Parents' Country of Origin and Intergenerational Mobility of School Performance.*

Marta De Philippis†

September 2013

Abstract

How much of the large difference in school performance across countries in international comparison tests is due to the country specific education system and how much is due to different cultural environments and type of parental inputs? This paper points out that the second factor may be of great importance. It uncovers a new fact: children from high (low) performing countries in international comparison tests are not only the best (worst) students when educated in these countries educational systems. They perform better (worse) even as second generation immigrants, born and educated in other countries school systems. This holds true even after accounting for different family background characteristics, for different schools attended and for selection into immigration. This pattern questions whether Pisa test scores should be interpreted only as a measure of the quality of a country educational system. They actually contain an important intergenerational and cultural component.

*I thank Steve Pischke for very precious guidance, supervision and encouragement. I thank Tommaso Frattini for providing me the dofiles for implementing the unbiased shortcut with pisa data. VERY PRELIMINARY AND INCOMPLETE.
†London School of Economics. e-mail address: M.de-philippis@lse.ac.uk

1 Introduction

This paper bridges the gap between two empirical regularities. On one side the large heterogeneity in migrant students' performance, depending on their country of origin. Previous analyses usually neglect this aspect and consider migrants as a uniform group. On the other side, the large cross-country differences in student performances in international comparison tests. Asian countries such as Korea, Japan, China and Singapore consistently perform better than most Western countries. This is an hot topic in the Western world and the current debate on the possible explanations is still open and largely under-researched. What could explain these differences? Some explanations, mainly anecdotical, say the gap is due to Asian more severe or better school curricula, others show Asians take more private out-of-school lessons. Finally, a third explanation are tiger moms, name taken from the very influential bestseller by Chua [2011] "Battle Hymn of the Tiger Mother" on the strict Chinese way of raising up children, pushing on academic excellence and very long studying hours.

This paper points out that the environmental and cultural component is important. I uncover a new fact. The way (second generation) immigrant students perform in host countries, relatively to other immigrant children, is very closely related to the way natives from the country of origin of their parents perform in cross-country international comparison tests, relatively to natives in other countries. Column 1 of Table 1 lists the 10 best and worst performing countries in the math PISA assessment test, based on test scores of native children born from non immigrant parents and still studying in the considered country. For instance "China" represents the average PISA score of students born and studying in China, whose mothers are Chinese as well. Column 2 shows the 10 best and worst performing countries in the math PISA assessment, based on test scores of second generation immigrant students born and studying in different countries but whose mothers were born in the considered country and migrated before their birth. For instance "China" represents the average PISA score of students born by Chinese mothers in any other country (Canada, France, UK...) and studying in these countries. 7 out of 10 countries are the same in both rankings. This stays true even after accounting for different family background characteristics, for different schools attended (if migrated) and for selection into immigration.

We tend to consider performance at PISA as a measure of the quality of a country educational system. What Table 1 shows is that Finnish or Chinese students are not only the best students at PISA when they are educated in the Finnish or Chinese school systems. They perform better even as second generation immigrants, born and educated in other educational systems. And this is not fully explained by differences in family background and selection into migration.

The first panel of Figure 1 shows this pattern for the full set of countries. Figure 1 plots average PISA math score for second generation immigrants born and studying in (any) country c, whose mothers were born in country m (y axis) against the average PISA math score of children born and studying in country m, whose mothers were born in country m as well (x axis). The correlation is positive and strong for the entire distribution. Panel b shows the same relationship, after taking into account differences in parental education and family background characteristics.

Table 1 and Figure 1 highlight that performance at school has an important intergenerational and environmental component.

In his seminal work Borjas [1992] uses data from the General Social Survey (GSS) and the National Longitudinal Survey of Youth (NLSY) to show that the quantity of education in the ethnic environment of parents, what he calls “ethnic capital”, acts as an externality in the human capital accumulation process of second generation immigrants in the US. I use a slightly different methodology and different datasets, that allow me to use a larger number of ethnic groups and controls, to show that this is not only true for the quantity of children’s education but also for their performance at school.

To understand how much of a child school performance is generated by the actual educational system one is exposed to and how much by environmental and cultural factors, I exploit the so-called epidemiological approach (for a review see Fernandez [2011], Fernandez and Fogli [2009], Giuliano [2007]). In particular, I exploit the difference in the “portability” of cultural and environmental values relative to economic and institutional conditions. When individuals emigrate, they take some aspects of their culture and education with them and transmit them intergenerationally, but they live in the economic and formal institutional environment of the host country. Studying emigrants and their descendants is therefore a useful strategy[1].

I base my analysis on four different datasets. First, I use the 2003-2006-2009 PISA students’ surveys and test scores, based on children aged 15. This allows me to analyze around 40 host countries[2]. Second, I use second generation immigrant children between age 7 and 18 from the 1970 and 1980 individual U.S. census microdata files[3]. This allows me to study different age groups. Third, I use the US time use survey data, to explore some of the mechanisms behind my findings. Finally, I use the UK Millennium Cohort Study dataset that analyzes cognitive ability at very early stages of children’s development and includes a very detailed parents’ and children’s questionnaire. This allows me to control for different types of parental inputs.

I find a positive and strong relationship. A one standard deviation larger natives PISA score in country m is associated with a 0.7 standard deviation larger PISA performance and 0.08 percentage points

[1]When I say native children I mean all children born in the home country and whose parents were born in the home country as well, this definition excludes therefore second generation immigrants. My main analysis focuses on second generation immigrants only, who were fully raised and educated in the host country.

[2]Some countries do not include in the questionnaire information on parents’ country of origin. Therefore it is impossible to run my analysis for these countries.

[3]I cannot use more recent year because there is no information on the exact grade children are attending.

lower probability of repeating a grade for second generation immigrant students whose mothers were born in country m. Once I control for family background characteristics and school fixed effects, these conditional correlations are still significant, but smaller (0.22 standard deviations and 0.03 percentage points respectively). My results are robust to different specifications, different sets of controls and different datasets.

This paper contributes to the literature along several dimensions. First, it points out that performance in low stake international comparison tests, such as PISA, should not only be interpreted as a measure of the quality of a country educational system. It contains an important intergenerational and cultural component. Second, this paper stresses the importance of family and ethnic environment in affecting children's school performance. Finally, this paper highlights and points out a regular pattern for the vast and very much under-researched heterogeneity in immigrant students school performance. Any analysis of immigrant-native score gap should take extensive care of this heterogeneity.

The plan of the paper is as follow: Section 1.1 briefly describes the related literature, Section 2 provides a simple framework that justifies the presence of this relationship in the data. Section 3 describes the data. Section 4 presents my main results and discusses some concerns that undermine my interpretation of the relationship of interest: omitted variables and specific patterns of selection into immigration (Section 5). Section 6 explores some of the mechanisms behind my results: whether it is transmitted quality of parents' education, parenting style or cultural[4] and ethnic environment. Finally, Section 7 concludes.

1.1 Related Literature

My analysis speaks to many different strands of the economic literature.

First, the literature on intergenerational transmission of human capital, values and attitude. While there is rich evidence of the importance of intergenerational transmission of human capital (Black et al. [2005], Holmlund et al. [2011], Oreopoulos and Page [2006], see Black and Devereux [2011] for a review), of IQ scores (Black et al. [2009]) and of other economic behaviours such as labour market participation and fertility (Blau et al. [2013], Blau et al. [2011]), evidence of intergenerational transmission of attitudes and beliefs is much scarcer. A recent paper by Dohmen et al. [2012] uses the German SOEP to show how risk aversion and trust are transmitted from parents to children.

Second, the so-called 'cultural economics literature' that circumvents the difficulty in measuring values and belifs by using the previously mentioned epidemiological approach [Fernandez, 2011]. My paper

[4]Throughout this paper I mean by culture the entire set of beliefs, aspirations, behaviors, attitudes that are probably influenced by parents and the social context where children live.

takes from this literature the methodology and the definition of 'culture'[5]. Examples are Guiso et al. [2006], Tabellini [2013], Gorodnichenko and Roland [2011], Algan and Cahuc [2010] who study the impact of 'culture' on economic growth, Guiso et al. [2009] who presents evidence that similar 'culture' affects trust and trade among countries, Giuliano [2007] who shows 'culture' affects living arrangements. Moreover a large literature (Fernandez and Fogli [2009], Alesina et al. [2013], Olivetti and Patacchini [2012]) shows inherited gender roles affect women labour market participation and fertility. My paper suggests that intergenerational transmission of cultural values may also affect school achievement. This finding is supported by the available evidence on the importance, for children educational attainment, of transmittable cultural values such as attitudes towards school, aspirations and non cognitive skills (Heckman and Rubinstein [2001], Brunello and Schlotter [2011], Behncke [2009], Borghans et al. [2008], Carneiro et al. [2007] etc.).

Moreover, my paper relates to the literature that analyzes cross-country differences in education quality (Hanushek and Woessmann [2012], Kimko and Hanushek [2000], Schoellman [2012], Hendricks [2002]), by looking at average country performance in the PISA test. These papers look at the correlation of school quality (measured by average PISA score) in country m with wages of emigrants from country m, once in the US. My results may be useful for this literature in two dimensions. First, I look at a different outcome: the performance of immigrants' children at school. Second, I deeply analyze what the average PISA scores actually measures. I suggest it has a strong intergenerational component and long run consequences. Some papers (Torija [2012], Boe and Boruch [2002], Borghans et al. [2008]) show that the performance in PISA and similar international tests is very much related to the effort students put in the test. PISA is a low stake exam for students: results are secret, no feedback on individual performance is provided, neither solutions. Torija [2012] uses a question in the PISA 2000 test that is very similar to the 'Dot Counting Test'[6]. The question[7] asks to count a certain number of points and crosses ranging from 1 to 32. The validity of this tool relies on the floor-effect: the counting task is so easy that all individuals putting a minimum amount of effort should complete it correctly. 32% made a mistake in counting dots, three times more than what is considered normal in dot-counting tests. Moreover, differences in effort in the test, are able to explain a big part of the cross country variation in PISA score. Figure 2 shows that the variation across country is large and strongly correlated with the overall result in PISA tests.

Finally, my findings help rationalizing and supporting some of the incredibly rather scarce results on the large heterogeneity of students (Dustmann et al. [2012], Dustmann et al. [2010], Dronkers and de Heus

[5]'Culture' is defined by shared beliefs and preferences of respective groups, usually identified by country or region of origin.

