)	(0.07)
Poland	0.42	0.14	0.00	0.00	0.04	0.10
			(0.00)	(0.03)	(0.07)	(0.08)
Slovakia	0.37	0.09	0.01	0.02	0.07	-0.08
			(0.00)	(0.03)	(0.08)	(0.09)
United States	0.35	0.07	0.05	0.12	0.13	0.12
			(0.00)	(0.03)	(0.10)	(0.12)
Spain	0.33	0.05	0.04	0.04	-0.07	-0.11
			(0.00)	(0.03)	(0.08)	(0.10)
Italy	0.27	-0.01	0.03	0.05	-0.18	-0.33
			(0.00)	(0.03)	(0.09)	(0.09)
Portugal	0.27	-0.01	-0.03	-0.11	-0.02	0.01
			(0.00)	(0.03)	(0.07)	(0.07)
Russia	0.22	-0.06	0.05	0.11	0.05	0.08
			(0.00)	(0.03)	(0.03)	(0.05)
Croatia	0.13	-0.15	-0.04	-0.05	-0.09	-0.04
			(0.00)	(0.03)	(0.13)	(0.13)
Greece	0.06	-0.22	0.02	0.05	-0.30	-0.30
			(0.00)	(0.03)	(0.16)	(0.17)
Serbia-Mont.	-0.15	-0.43	-0.04	-0.04	-0.11	-0.14
			(0.00)	(0.03)	(0.06)	(0.07)
Turkey	-0.17	-0.45	-0.10	-0.25	-0.22	-0.35
			(0.01)	(0.03)	(0.06)	(0.09)
Lebanon	-0.38	-0.66	0.01	0.00	-0.31	-0.42
			(0.01)	(0.04)	(0.10)	(0.09)

Continued on next page

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Country	PISA Score	PISA Gap	$\widehat{ParentsObs_c}$ Gap		$\widehat{ParentsUnobs_c}$ Gap	
			School FE	Country FE	School FE	Country FE
Albania	-0.61	-0.89	-0.12	-0.22	-0.09	-0.07
			(0.00)	(0.03)	(0.05)	(0.07)
Jordan	-0.62	-0.90	-0.09	-0.15	-0.10	-0.18
			(0.00)	(0.03)	(0.07)	(0.08)
Brazil	-0.65	-0.93	-0.13	-0.26	0.17	0.28
			(0.00)	(0.03)	(0.14)	(0.13)
India	-0.89	-1.17	-0.17	-0.36	0.05	0.10
			(0.01)	(0.03)	(0.10)	(0.12)

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.

Table 10: Interactions - US CENSUS

	[1]	[2]	[3]	[4]	[5]	[6]
				Dependent variable: 1 = Never repeated a grade		
			All			Mothers Educated in m
Score Country m	0.032***	0.101***	0.138***	0.200***	0.190***	0.201***
	(0.008)	(0.030)	(0.046)	(0.050)	(0.061)	(0.057)
Female	0.068***	0.067***	0.067***	0.067***	0.067***	0.068***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Yrs Schooling Father	0.006***	0.006***	0.006***	0.006***	0.006***	0.007***
	(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	-0.002	
			(0.002)	(0.002)	(0.002)	
Score Country m × Yrs Schooling Moth in m			-0.006**	-0.007***	-0.007***	-0.009***
			(0.002)	(0.002)	(0.002)	(0.002)
Yrs Schooling Moth in US			0.007***	0.002	0.002	
			(0.001)	(0.002)	(0.002)	
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)	(0.000)	(0.001)
Score Country m × Yrs Since Migr Mother				-0.003***	-0.003***	-0.003***
				(0.001)	(0.001)	(0.001)
Age Migration Moth					-0.000	-0.000
					(0.001)	(0.001)
Score Country m × Age Migration Moth					0.000	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	0.14
Comm Zone FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 11: 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%.