[6]a psychometric tool used by psychologists to measure children willingness to answer (Nitch and Glassminre [2007]).

[7]Question M136Q01T in PISA 2000 test.

[2012]) and workers [Algan et al., 2010] performance, depending on country of origin or ethnicity.

2 A Conceptual Framework

Let T_{iscm} denote the school grade of children i, studying (and born) in country c and in school s, whose mother was born in country m. Suppose that the true model for T_{iscm} was:

$$T_{iscm} = \alpha_0 + \alpha_1 MothQual_{iscm} + \alpha_2 X_{iscm} + \alpha_{sc} + u_{iscm} \tag{1}$$

where $MothQual_{iscm}$ indicates mother's (im) inputs and environmental (m) factors that affect school performance of children, studying in school s in country c. This variable includes the mother level of education, but also other elements influencing the quality of parental inputs, such as the quality of her education, her parenting style or her cultural values and attitudes and elements influencing the type of cultural environment children are raised in. X_{iscm} is a vector of all the other student and family background characteristics that affect the child's outcome, α_{sc} are school (and country of living) fixed effects, they include effects given by the country school system and institutions. u_{iscm} is an error term representing the effects of individual specific factors that are uncorrelated with family background and country fixed effects.

The quality of parental inputs is difficult to quantify: it is a combination of factors that depend on specific parental characteristics (time spent with children, educational level, attitudes, values, preferences etc.) and factors that vary mostly at their country of birth level (quality of the school system where educated and cultural environment[8]). I capture this effect with:

$$MothQual_{iscm} = \beta_0 + \beta_1 Qual_m + \beta_2 Z_{iscm} + v_{iscm} \tag{2}$$

where $Qual_m$ is a measure of average quality of parental inputs at the country level and Z_{iscm} are parental characteristics affecting the quality of their inputs.

Equation 1 and 2 are the core relationships of this analysis. I combine them substituting equation 2 into equation 1, which gives:

$$T_{iscm} = \theta_0 + \theta_1 Qual_m + \theta_2 Z_{iscm} + \theta_3 X_{iscm} + \alpha_{sc} + \eta_{iscm} \tag{3}$$

where $\theta_0 = \alpha_0 + \alpha_1\beta_0$, $\theta_1 = \alpha_1\beta_1$, $\theta_2 = \alpha_1\beta_2$, $\theta_3 = \alpha_3$.

[8] I call culture the distribution of social preferences and beliefs possessed by different societies (see Fernandez [2011]). Differences in culture are therefore systematic variations in beliefs and preferences across time, space and social groups. Individual preferences are affected by average preferences and beliefs in the environment of origin.

The parameter of interest is θ_1. It describes how much of the cross country differences in test scores is actually driven by differences in parental inputs[9], once I control for the quality of the school/the educational system the child is raised in (through α_{sc}).

However, estimating equation 3 is problematic. First, $Qual_m$ and Z_{iscm} may not be fully observable. I cannot just control for these variables in equation 3. I need to infer them indirectly.

Second, if children and mothers are born in the same country ($m = c$), $Qual_m$ will be perfectly multicollinear and it will be impossible to estimate θ_1. Intuitively, if $m = c$ mothers and children are raised under the same institutions and economic conditions (which are usually very persistent). This will spuriously generate intergenerational correlations.

As mentioned in the introduction, I address these issues by making use of the epidemiological approach. I analyze second generation immigrants, for whom $m \neq c$. I can therefore include fixed effects for the host countries/schools. This allows me to distinguish between factors related to α_{sc} (the school and the educational system the child is exposed to) and factors related to $Qual_m$ (the quality of parental inputs and cultural and environmental differences).

Guided by equation 3, I estimate the following relationship on second generation immigrants:

$$T_{iscm} = \gamma_0 + \gamma_1 PISAnat_m + \gamma_2 X_{iscm} + \gamma_3 W_{iscm} + \delta_{cs} + \epsilon_{iscm} \tag{4}$$

where T_{iscm} is test score of child i, born in country c, studying in school s, whose mother was born in country m; $PISAnat_m$ is the average test score of 15 year old natives in country m; X_{iscm} are family background characteristics (i.e. mother and father educational level, type of household, whether the father is an immigrant himself, parents' years since migration), W_{iscm} are student's characteristics (gender, age, full interaction between birth region and cohort); δ_{cs} are school (or host country/US counties) fixed effects. The exact controls will depend on the dataset I use and will be described more in detail in the Section 3.

The coefficient γ_1 represents the correlation in school performances of children, born and studying in different countries, but whose mothers are all born in country m. What drives γ_1 must therefore be something related to the country of origin of their parents.

Notice that $PISAnat_m$ is an indirect measure of $MothQual_{iscm}$. To understand which (observable) factors are more correlated with the (observable and unobservable) factors driving γ_1, in my empirical analysis I pay particular attention at how the coefficient of interest behaves once I control for different observable characteristics.

Finally, it is important to notice that this method raises another complication: immigrant self-select

[9] $Qual_m$ represents parenting style, type of environment, quality of parents' education, values, expectations.

into immigration. If the choice of migrating is correlated with quality of parental inputs at the country of origin level, an analysis based on second generation immigrants would not generate consistent estimates of θ_1 and θ_2. I discuss this issue in section 5.

3 Data

I use many sources of data in this study. The exact specification will depend on the dataset I am using and on the available controls.

First, I use results of the 2003, 2006 and 2009 PISA tests. PISA is a triennial survey of the knowledge and skills of 15-year-old children explicitly designed to allow comparisons across countries. It is administrated by all OECD countries as well as some partner countries (Brazil, Russia, Croatia, Chile etc.). In 2009, 65 countries participated to the PISA tests. Tests are typically administered to between 4,500 and 10,000 students in each country. Most PISA countries employ a two-stage stratified sampling technique. The first stage draws a random sample of schools, which enrol 15-year-old students, yielding a minimum sample of 150 schools per country. The second stage randomly samples 35 of the 15-year-old students in each of these schools, with each 15-year-old student in a school having equal probability of selection. In my analysis, I weight students by their final weight provided by OECD.

The assessment includes reading comprehension, science and mathematics. Results are secret. Each student in PISA is tested on a randomly drawn subset of the total set of questions. For this reason, test results are not presented as point estimates. Rather, a probability distribution of test scores is estimated for each pupil based on their answers. Then, for each pupil five random draws are taken from the estimated distribution and reported in the dataset. These draws are referred to as "plausible values", and are a selection of likely proficiencies for students that attained each score (see OECD [2011] for details). Throughout the analysis, I account for the use of imputed regressors in computing the standard errors of my estimates by using the "unbiased shortcut" procedure described in OECD [2009] and followed by Dustmann et al. [2012]. PISA test scores are internationally standardized, to have mean 500 and standard deviation 100 across OECD countries. I further standardize them to have mean 0 and standard deviation 1.

The PISA data include a detailed questionnaires on students, families and institutional factors in every wave. Information on the exact country of origin of parents is, however, not available in all participating countries questionnaires and for the wave 2000[10]. For this reason, I only have 39 host countries and about 8,300 schools in my analysis.

[10]Countries can actually choose how to classify parents' country of origin. While most have indicators for each country, some group small countries in broad categories (i.e. other, African countries, other European countries etc.). I have to drop all second generation immigrants whose mothers were born in countries included in these categories.

I keep only second generation immigrants, defined as those children born in the host country but whose mother was born abroad. I am left with about 35,000 observations and on average 4 second generation immigrants in each school[11]. Descriptive statistics are provided in Table 2.

The second source of data is the Integrated Public Use Microdata Series (IPUMS) created by the US Census Bureau. The IPUMS consists of individual and household level data from the decennial census in the US and includes nearly all of the detail originally recorded by the census enumerations. I use the 1% samples from the 1970 and 5% sample from the 1980 censuses. Even if IPUMS contains little information on children's outcomes, it does, however, contain information on each individual's exact grade attending at school[12]. I use this information, together with information on the child's age, to determine whether or not she has repeated a grade. As pointed out by Oreopoulos and Page [2006], grade repetition is a widespread phenomenon in the United States and is correlated with many more commonly used measures of educational achievement and socioeconomic success. I classify a child as a repeater if her educational attainment is below the mode for her state, age, quarter of birth, and census year cell.

The construction of my performance variable follows Oreopoulos and Page [2006] and focuses on children between the ages of 8 and 15. Children younger than age 8 are not included because they are not old enough to have had the opportunity to repeat a grade. I exclude children older than age 15 in order to avoid overrepresenting children who left home at late ages, or endogenous dropouts. To adjust for the fact that older sample members have had more of an opportunity to repeat a grade, and to adjust for possible gender differences in grade repetition, all my regressions include controls for age dummies and gender. Moreover my results are robust to many other definition of grade repetition and other sample selections.

Again, I keep only second generation immigrants, defined as those children born in the US whose mother was born outside the US. I am left with around 45,000 observations, and 50 mother countries of birth. Descriptive statistics are shown in Table 3.

Moreover, I use the October supplement of CPS data, even if the sample size is smaller, because it contains the exact information to build a dummy variable for grade repetition the previous year. It asks whether the child is attending the same grade as last year. Descriptive statistics are shown in Table 4

For Section 6, I use the ATUS-US Time Use Survey to analyze how immigrant parents spend their time with children. Again, I pool together all waves between 2003 and 2011. I consider all households with at least one parent not born in the US[13].

Finally, I base some of the analysis on the UK Millennium Cohort Study (MCS). The MCS is a

[11] This statistics is only for school where there is at leas 1 second generation immigrant.
[12] This information is only available till 1980, this prevents me from using more recent waves
[13] when both parents were born abroad, I imputed the PISA score of natives from the country of birth of the mother

longitudinal survey of around 19000 children (of whom 2500 second generation immigrants[14]) born in the UK over a 12 month period between 2000-2001 and living in selected electoral wards at age 9 months. The sample was disproportionately stratified to ensure adequate representation of all four UK countries, deprived areas and areas with high concentrations of Black and Asian families. Families (and, if possible, children) are interviewed at approximately 9 months (MCS 1), 3 years (MCS 2), 5 years (MCS 3) and 7 years (MCS 4). Unfortunately, even if the number of mothers' countries of origin of second generation immigrants is rather large, the number of observation is small. This reduces my ability of exploiting the very rich questionnaire by controlling for many different possible channels behind my relationship. For the analysis, I only include families participating to all 4 sweeps[15].

Table 7 lists all source countries I use for different datasets in my analysis.

4 Results

The relationship between average PISA score of natives from country m and school performance of second generation immigrants whose mother was born in country m is extraordinarily robust to alternative samples, to different control sets and to different specifications of the skills measure.

I will first show my baseline results for three of my data sources.

Tables 5, 6 and 7 show results for the main equation using PISA data, the US census data and the CPS data respectively. In panel A I use the average PISA score in 2003, 2006 and 2009 of natives in country m[16] as main regressor, in panel B I use the measure of cognitive skills estimated by Kimko and Hanushek [2000] and updated in Hanushek and Woessmann [2012][17], which represents the plausible average performance in PISA tests of primary and secondary school students in the period between 1970 and 2000. The two variables are very highly correlated.

I proceed by progressively adding controls. Column (1) of Table 5 displays the raw correlation between PISA scores of second generation immigrant students from country m and average PISA grade of natives in country m. I use student level data and cluster standard errors at the mother country of origin level. The correlation is also shown in panel A of Figure 1. In the vertical axis I plot the average PISA score of second generation immigrants from country m, in the horizontal axis I plot the average PISA score of natives in country m. In the following columns of Table 5 I start adding controls: in column (2) I control for host country fixed effects, in column (3) I control for parents' educational attainment, in column (4) I include school fixed effects. School fixed effects, even if potentially endogenous, are included to

[14]the sample size is much lower at the end because of attrition between different sweeps of the survey, because of the presence of immigrants from countries without a PISA assessment, and because of missing values in relevant variables.

[15]I take attrition into account using weights.

[16]I average scores for all the available years in each country.

[17]I standardize the scores to have mean equal 0 and standard deviation equal 1

proxy for neighborhood and families observable and unobservable characteristics related to sorting into neighborhoods and schools. In column (5) I control for mother continent of birth, to eliminate the concern that the correlation is driven by across continents macro differences. Finally, in column (6) I exclude Asia from the regression. A one standard deviation increase in the average PISA score of natives in country m is associated to a 0.2 standard deviation increase in performance of second generation immigrant whose mother was born in country m, compared to the performance of other second generation immigrant students in the same school and with the same family background, but whose mothers were born in different countries.

Table 6 reports the same correlations using the US Census data. In this case, there is no information on the particular school children are attending. However, the US census contains very precious information on the parents' immigration history. In particular, I can control for mother year of arrival in the US[18]. Moreover, while the PISA dataset contains only 15 year old children, the US data allow me to analyze whether the relationship holds also for children at different ages. In all specifications I control for the interaction of children cohort fixed effect with state of birth (in the US) fixed effects and for the interaction between the state of residence fixed effect and the census year.

My dependent variable is a dummy equal to one if the children has never repeated any grade.

Again, I proceed by progressively adding controls. Column (1) displays the raw correlation. In column (2) of Table 6 I add both the interaction between children cohort and state of birth (in the US) fixed effects and the interaction between the county of residence and the census year fixed effects. In column (3) I control for parents' educational attainment and in column (4) I add a control for the mother year of arrival in the US[19]. Finally, in column (5) I include mother continent of birth fixed effects and in column (6) I exclude Asian countries. Results are very robust to different controls and different measure of family background characteristics. A 1 standard deviation increase in natives PISA scores in country m is associated to a 0.03 increase in the probability of not repeating any grade for second generation immigrants whose mother is from country m, compared to other second generation immigrants, with similar family background, but whose mother was born in a different country.

Figure 3 reproduces Figure 1 with US census data. Panel A displays the raw correlation between the probability of not having repeated any grade for second generation children whose mother was born in country m (vertical axis) and the $PISAnat_m$ score (horizontal axis). Panel B show the same relationship, once I correct for differences in family background, gender, age, county of residence and state of birth[20].

[18](categorical variable, every 5 years)

[19]This is a categorical variable including 5 years interval.

[20]These graphs are plotting γ_m from the regression

$$T_{iscm} = \gamma_m + \gamma_2 X_{iscm} + \gamma_3 W_{iscm} + \delta_{cs} + \epsilon_{iscm} \tag{5}$$

. I control for the same controls as in Column 4.

The relationship is still tight and clear.

Table 7 shows the same specifications using CPS data. A 1 standard deviation higher PISA score in the country of origin is associated to a probability of repeating the grade in the considered year 0.006 percentage points lower.

Two points are worth noticing. The first is that the relationship is not driven by particularly good performances of Asian students, because the coefficient is robust to the inclusion of continent fixed effects and to the exclusion of Asia. Figure 4 shows that the relationship is not driven by any particular country. It plots the coefficient (and confidence interval) of 49 different regressions obtained by estimating equation 4 with PISA data, eliminating one (source) country every time.

The second point is that the coefficient of $PISAnat_m$ does not change much when I add controls for parents' education level. The comparison between Column 2 and 3 in the last three tables is key to understand what the coefficient of $PISAnat_m$ is actually measuring. It tells how much the quantity of parental education is correlated with the variable $PISAnat_m$. If θ_1 picks up the effect of unmeasured dimensions related to parental education (i.e. ability), than the inclusion of their educational level should matter a lot. Results show instead that the introduction of parental education as a control has very little importance in terms of the size and significance of the coefficient of interest θ_1.

Table 8 explores the persistence of the relationship of interest. It provides information on whether possible channels driving the correlation are fixed over time, such as ability. The last three columns of Table 8 refer to children born in the US, whose parents were born in the US and (self) report having non-US origins. I correlate the performance at school of these children with the average performance of children still living the the country of origin of their parents ancestors. Once I include the usual controls, the correlation is zero.

5 Selection

Another potential concern is selection into immigration. First, immigrants self-select into immigration. Second, immigrants are selected by the immigration policy of the host country.

Selection driven by host countries immigration policies is likely not to be an issue in this context. First, the PISA data allow me to consider many different host countries and to include a host country fixed effect in my regressions. Second, immigration policies are often based on observable characteristics, such as education or employment status, which I can control for.

The most relevant concern is selection based on unobservable characteristics. Figure 5 shows what different types of selection imply for the relationship between children performance at school and performance of native children in their parents' country of origin (equation 4). The solid line represents the true relationship, in the absence of selection. The first panel describes the case when selection is the same for all countries of origin. In this case, only the intercept will be biased. The second panel describes the case when parents emigrated from countries with high PISA scores are more positively selected than parents emigrated from countries with low PISA scores. Finally, panel c describes the opposite case, where selection is negative in countries with high PISA scores. In the last two cases, the coefficient of interest will be biased.

To test patterns of selection I use observable measures of immigrants' quality with respect to natives.

My measure for positive selection into emigration is the ratio of the average characteristics of emigrants from country m to those of individuals born in country m as well but did not emigrate. I build the measure such that, if the ratio is larger than 1, it signals positive selection into emigration, viceversa if it is smaller than 1. As measures of selection I use the ratio parents' educational attainment (overall and for men and women separately) and of parents' occupational prestige[21].

Information on parents characteristics in the PISA data is available both for immigrants and for natives. I compute the average of the described characteristics of both parents born in country m and emigrated (from the sample of second generation immigrant students) and parents born in country m and not emigrated (from the sample of native students).

As a robustness check, in order to exclude possible problems of misreporting of educational attainment in the PISA data or of small sample size, I also use the Docquier and Marfouk [2006] dataset on skilled and unskilled emigration.

Table 10 and Figure 6 shows results of a regression of my measure of emigrant quality with respect to non-emigrants from country m on average PISA score of children of non-emigrants in country m, $PISAnat_m$. Column (2) includes continent of origin fixed effects. Overall, for the subset of countries considered in the analysis, there is no specific pattern of selection on observables related to the average PISA test score of natives or to per capita GDP (in ppp). If anything, the relationship is negative and goes against finding a positive θ_1.

Finally I control, in all specifications, for some host country characteristics, such as per capita GDP. Estimates of θ_1 are mostly unchanged. Results are available under request.

6 Inspecting the mechanism

A clear identification of the exact contribution of each mechanism that may generate the described relationship is difficult to achieve. In the following section I will mainly consider two channels:

[21] I use the Duncan Socioeconomic Index (SEI). It is based on two factors, occupational earnings and occupational education. Notice that this assumes occupation (industry) is mainly determined by facters decided before the decision of emigrating.

1. the quality of parents' education

2. "transmitted culture"[22].

I will describe how my relationship behaves (i) if I include interactions in equation 4 for parents' education level and for year since migration (Section 6.1), (ii) if I change dependent variable and I analyze how much $PISAnat_m$ explains the way parents spend their time with their children (Section 6.2) and (iii) if I include additional controls to equation 4 at the country of origin level or at the individual level, in the attempt of shutting down possible channels (Section 6.3).

6.1 Interactions

There are some testable implications that differ according to the two previously mentioned mechanisms. If the correlation depends on the quality of the home country educational system itself, then it should be that: (i) transmission takes place only if parents were educated in the home country, (ii) the effect is stronger the longer is the time spent in education (in the home country). At the extreme, if parents have zero education, they will not be able to transmit to their children the quality of the educational system in the country where raised.

This translates into the assumption that θ_1 is increasing in years of education in the home country.

$$\frac{\partial T_{iscm}}{\partial Qual_m \partial S^m_{iscm}} > 0. \tag{6}$$

Where S^m_{iscm} are mother's years of schooling (in the home country) for student i, studying in school s in host country c and whose mother is from country m.

If what matters is "transmitted culture", then it should be that: (i) the relationship with country of origin gets weaker as parents' assimilation to the host country increases.

This translates into the assumption that:

$$\frac{\partial T_{iscm}}{\partial Qual_m \partial ysm^m_{iscm}} < 0. \tag{7}$$

Where ysm^m_{iscm} are mother's years since migration.

However, there are confounding factors both in interpreting Equation 6 and 7. First, we may think assimilation itself is a function of education. There is widespread evidence that more educated migrants have a higher propensity to intermarry with natives (see Schoen and Wooldredge [1989]; Sandefur and McKinnell [1986]; Lichter and Qian [2001]; Meng and Gregory [2005]; Chiswick and Houseworth [2011]).

[22] Transmitted culture includes for example different types of parenting styles (i.e. "tiger mom'), of attitudes towards school and children education in general.

There are also studies that show education reduces ethnic identity (Constant et al. [2008]). Therefore, results of equation 6 can also be generated by "transmitted culture". However, if education plays a role through the assimilation channel, then, if anything, equation 6 should be negative.