Table 12: Country of Origin Characteristics - Economic and Educational Development

		Dependent variable: Math Test Score			
	[1]	[2]	[3]	[4]	[5]
Score Country m	0.228***	0.327***	0.226***	0.279***	0.301***
	(0.073)	(0.066)	(0.081)	(0.077)	(0.062)
Female	-0.202***	-0.201***	-0.202***	-0.201***	-0.200***
	(0.023)	(0.022)	(0.023)	(0.022)	(0.023)
Father Sec Edu	0.022	0.020	0.022	0.021	0.018
	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
Father Ter Edu	0.011	0.007	0.011	0.009	0.006
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Mother Sec Edu	-0.036	-0.038	-0.036	-0.036	-0.044
	(0.032)	(0.031)	(0.032)	(0.032)	(0.030)
Mother Ter Edu	-0.034	-0.035	-0.034	-0.032	-0.044
	(0.033)	(0.033)	(0.034)	(0.033)	(0.034)
Mother Working × Mother ISEI	0.001	0.001*	0.001	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father Working × Father ISEI	0.002***	0.002***	0.002**	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Different Lang at Home	-0.075***	-0.085***	-0.075***	-0.082***	-0.082***
	(0.028)	(0.029)	(0.029)	(0.029)	(0.028)
11-25 Books	0.099***	0.100***	0.099***	0.099***	0.102***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)
26-100 Books	0.207***	0.208***	0.207***	0.207***	0.209***
	(0.039)	(0.039)	(0.040)	(0.039)	(0.040)
101-200 Books	0.264***	0.266***	0.264***	0.264***	0.268***
	(0.045)	(0.046)	(0.046)	(0.045)	(0.046)
201-500 Books	0.395***	0.401***	0.395***	0.397***	0.403***
	(0.064)	(0.065)	(0.064)	(0.064)	(0.065)
500+ Books	0.407***	0.413***	0.407***	0.408***	0.415***
	(0.074)	(0.074)	(0.074)	(0.074)	(0.075)
Log GDP in m		-0.113***			-0.185***
		(0.033)			(0.040)
Avg Years Edu in m			0.000		0.010
			(0.012)		(0.007)
Expenditure per Student in m				-0.006**	0.006*
				(0.003)	(0.003)
N	48671	48671	48671	48671	48671
# Country m	53	53	53	53	53
R Squared	0.78	0.78	0.78	0.78	0.78
Host Country × Wave FE	Yes	Yes	Yes	Yes	Yes
School × Wave FE	Yes	Yes	Yes	Yes	Yes

Notes: The Table shows results for second generation immigrants on the mother's side. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. All specifications control for intercept, students' age (in months), wave fixed effect, a dummy for father's immigrant status and dummies for parents' employment status (full-time employed, part-time employed, not working). *Working* refers to either full-time or part-time employed. *Log GDP in m*, *Avg Years Edu in m* and *Expenditure per Student in m* are respectively the wave-specific contemporaneous log real GDP per capita, the average years of schooling in 2010 of 35- to 45-year-old adults and the cumulative expenditure per pupil in secondary schools in the country of birth of the mother. Observations are weighted according to the provided sample weights. Standard errors are clustered by mother's country of origin, and inflated by the estimated measurement error in test scores. * denotes significance at 10%, ** at 5%, *** at 1%.