Second, age of arrival in Equation 7 is very strongly related to assimilation (Nielsen and Schindler Rangvid [2012] and Bleakley and Chin [2010]) and to whether parents were educated in the host country or in the home country. In this case, if θ_1 is not significant when parents were educated in the US (and therefore migrated in the US when children and have large ysm^m_{iscm}), it is difficult to disentangle whether it is due to their higher level of cultural assimilation or to the educational system they have studied in.

Table 9 shows results for some of the previously mentioned interactions. The interaction of natives' PISA score with mother level of education in Column (2) (and Figure **??**) is negative and significant. This is not consistent with the quality of parents' education channel: it goes against prediction in equation 6. Column (3) shows the relationship with natives PISA scores is lower the longer parents have been living in the US, consistently with the "transmitted culture" channel (equation 7). Column (4) shows that, even controlling for the interaction of year since migration and natives' PISA score, the correlation is even smaller if parents were educated in the US. Column (5) shows parents' age of arrival generates the same results of column (4). The pattern of columns (4) and (5) is therefore consistent with both channel 1 and 2. Finally, column (6) shows the correlation is larger if immigrants (endogenously) live in more segregated states[23].

Finally, to understand whether the effect is mainly driven by factor correlated with years of schooling or not, I estimate the following equation in the spirit of Card and Krueger [1992]:

$$T_{iscm} = \delta_m + \mu_m S^m_{iscm} + \delta_1 X_{iscm} + \delta_2 W_{iscm} + \delta_{cs} + \omega_{iscm} \tag{8}$$

where δ_m and μ_m are mother country of birth fixed effects, S^m_{iscm} are mother's year of schooling and X_{iscm}, W_{iscm} and δ_{cs} are usual controls. This regression says that children performance at school are determined by an intercept term, parents' years of schooling and other controls. A standard equation for intergenerational transmission would have a single intercept and a common return to parents' schooling. The above equation is augmented in allowing both the intercept and the returns to schooling to vary based on parents' country of birth. I only use parents fully educated in the home country.

If the relationship of Equation 4 is explained more by the intercepts δ_m, it means it is driven by the country of origin itself, independently of the amount of education received. If instead the returns to education, μ_m, matter more (with a positive sign), then it is more likely that the relationship is driven by the amount of education received by parents.

[23]When the information is available in the PISA data (for parents' education and segregation in schools), results of these interactions are the same as with the US census data.

Figure 7 and 8 show results from Equation 8 using PISA data and US Census data respectively. The effect is mainly driven by the intercept δ_m and not by different returns to education μ_m. Importantly, this is different from the result obtained by Schoellman [2012] on wages of immigrants. Schoellman [2012] uses US Census microdata and finds that the returns to education, in terms of wages, are positively related to PISA score of immigrant home country. While this is the case, for returns in terms of wages, it is the opposite for returns in terms of children educational attainment.

Overall, results of this section are more consistent with the "transmitted culture" channel.

6.2 Time Use Survey

For what concerns differences in behaviours, Table 11 analyzes data from the US Time Use Survey. It shows parents' behaviour in term of time spent investing in their children is positively related to natives' PISA score. In the first panel I regress time spent by parents investing in their children health and education, in the second panel I use total time spent in child care as dependent variable. 1 standard deviation higher PISA scores in home country are associated to 0.014 more minutes spent investing in children and 0.1 more minutes in general child-care. This result is particularly driven by mothers.

6.3 Additional controls

I now present results of Equation 4, augmented by a series of controls at the country of origin level and at the individual level.

Given Equation 4 and results in Section 4, the relevant issue becomes what does $PISAnat_m$ actually pick up. One possibility is that the PISA score picks up (omitted) variation at the family/individual level, such as attitudes, parenting style, cultural values or even innate ability, that is really attributable to Z_{iscm} in Equation 2. If this is the case, controlling for these variables should make γ_1 insignificant.

Another possibility is that the PISA score picks up variation at the country of origin level, such as higher GDP, larger expenditure in education etc. Again, if this is the case, then the introduction of these controls should reduce the significance of γ_1.

Table 12 includes controls at the country of origin level, related to the quality of the educational system . In particular: per capita GDP, the share of high skilled mothers in country m, the average years of education of individuals aged 20/30 in 1990 (presumably before the parents' decision to immigrate) and the pupil teacher ratio in primary school. None of these controls significantly affects the coefficient on $PISAnat_m$ [24].

Table 13 includes controls at the country of origin level related to religion and cultural values.

[24] regressions with other controls of school quality are available under request. However, the main result does not change.

Columns 2 and 3 control for the religious composition on the population in 1970 and 1900 respectively[25]. In this case the coefficient on $PISAnat_m$ shrinks and looses significance. Columns 5 and 6 control for answers at some World Value Survey questions. In particular I control in Column 5 for whether on average individuals in country m believe they can change their own destiny (inner locus of control) and in Column 6 I control for whether on average they think one of the most important value to teach to children is determination. None of the controls appear to change the main coefficient.

Finally, Tables 14, 15 and 16 report regressions using the Millennium Cohort Study dataset and including parents' controls at the individual level. As discussed in Section 3, due to the small number of observation I can use, I will not be able to fully exploit the richness of potential controls in the MCS.

I use the Bracken school readiness assessment (Table 14) as a measure of cognitive ability at age 3 (MCS 2). It measures 88 functionally relevant educational concepts in six sub-tests: colours; letters; numbers/counting; shapes; comparisons and shapes. I use the foundation stage profile (FSP) as a measure of cognitive assessment at age 5 in Table 15. The FSP is a teacher-based assessment of children's development and learning at age 5. The FSP evaluation is part of the English assessment, there is no equivalent measure in Wales, Scotland and Northern Ireland. A questionnaire was therefore developed and sent to teaches of cohort children attending schools in Wales, Scotland and Northern Ireland (named the Celtic Country Teacher Survey) to replicate the information collected by the FSP. Finally, in Table 16, I use the score in the pattern construction test at age 7 (MCS W4). This test is the most strongly linked to later outcomes, such as wages at age 30 [Duckworth and Feinstein, 2006].

In all cases the relationship of cognitive ability and average PISA score of natives from the parents' country of origin is positive and significant. Moreover, in each Table, I control for a measure of activities done with children (time spent reading with the kid), a measure of assimilation (which language is spoken at home) and for parents' religion (9 dummies) and religiosity. Despite all these variables are significant, the only one that actually shrink the coefficient on $PISAnat_m$ is religion.

7 Conclusions

TO BE ADDED

References

Daron Acemoglu, Simon Johnson, and James A. Robinson. The colonial origins of comparative development: An empirical investigation. *American Economic Review*, 91(5):1369–1401, December 2001.

[25] Data are taken from the Barro database.

Alberto Alesina, Paola Giuliano, and Nathan Nunn. On the origins of gender roles: Women and the plough. *The Quarterly Journal of Economics*, 2013.

Yann Algan and Pierre Cahuc. Inherited trust and growth. *American Economic Review*, 100(5):2060–2092, 2010.

Yann Algan, Christian Dustmann, Albrecht Glitz, and Alan Manning. The economic situation of first and second-generation immigrants in france, germany and the united kingdom. *Economic Journal*, 120(542):F4–F30, 02 2010.

Douglas Almond, Lena Edlund, and Kevin Milligan. Son preference and the persistence of culture: Evidence from south and east asian immigrants to canada. *Population and Development Review*, March 2013.

Stefanie Behncke. How do shocks to non-cognitive skills affect test scores? IZA Discussion Papers 4222, Institute for the Study of Labor (IZA), June 2009.

Sandra E. Black and Paul J. Devereux. *Recent Developments in Intergenerational Mobility*, volume 4 of *Handbook of Labor Economics*, chapter 16, pages 1487–1541. Elsevier, 2011.

Sandra E. Black, Paul J. Devereux, and Kjell G. Salvanes. Why the apple doesn't fall far: Understanding intergenerational transmission of human capital. *American Economic Review*, 95(1):437–449, March 2005.

Sandra E. Black, Paul J. Devereux, and Kjell G. Salvanes. Like father, like son? a note on the intergenerational transmission of iq scores. *Economics Letters*, 105(1):138–140, October 2009.

Francine D. Blau, Lawrence M. Kahn, and Kerry L. Papps. Gender, source country characteristics and labor market assimilation among immigrants: 1980-2000. *The Review of Economics and Statistics*, 93 (1):45–58, February 2011.

Francine D. Blau, Lawrence M. Kahn, Albert Yung-Hsu Liu, and Kerry L. Papps. The transmission of women's fertility, human capital, and work orientation across immigrant generations. *Journal Population Economics*, 26(2):405–435, 2013.

Hoyt Bleakley and Aimee Chin. Age at arrival, english proficiency, and social assimilation among us immigrants. *American Economic Journal: Applied Economics*, 2(1):165–92, January 2010.

Erling E. abd Henry May abd Gema Barkanic Boe and Robert F. Boruch. Predictors of national differences in mathematics and science achievements: Data from timss for eight grade students. Technical report, Center for Research and Evaluation in Scoial Policy, Graduate School of Education, University of Pennsylvania, February 2002.

Lex Borghans, Huub Meijers, and Bas Ter Weel. The role of noncognitive skills in explaining cognitive test scores. *Economic Inquiry*, 46(1):2–12, 01 2008.

George J Borjas. Ethnic capital and intergenerational mobility. *The Quarterly Journal of Economics*, 107(1):123–50, February 1992.

George J Borjas. Ethnicity, neighborhoods, and human-capital externalities. *American Economic Review*, 85(3):365–90, June 1995.

Giorgio Brunello and Martin Schlotter. Non cognitive skills and personality traits: Labour market relevance and their development in education & training systems. IZA Discussion Papers 5743, Institute for the Study of Labor (IZA), May 2011.

David Card and Alan B Krueger. Does school quality matter? returns to education and the characteristics of public schools in the united states. *Journal of Political Economy*, 100(1):1–40, February 1992.

David Card, John DiNardo, and Eugena Estes. The more things change: Immigrants and the children of immigrants in the 1940s, the 1970s, and the 1990s. In *Issues in the Economics of Immigration*, NBER Chapters, pages 227–270. National Bureau of Economic Research, Inc, March 2000.

Pedro Carneiro, Claire Crawford, and Alissa Goodman. The impact of early cognitive and non-cognitive skills on later outcomes. CEE Discussion Papers 0092, Centre for the Economics of Education, LSE, October 2007.

Barry Chiswick and Christina Houseworth. Ethnic intermarriage among immigrants: human capital and assortative mating. *Review of Economics of the Household*, 9(2):149–180, June 2011.

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

Amelie Constant, Liliya Gataullina, Klaus F. Zimmermann, and Laura Zimmermann. Human capital and ethnic self-identification of immigrants. *Economics Letters*, 98(3):235–239, March 2008.

Frederic Docquier and Abdeslam Marfouk. International migration by educational attainment (1990-2000). In *International Migration, Remittances and Development.* Palgrave Macmillan, 2006.

Thomas Dohmen, Armin Falk, David Huffman, and Uwe Sunde. The intergenerational transmission of risk and trust attitudes. *Review of Economic Studies*, 79(2):645–677, 2012.

Jaap Dronkers and Manon de Heus. Immigrants' children scientific performance in a double comparative design: The influence of origin, destination, and community. CReAM Discussion Paper Series 1213, Centre for Research and Analysis of Migration (CReAM), Department of Economics, University College London, April 2012.

K. Duckworth and L. Feinstein. Development in the early years: Its importance for school performance and adult outcomes wider benefits of learning. Technical Report 20, London: Centre for Research on the Wider Benefits of Learning, 2006.

Christian Dustmann, Stephen Machin, and Uta Schonberg. Ethnicity and educational achievement in compulsory schooling. *Economic Journal*, 120(546):272–297, 08 2010.

Christian Dustmann, Tommaso Frattini, and Gianandrea Lanzara. Educational achievement of second-generation immigrants: an international comparison. *Economic Policy*, 27(69):143–185, 01 2012.

Raquel Fernandez. Does culture matter? In *Handbook of Social Economics*. Elsevier, 2011.

Raquel Fernandez and Alessandra Fogli. Culture: An empirical investigation of beliefs, work, and fertility. *American Economic Journal: Macroeconomics*, 1(1):146–77, January 2009.

Paola Giuliano. Living arrangements in western europe: Does cultural origin matter? *Journal of the European Economic Association*, 5(5):927–952, 09 2007.

Yuriy Gorodnichenko and Gerard Roland. Which dimensions of culture matter for long-run growth? *American Economic Review*, 101(3):492–98, May 2011.

Luigi Guiso, Paola Sapienza, and Luigi Zingales. Does culture affect economic outcomes? *Journal of Economic Perspectives*, 20(2):23–48, Spring 2006.

Luigi Guiso, Paola Sapienza, and Luigi Zingales. Cultural biases in economic exchange? *The Quarterly Journal of Economics*, 124(3):1095–1131, August 2009.

Eric A. Hanushek and Ludger Woessmann. Do better schools lead to more growth? cognitive skills, economic outcomes, and causation. *Journal of Economic Growth*, 17(4):267–321, December 2012.

James J. Heckman and Yona Rubinstein. The importance of noncognitive skills: Lessons from the ged testing program. *American Economic Review*, 91(2):145–149, May 2001.

Lutz Hendricks. How important is human capital for development? evidence from immigrant earnings. *American Economic Review*, 92(1):198–219, March 2002.

Helena Holmlund, Mikael Lindahl, and Erik Plug. The causal effect of parents' schooling on children's schooling: A comparison of estimation methods. *Journal of Economic Literature*, 49(3):615–51, September 2011.

Dennis D. Kimko and Eric A. Hanushek. Schooling, labor-force quality, and the growth of nations. *American Economic Review*, 90(5):1184–1208, December 2000.

Daniel T. Lichter and Zhenchao Qian. Measuring marital assimilation: Intermarriage among natives and immigrants. *Social Science Research*, 30:289–312, 2001.

Richard Lynn and Gerhard Meisenberg. National iqs calculated and validated for 108 nations. *Intelligence*, 38:353–360, 2010.

Xin Meng and Robert G. Gregory. Intermarriage and the economic assimilation of immigrants. *Journal of Labor Economics*, 23(1):135–176, January 2005.

Helena Skyt Nielsen and Beatrice Schindler Rangvid. The impact of parents' years since migration on children's academic achievement. *IZA Journal of Migration*, December 2012.

S.R. Nitch and D.M. Glassminre. Non-forced-choice measures to detect noncredible cognitive performance. In *Assesment of feigned cognitive impairment: A neuropsychological perspective.* Guilford, 2007.

OECD. *PISA Data Analysis Manual: SPSS, Second Edition.* 2009.

OECD. *PISA 2009 Technical Report.* 2011.

Claudia Olivetti and Eleonora Patacchini. Mothers and friends: Intergenerational preference transimission and womens work choices. Technical report, 2012.

Philip Oreopoulos and Marianne E. Page. The intergenerational effects of compulsory schooling. *Journal of Labor Economics*, 24(4):729–760, October 2006.

Gary Sandefur and Trudy McKinnell. American indian intermarriage. *Social Science Research*, 347: 347–348,, 1986.

Todd Schoellman. Education quality and development accounting. *Review of Economic Studies*, 79(1): 388–417, 2012.

Robert Schoen and John Wooldredge. Marriage choices in north carolina and virginia, 1969-1971 and 1979-1981. *Journal of Marriage and the Family*, 51:465–481,, 1989.

Guido Tabellini. Culture and institutions: Economic development in the regions of europe. *Journal of the European Economic Association*, 2013.

Pablo Torija. Straightening pisa: When students do not want to answer standardized tests. Technical report, University of Padova, 2012.

Figures

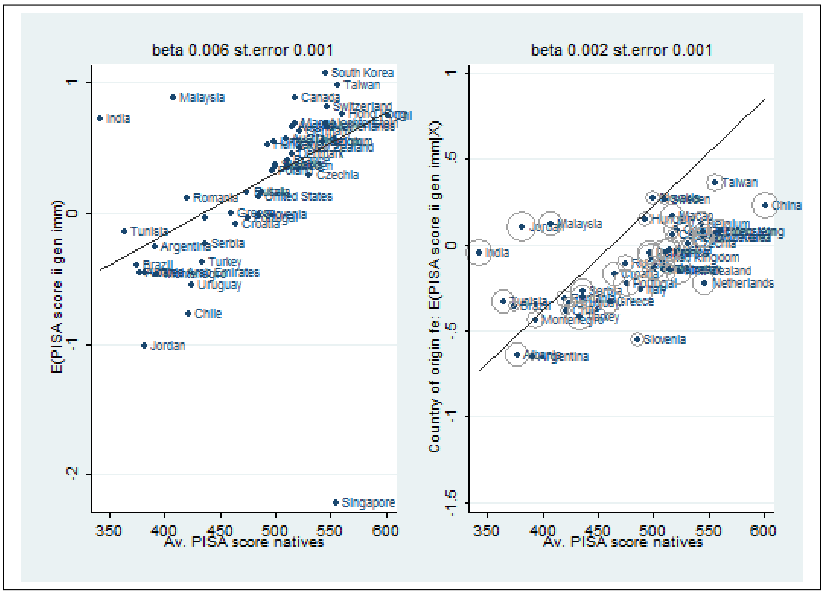

Figure 1: Performance of second generation immigrants and performance of natives from country m - PISA data

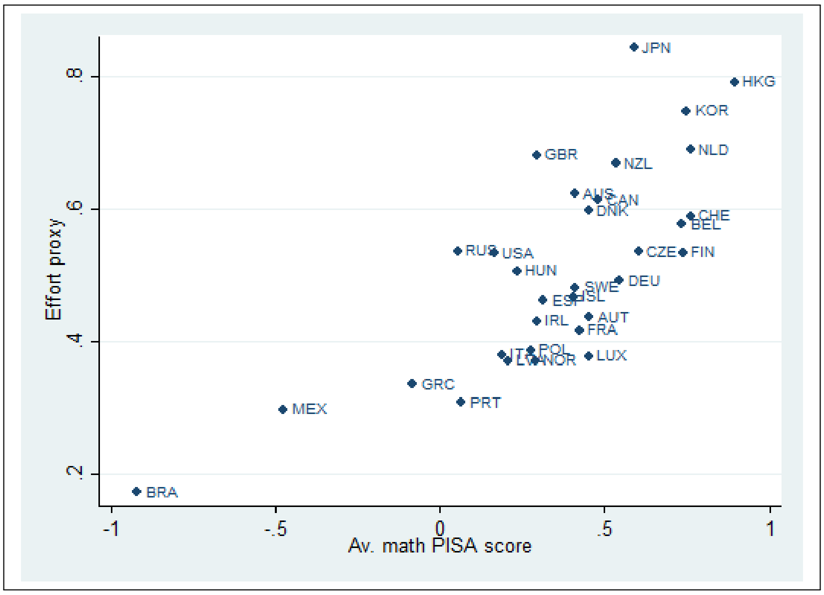

Figure 2: Proxy for effort (% of individuals answering correctly at the dot counting task) and performance of natives from country m - PISA data

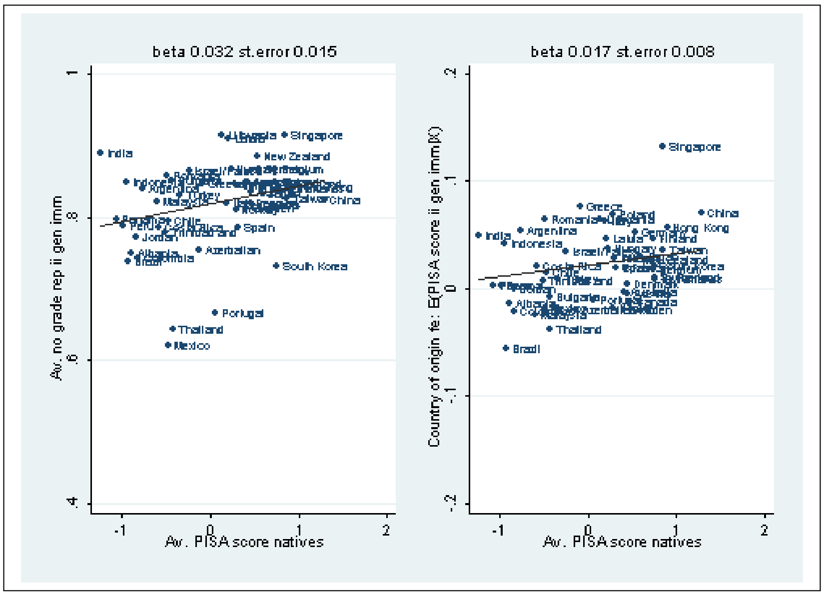

Figure 3: Performance of second generation immigrants and performance of natives from country m - US Census data