Table 13: Country of Origin Characteristics - Cultural Traits

	\[1\]	\[2\]	\[3\]	\[4\]	\[5\]	\[6\]
			Dependent variable: Math Test Score			
Score Country m					0.214***	0.158***
					(0.068)	(0.056)
Female	-0.198***	-0.201***	-0.199***	-0.198***	-0.200***	-0.198***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)
Father Sec Edu	0.025	0.023	0.025	0.022	0.028	0.025
	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
Father Ter Edu	0.011	0.012	0.011	0.007	0.016	0.010
	(0.028)	(0.027)	(0.027)	(0.027)	(0.028)	(0.027)
Mother Sec Edu	-0.031	-0.036	-0.033	-0.041	-0.040	-0.044
	(0.033)	(0.032)	(0.033)	(0.031)	(0.032)	(0.030)
Mother Ter Edu	-0.029	-0.035	-0.032	-0.044	-0.038	-0.045
	(0.031)	(0.032)	(0.031)	(0.032)	(0.032)	(0.033)
Mother Working × Mother ISEI	0.001*	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Father Working × Father ISEI	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Different Lang at Home	-0.087***	-0.078***	-0.080***	-0.082***	-0.072**	-0.079***
	(0.032)	(0.029)	(0.031)	(0.030)	(0.029)	(0.030)
11-25 Books	0.098***	0.102***	0.098***	0.101***	0.096***	0.098***
	(0.028)	(0.029)	(0.028)	(0.029)	(0.028)	(0.028)
26-100 Books	0.209***	0.215***	0.209***	0.211***	0.206***	0.207***
	(0.039)	(0.041)	(0.040)	(0.040)	(0.039)	(0.039)
101-200 Books	0.267***	0.270***	0.265***	0.268***	0.261***	0.263***
	(0.046)	(0.047)	(0.046)	(0.047)	(0.045)	(0.045)
201-500 Books	0.408***	0.407***	0.402***	0.408***	0.395***	0.403***
	(0.064)	(0.065)	(0.064)	(0.065)	(0.063)	(0.064)
500+ Books	0.416***	0.418***	0.410***	0.420***	0.406***	0.415***
	(0.075)	(0.075)	(0.075)	(0.075)	(0.074)	(0.074)
Leisure Important in Life	-0.232***			-0.260***		-0.303***
	(0.074)			(0.054)		(0.061)
Locus of Control		0.320***		0.438***		0.289***
		(0.116)		(0.081)		(0.099)
Long Term Orientation			0.247	0.218*		0.073
			(0.151)	(0.113)		(0.125)
N	48499	48499	48499	48499	48499	48499
# Country m	53	53	53	53	53	53
R Squared	0.67	0.67	0.67	0.67	0.67	0.67
Host Country × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes
School × Wave FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The Table shows results for second generation immigrants on the mother's side. *Score Country m* is the average math PISA score of natives (standardized to have mean 0 and standard deviation 1 across all countries participating to the test) in the country of birth of the mother, across all available waves. All specifications control for intercept, students' age (in months), wave fixed effect, a dummy for father's immigrant status and dummies for parents' employment status (full-time employed, part-time employed, not working). *Working* refers to either full-time or part-time employed. *Leisure Important in m* and *Locus of Control in m* are constructed from answers of natives in the mother's country of birth to 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 in m* is from Hofstede et al. (2010) and ranges from 0 to 1. Observations are weighted according to the provided sample weights. Standard errors are clustered by mother's country of origin, and inflated by the estimated measurement error in test scores. * denotes significance at 10%, ** at 5%, *** at 1%.

Figures

Figure 1: Performance of Native Students across Countries
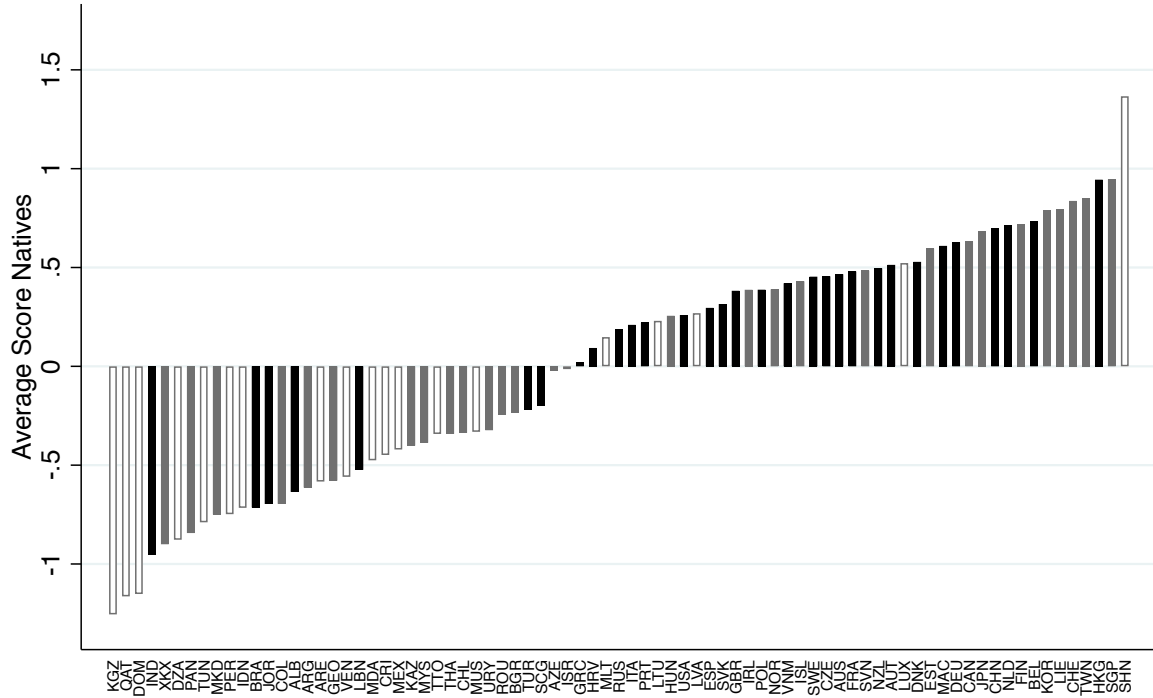
Notes: The height of the bar represents the average PISA score in mathematics for native students. Scores are standardized to have mean 0 and (individual-level) standard deviation 1 across the (pooled, equally weighted) countries participating to at least one wave of the test. Black bars refer to countries 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 in the sample. The size of the circles is proportional to the number of second generation immigrants on the mother's side in the sample. The line shows the best (weighted) linear fit.