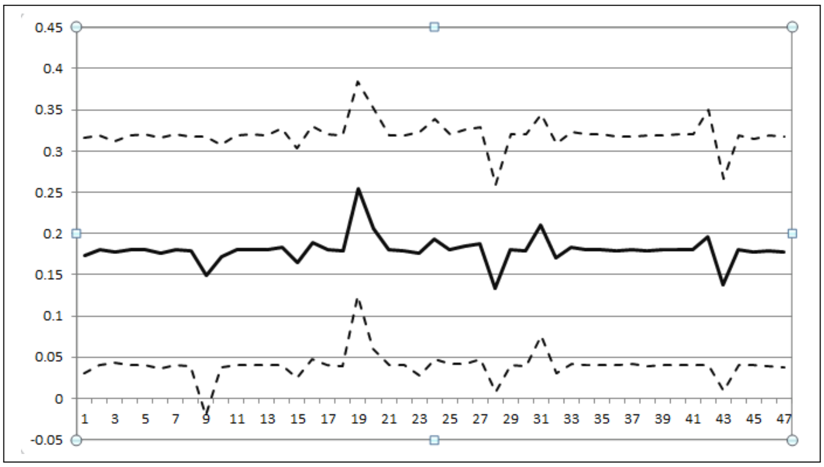

Figure 4: Effect eliminating single countries one by one

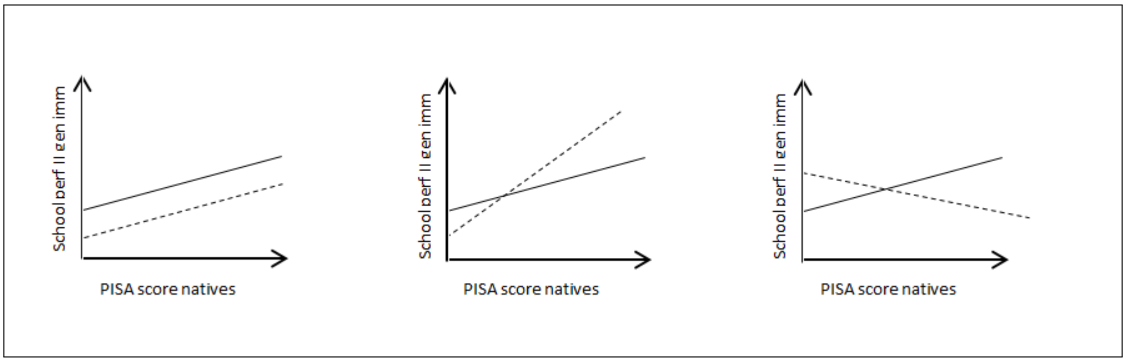

Figure 5: Patterns of Selection

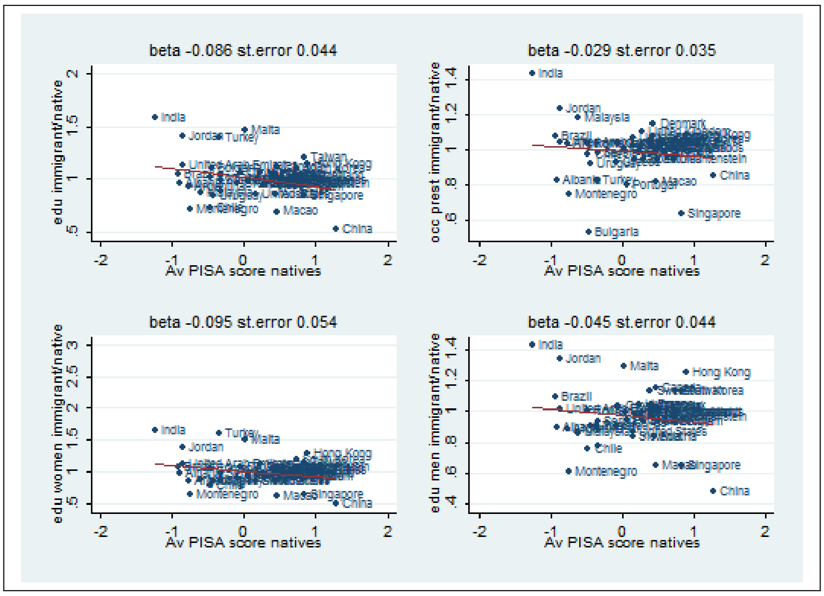

Figure 6: Selection checks

Figure 7: δ_m and μ_m, PISA data

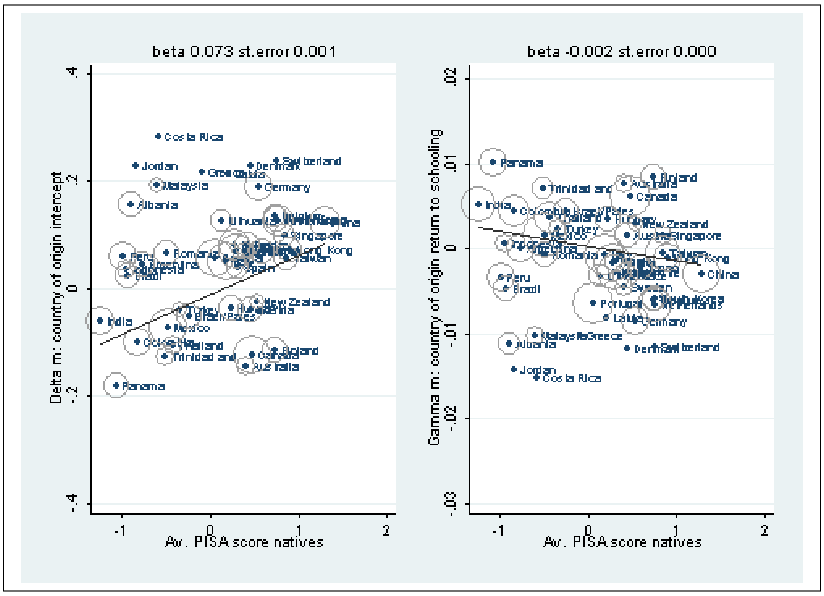

Figure 8: δ_m and μ_m, US Census data

Tables

Table 1: Rankings for natives and second generation immigrants - PISA

Best natives	Best second gen immigrants
Czech Republic	Canada
Belgium	Netherlands
Finland	India
Liechtenstein	Finland
Korea	Macao-China
Switzerland	Liechtenstein
Netherlands	Shanghai-China
Singapore	Korea
Hong Kong-China	Singapore
Shanghai-China	Hong Kong-China
Worst natives	**Worst second gen immigrants**
Qatar	Indonesia
Kyrgyzstan	Qatar
India	Kyrgyzstan
Panama	Colombia
Tunisia	Peru
Peru	Brazil
Indonesia	Argentina
Brazil	Panama
Albania	Mexico
Jordan	Jordan

Results for Indian natives refer only to the states Tamil Nadu and Himachal Pradesh, not to the entire country. Results from Chinese natives refer only to Shanghai.

Table 2: Summary statistics - PISA

Variable	Mean	Std. Dev.	Min.	Max.
Av grade ii gen imm fom m[a]	0.121	0.936	-3.162	3.184
Av grade natives in m[a]	0.093	0.457	-1.246	1.286
N obs in host country[b]	2397.467	1577.511	2	6929
N obs from home country[c]	2185.419	1526.84	13	6696
Father and mother from same country	0.775	0.418	0	1
Mother high skilled	0.728	0.445	0	1
Father high skilled	0.746	0.435	0	1
Female	0.476	0.499	0	1
Observations (ii gen imm)		32301		

[a] I normalized average pisa score to have mean 0 and standard deviation 1 for the entire sample (of both natives and immigrants, from all countries). My final sample includes only second generation immigrants, in countries where parents report their country of origin and only if the country of origin runs a PISA test on natives.
[b] These are descriptive statistics on the number of second generation immigrants included in my analysis for each 39 host countries.
[c] These are descriptive statistics on the number of second generation immigrants included in my analysis from each 50 home countries.
Weighted by final student weight provided by OECD.

Table 3: Summary statistics - US CENSUS

Variable	Mean	Std. Dev.	Min.	Max.
1=never repeated a grade	0.809	0.393	0	1
Av grade natives in m	0.052	0.521	-1.232	1.29
N obs from home country[a]	5374.439	4753.431	11	12598
father and mother from same country	0.422	0.494	0	1
High skilled mother	0.231	0.422	0	1
High skilled father	0.356	0.479	0	1
Years in the US, intervalled [of mother]	3.869	1.273	0	9
Years in the US, intervalled [of father]	1.956	2.106	0	9
1=Father immigrant	0.51	0.5	0	1
1=Female	0.487	0.5	0	1
Student age	11.353	2.301	8	15
Observations (ii gen imm)		46339		

[a] These are descriptive statistics on the number of second generation immigrants included in my analysis from each 50 home countries.

Table 4: Summary statistics - CPS

Variable	Mean	Std. Dev.	Min.	Max.
1=no repeated grade last year	0.975	0.156	0	1
Av grade natives in m	-0.217	0.561	-1.232	1.29
N obs from home country[a]	3219.929	2627.974	3	5545
High skilled mother	0.584	0.493	0	1
High skilled father	0.593	0.491	0	1
Mother year in US	20.979	8.872	2	51
Female	0.499	0.5	0	1
Student age	11.666	3.224	6	20
Observations (ii gen imm)		9893		

[a] These are descriptive statistics on the number of second generation immigrants included in my analysis from each 50 home countries.

Table 5: Main results-PISA

Variables	Dependent variable: test score math					
	[1]	[2]	[3]	[4]	[5]	[6]
			All			No Asia
PISA current values (average 2003-2009)						
PISA nat[a]	0.730***	0.392**	0.320***	0.179**	0.189**	0.155**
	(0.038)	(0.046)	(0.043)	(0.043)	(0.043)	(0.078)
female	-0.088**	-0.086***	-0.069**	-0.216***	-0.216***	-0.211***
	(0.036)	(0.030)	(0.030)	(0.030)	(0.030)	(0.047)
father imm	-0.294***	-0.340***	-0.296***	-0.247***	-0.246***	-0.315***
	(0.038)	(0.042)	(0.041)	(0.045)	(0.046)	(0.056)
edu moth=2			0.125***	0.017	0.013	0.014
			(0.039)	(0.037)	(0.037)	(0.047)
edu moth=3			0.256***	0.090*	0.087*	0.119*
			(0.052)	(0.048)	(0.047)	(0.073)
edu fath=2			0.112**	-0.011	-0.012	0.031
			(0.046)	(0.036)	(0.036)	(0.055)
edu fath=3			0.337***	0.119***	0.118***	0.168***
			(0.056)	(0.044)	(0.045)	(0.059)
Observation	32301	32301	32301	32301	32301	17705
N cob mother	49	49	49	49	49	38
R Squared	0.137	0.207	0.236	0.608	0.608	0.52
Estimated past values PISA (Hanushek)						
PISA nat 1970 (Hanushek)	0.642***	0.422***	0.337***	0.135***	0.306***	0.072
	(0.057)	(0.053)	(0.047)	(0.051)	(0.054)	(0.052)
Observation	29661	29661	29661	29661	29661	15382
N cob mother	48	48	48	48	48	37
R Squared	0.108	0.22	0.246	0.61	0.611	0.502
host country fe	no	yes	yes	yes	yes	yes
host school fe	no	no	no	yes	yes	yes
mother cob continent	no	no	no	no	yes	yes

[a] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the mother.

[b] This measure is taken from Hanushek and Woessmann [2012] and refers to estimated performance in international tests between 1970 and 2000.

Robust standard errors clustered by mother country of origin. All coefficients and standard errors are estimated according to the "Unbiased Shortcut" procedure (PISA Technical Report, 2009), using the replicate weights provided by PISA. education=2 refers to secondary education; education=3 refers to tertiary education. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 6: Main results-US CENSUS

Variables	Dependent variable: 1=never repeated a grade					
	[1]	[2]	[3]	[4]	[5]	[6]
			All			No Asia
PISA current values (average 2003-2009)						
PISA nat [a]	0.084**	0.046***	0.032***	0.027**	0.011**	0.029***
	(0.036)	(0.017)	(0.010)	(0.011)	(0.005)	(0.009)
female	0.070***	0.069***	0.069***	0.069***	0.069***	0.073***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
edu m=2			0.043***	0.040***	0.042***	0.044***
			(0.008)	(0.008)	(0.008)	(0.008)
edu m=3			0.058***	0.056***	0.057***	0.056***
			(0.007)	(0.007)	(0.007)	(0.007)
edu f=2			0.038***	0.038***	0.035***	0.036***
			(0.011)	(0.010)	(0.011)	(0.011)
edu f=3			0.072***	0.072***	0.066***	0.069***
			(0.014)	(0.013)	(0.014)	(0.015)
N	46352	46352	46352	46352	46352	41727
N cob moth	51	51	51	51	51	38
Estimated past values PISA (Hanushek)						
PISA nat 1970 (Hanushek)	0.119***	0.069***	0.042***	0.037***	0.014**	0.035***
	(0.029)	(0.016)	(0.011)	(0.011)	(0.007)	(0.009)
N	45437	45437	45437	45437	45437	40812
N cob moth	46	46	46	46	46	33
County fe	no	yes	yes	yes	yes	yes
Ysm moth	no	no	no	yes	yes	no
Continent moth fe	no	no	no	no	yes	no

[a] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the mother.

[b] This measure is taken from Hanushek and Woessmann [2012] and refers to estimated performance in international tests between 1970 and 2000.

Robust standard errors clustered by mother country of origin. education=2 refers to individuals who did not dropout but reached at most secondary education; education=3 refers to tertiary education. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. Additional controls: family size, foxed effect for the interaction of state of birth and year of birth and quarter of birth.

Table 7: Main results-CPS

Variables	Dependent variable: 1=no repeated the grade last year					
	[1]	[2]	[3]	[4]	[5]	[6]
	All	All	All	All	All	No China
PISA nat[a]	0.010***	0.011***	0.010***	0.010***	0.004**	0.011***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)
female	0.004	0.004*	0.004*	0.005*	0.005*	0.006**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Age	0.018**	0.019***	0.019***	0.020***	0.019***	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Age squared	-0.001**	-0.001**	-0.001**	-0.001***	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year edu mother			0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.001)	(0.000)
Year edu father			0.001**	0.001**	0.001	0.001
			(0.000)	(0.000)	(0.000)	(0.000)
N	6014	6014	6014	6014	6014	5778
N cob moth	46	46	46	4	46	45
state*year fe	no	yes	yes	yes	yes	yes
year arrival moth	no	no	no	yes	no	no
continent moth fe	no	no	no	no	yes	no

[a] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the mother, if the mother is foreign, or of the father if the father is foreign and the mother was born in the US.
Robust standard errors clustered by parents country of origin. high skilled refers as parents having at least secondary education. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 8: Persistency. US CENSUS

Variables	Dependent variable: 1=never repeated a grade				
	[1]	[2]	[3]	[4]	[5]
	child born in US at least 1 parent immigrant		child born in US parents born in US		
PISA nat mother[a]	0.012***	0.010***			
	(0.004)	(0.003)			
PISA nat father[b]	0.027***	0.026***			
	(0.004)	(0.004)			
PISA nat mother*PISA nat fath		0.019***			
		(0.006)			
PISA nat moth self def anchestry[c]			-0.002		-0.002
			(0.002)		(0.001)
PISA bat fath self def anchestry[d]				-0.000	-0.000
				(0.000)	(0.000)
female	0.071***	0.071***	0.086***	0.086***	0.086***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Edu mother	0.007***	0.007***	0.022***		0.014***
	(0.001)	(0.001)	(0.001)		(0.001)
Edu father	0.006***	0.006***		0.015***	0.009***
	(0.001)	(0.001)		(0.001)	(0.001)
N	65195	65195	8.09e+05	8.10e+05	7.46e+05

[a] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the mother.
[b] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the father.
[c] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country defined by the mother to be the country her ancestors are from.
[d] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country defined by the father to be the country his ancestors are from.
Robust standard errors clustered by mother country of origin. Edu mother and father refer to years of schooling. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 9: Interactions - US CENSUS

Variables	Dependent variable: 1=never repeated a grade					
	[1]	[2]	[3]	[4]	[5]	[6]
PISA nat m[a]	0.030***	0.082***	0.077***	0.109***	0.115***	0.018*
	(0.010)	(0.022)	(0.016)	(0.029)	(0.033)	(0.009)
female	0.069***	0.068***	0.069***	0.069***	0.069***	0.069***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
edu m=2	0.050***	0.044***	0.045***	0.051***	0.049***	0.041***
	(0.009)	(0.010)	(0.008)	(0.011)	(0.009)	(0.012)
edu m=3	0.066***	0.063***	0.061***	0.069***	0.063***	0.054***
	(0.008)	(0.014)	(0.008)	(0.009)	(0.008)	(0.009)
edu f=2	0.042***	0.040***	0.043***	0.043***	0.044***	0.041***
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.014)
edu f=3	0.079***	0.077***	0.081***	0.081***	0.080***	0.076***
	(0.016)	(0.017)	(0.015)	(0.015)	(0.015)	(0.017)
father imm	0.023**	0.022**	0.030***	0.029***	0.027***	0.031***
	(0.009)	(0.010)	(0.007)	(0.007)	(0.007)	(0.006)
PISA nat m*edu m=2		-0.056**				
		(0.022)				
PISA nat m*edu m=3		-0.072***				
		(0.021)				
PISA nat m*ysm m			-0.003***	-0.004***	-0.004***	
			(0.001)	(0.001)	(0.001)	
ysm m			0.002***	0.003***	0.005***	0.002**
			(0.000)	(0.001)	(0.001)	(0.001)
no edu in US [b]				0.033***		
				(0.012)		
PISA nat m*no edu in US				-0.029*		
				(0.015)		
age migration m[c]					0.010***	
					(0.002)	
age migration m 2					-0.000***	
					(0.000)	
PISA nat*age migration m					-0.001*	
					(0.001)	
PISA nat*segr=1						0.061**
						(0.024)
1=high segregation[d]						-0.020*
						(0.010)
N	46339	46339	44809	44809	44809	44809

[a] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the mother.
[b] dummy=1 if age of arrival > age finished to study. Since year of arrival in US is a categorical variable, I categorized variables such that this is the most restrictive (for sure not studied in the US).
[c] Built as the difference between year of arrival in the US and year of birth.
[d] This is a dummy=1 if the share of immigrant in a certain US state/year is above the overall median.
Robust standard errors clustered by mother country of origin. education=2 refers to individuals who did not dropout but reached at most secondary education; education=3 refers to tertiary education. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. Controls are the same of column (3) of Table 6.

Table 10: Selection

Dep variable: (high or medium edu emigrants /high or medim edu nat)				
	[1]	[2]	[3]	[4]
	All	All	female	male
Education from PISA dataset				
PISA nat[a]	-0.086	-0.127*	-0.095	-0.045
	(0.062)	(0.069)	(0.073)	(0.064)
N	49	49	49	49
log gdp ppp	-0.065	-0.044	-0.086	-0.023
	(0.064)	(0.066)	(0.073)	(0.060)
N	46	46	46	46
Education from Docquier and Marfouk [2006] database				
PISA nat[a]	0.008	-0.005	-	-
	(0.022)	(0.025)	-	-
N	59	59	-	-
log gdp ppp	0.014	0.002	-	-
	(0.017)	(0.018)	-	-
N	57	57	-	-
Education from Docquier and Marfouk [2006] database for emigrants in US				
PISA nat[a]	-0-006	-0.008	-	-
	(0.015)	(0.016)	-	-
N	59	59	-	-
log gdp ppp	0.05	-0.02	-	-
	(0.013)	(0.012)	-	-
N	57	57	-	-
Continent fe	no	yes	no	no

[a] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the mother, if the mother is foreign, or of the father if the father is foreign and the mother was born in the US. Robust standard errors in parenthesis. High skilled refers as parents having at least secondary education. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 11: Time Use Survey US

Variables	Dep variable: time in health and edu child			
	[1]	[2]	[3]	[4]
	All	All	Female	Male
PISA nat[a]	0.014*	0.040**	0.022*	0.005
	(0.008)	(0.017)	(0.013)	(0.006)
PISA nat * high sk		-0.001		
		(0.001)		
high skilled	0.158***	0.485*	0.154**	0.146***
	(0.044)	(0.248)	(0.068)	(0.036)
N child under 18 in hh	2.751**	2.781**	3.309**	1.791
	(1.260)	(1.284)	(1.416)	(1.193)
female	6.819***	6.813***		
	(0.807)	(0.810)		
Year of immigration	0.157**	0.164***	0.213**	0.047
	(0.059)	(0.056)	(0.082)	(0.060)
Variables	Dep variable: tot time in childcare			
PISA nat[a]	0.102**	0.225**	0.114**	0.078*
	(0.043)	(0.091)	(0.047)	(0.041)
PISA nat * high skilled		-0.004		
		(0.003)		
High skilled	1.866***	3.450**	2.085***	1.514***
	(0.370)	(1.377)	(0.447)	(0.261)
N child under 18 in hh	13.933***	14.087***	16.391***	9.559***
	(3.335)	(3.501)	(4.230)	(2.511)
Female	46.784*	41.812***		
	(27.540)	(2.446)		
Years of immigration	0.271*	0.309*	0.906***	-0.687***
	(0.148)	(0.155)	(0.241)	(0.237)
N	6383	6383	3740	2643
N cob moth	49	49	49	49