Figure 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
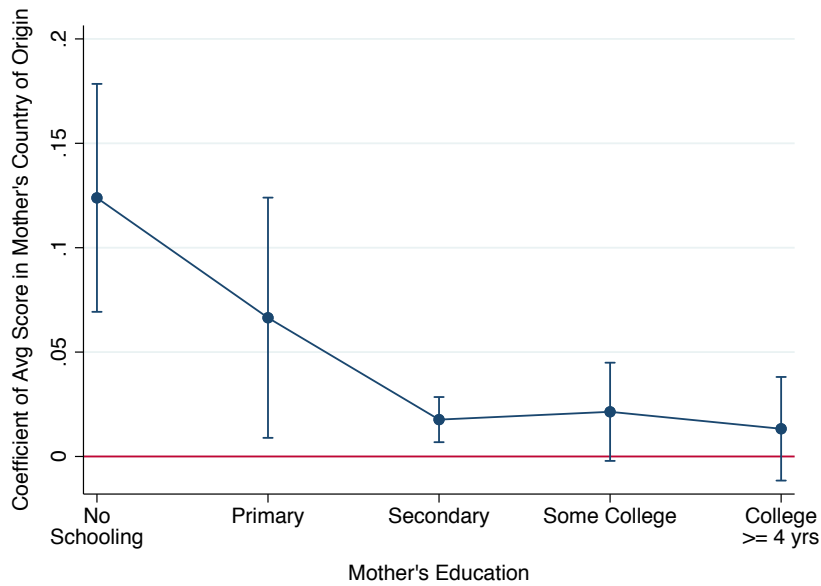
Notes: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in mother's country of origin and dummies corresponding to mother's educational achievement, with the dependent variable and other controls being the same as in 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
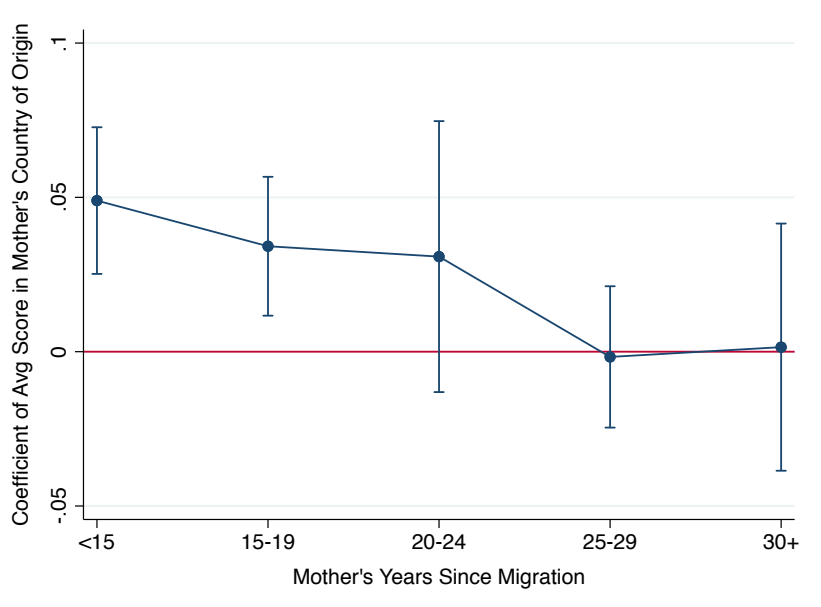
Notes: The Figure plots the estimated coefficients and 95% confidence intervals on the interactions between the average PISA score of natives in mother's country of origin and dummies corresponding to mother's years since migration, with the dependent variable and other controls being the same as in column 4 of Table 5. Standard errors are clustered by mother's country of origin.

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