[a] This refers to the average math PISA score of natives (standardized to have mean 0 and standard deviation 1) in the country of birth of the mother, if the mother is foreign, or of the father if the father is foreign and the mother was born in the US. Robust standard errors clustered by parents country of origin. high skilled refers as parents having at least secondary education. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 12: Country of origin characteristics

Variables	Dependent variable: test score math				
	[1]	[2]	[3]	[4]	[5]
grade math m	0.222***	0.240***	0.213***	0.275***	0.291***
	(0.070)	(0.058)	(0.070)	(0.063)	(0.068)
female	-0.209***	-0.208***	-0.209***	-0.209***	-0.209***
	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
Edu mother	0.014	0.015	0.014	0.015	0.015
	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)
Edu father	0.029*	0.029*	0.029*	0.029*	0.029*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Log GDP ppp		-0.077			
		(0.047)			
% high sk mother from cobm			0.029		
			(0.114)		
20/30 y edu 1990				-0.017	
				(0.012)	
pupil/teacher prim sch m					0.005
					(0.004)
N	26877	26877	26877	26877	26877
N cob moth	39	39	39	39	39

Robust standard errors clustered by mother country of origin. All coefficients and standard errors are estimated according to the "Unbiased Shortcut" procedure (PISA Technical Report, 2009), using the replicate weights provided by PISA. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. Mother and father education (categorical variable from 1 to 6) as reported by children in the student questionnaire are instrumented by the education level reported by parents in the parent questionnaire. Only the countries and the waves with the parent questionnaire are included.

Table 13: Country of origin characteristics

Variables	Dependent variable: test score math					
	[1]	[2]	[3]	[4]	[5]	[6]
grade math m	0.146**	0.118	0.034	0.209**	0.187*	0.186**
	(0.070)	(0.091)	(0.082)	(0.093)	(0.093)	(0.085)
female	-0.210***	-0.209***	-0.207***	-0.194***	-0.205***	-0.204***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.010)	(0.010)
Edu mother	0.016	0.015	0.014	0.005	0.021	0.021
	(0.018)	(0.019)	(0.019)	(0.013)	(0.022)	(0.021)
Edu father	0.029*	0.028*	0.028*	0.032***	0.033*	0.033*
	(0.016)	(0.016)	(0.016)	(0.011)	(0.019)	(0.019)
protestant		-0.032	0.098			
		(0.153)	(0.105)			
other Christian		-0.22	0.197			
		(0.476)	(0.417)			
orthodox		-0.104	-0.07			
		(0.065)	(0.074)			
Jewish		3.29	1.591**			
		(4.135)	(0.662)			
Muslim		-0.073	-0.074			
		(0.103)	(0.126)			
Hindu		0.348	0.341*			
		(0.236)	(0.191)			
Buddhist		0.4	1.622*			
		(0.446)	(0.910)			
eastern religions		0.455	0.364*			
		(0.326)	(0.196)			
other religions		-0.258	0.222			
		(0.359)	(0.184)			
non religious		0.141	0.38			
		(0.211)	(0.624)			
inner locus of control (wvs)					-0.013	
					(0.097)	
important teach determ (wvs)						-0.144
						(0.341)
N	27922	27922	27922	21945	21945	21945
N cob mother	43	43	43	36	36	36

Robust standard errors clustered by mother country of origin. All coefficients and standard errors are estimated according to the "Unbiased Shortcut" procedure (PISA Technical Report, 2009), using the replicate weights provided by PISA. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. Mother and father education (categorical variable from 1 to 6) as reported by children in the student questionnaire are instrumented by the education level reported by parents in the parent questionnaire. Only the countries and the waves with the parent questionnaire are included.

Table 14: Millennium cohort study W2

Variables	Dependent variable: w2 Bracken test (age 3)					
	[1]	[2]	[3]	[4]	[5]	[6]
PISA grade m	3.968***	3.557***	3.947***	2.964**	1.523	0.596
	(1.123)	(1.214)	(1.209)	(1.183)	(1.091)	(1.622)
1=female	4.222***	5.015***	5.896***	4.702***	4.984***	4.963***
	(1.065)	(1.112)	(1.105)	(1.131)	(1.070)	(1.091)
y edu mother		1.132***	1.129***	1.108***	0.839***	1.183***
		(0.171)	(0.157)	(0.174)	(0.168)	(0.175)
child height (cm, age 3)			0.568**			
			(0.215)			
1= no english at home				-10.148***		
				(2.405)		
how often read					3.746***	
					(0.502)	
N	686	686	686	686	686	686
N cob moth	50	50	50	50	50	50

[a] 1 if mother answered "any other language" to the question on whether the household speaks English at home at age 9 months (MCS 1).
[b] Mother's answer to the question "How often do you read with the child?" at age 3 (MCS 2). (6=every day, 1= not at all)
Robust standard errors clustered by mother country of origin. Weights take into account attrition and non response bias. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. The last column controls for mother's religion (no religion, Catholic, Protestant, Hindu, Muslim, Sikh, Buddhist, other Christian religions, other religions). Additional controls: age (in months) fixed effects.

Table 15: Millennium cohort study W3 FSP

Variables	Dependent variable: foundation stage profile (age 5)						
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
PISA grade m	5.751***	3.921***	3.402**	3.611**	3.236**	2.209	-0.898
	(0.615)	(1.359)	(1.522)	(1.466)	(1.468)	(1.615)	(1.450)
1=female	4.381**	3.671**	3.666*	3.150	3.560*	3.670*	3.560*
	(1.656)	(1.813)	(1.873)	(2.025)	(1.891)	(2.051)	(1.889)
y edu mother			1.208***	1.134***	1.175***	1.057***	1.336***
			(0.244)	(0.229)	(0.237)	(0.247)	(0.294)
child height (cm, age 3)				0.162			
				(0.261)			
1= no english at home					-3.136		
					(2.752)		
how often read						2.653***	
						(0.718)	
N	614	614	614	614	614	614	614
N cob moth	51	51	51	51	51	51	51
local authority[a] fe	no	yes	yes	yes	yes	yes	yes

[a] There are 140 local education authorities (lea) in the sample. It is impossible to use school fixed effects because there should be 407 fixed effects. Leas have responsibility for education within their jurisdiction.
Robust standard errors clustered by mother country of origin. Weights take into account attrition and non response bias. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. The last column controls for mother's religion (no religion, Catholic, Protestant, Hindu, Muslim, Sikh, Buddhist, other Christian religions, other religions). Additional controls: age (in months) fixed effects.

Table 16: Millennium cohort study W4

Variables	Dependent variable: w4 pattern construction test (age 7)						
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
PISA grade m	3.415***	3.200***	3.252***	3.314***	2.405***	1.490	4.188**
	(0.703)	(0.891)	(0.874)	(0.889)	(0.868)	(1.287)	(2.066)
1=female	-0.767	-0.332	-0.372	-0.218	0.042	-0.286	1.933
	(1.294)	(1.245)	(1.210)	(1.244)	(1.241)	(1.287)	(3.317)
y edu mother		0.964***	0.954***	0.972***	0.793**	0.954***	0.836
		(0.329)	(0.338)	(0.329)	(0.331)	(0.344)	(0.620)
child height (cm, age 3)			-0.030				
			(0.157)				
1= no english at home				2.127			
				(1.808)			
how often read					2.019***		
					(0.466)		
N	561	561	561	561	561	561	340
N cob moth	48	48	48	48	48	48	42
fe lea[b]	no	no	no	no	no	no	yes

[a] This is the score taken in a subsection of sweep 2 cognitive assessment, which is very similar to the picture comparison test taken by children in sweep 4.

[b] There are 117 local education authorities (LEA) in the sample (MCS 4). It is impossible to use school fixed effects because there should be 407 fixed effects. LEAs have responsibility for education within their jurisdiction.
Robust standard errors clustered by mother country of origin. Weights take into account attrition and non response bias. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. Column 6 controls for mother's religion (no religion, Catholic, Protestant, Hindu, Muslim, Sikh, Buddhist, other Christian religions, other religions). Additional controls: age (in months) fixed effects.

Table 17: Number of Countries

home country	US CENSUS	PISA	CPS
Albania	24	204	
Argentina	388	45	29
Australia	206	690	27
Austria	505	174	15
Azerbaijan	25		
Belgium	178	149	7
Brazil	236	148	38
Bulgaria	11		
Canada	5525	13	337
Chile	156	35	20
China	1406	6696	356
Colombia	662		227
Costa Rica	167		26
Croatia		211	
Czech Republic	215	14	
Denmark	232	54	9
Estonia		22	
Finland	132		10
France	793	886	77
Germany	1043	1051	550
Greece	1269	69	55
Hong Kong	182	174	63
Hungary	558	17	23
India	516	154	393
Indonesia	181		18
Ireland	2081		49
Israel/Palestine	327		51
Italy	4491	1195	200
Japan	1454		236
Jordan	69	68	20
Korea	83	41	
Latvia	212		
Liechtenstein	27		
Lithuania	218		
Macao		4026	
Malaysia	17	64	8
Mexico	12598		5545
Montenegro	917		
Netherlands	785	179	27
New Zealand	77	582	5
Norway	274		3
Panama	459		59
Peru	284		113
Poland	1255	214	174
Portugal	608	1767	208
Romania	205	35	33
Russia		2347	54
Serbia		2411	
Singapore	30	13	
Slovakia		417	4
Slovenia		13	
Spain	333		41
Sweden	277	277	10
Switzerland	257	225	13
Taiwan	153	81	194
Thailand	106	15	97
Trinidad and Tobago	177		97
Tunisia			
Turkey	99	371	22
United Arab Emirates	2058		
United Kingdom	4858	1287	290
United States	2342		
Uruguay	70	251	5
Venezuela	87	71	41