Mind the Gap: Compositional, Cultural and Institutional Explanations for Numeracy Skills Disparities Between Adult Immigrants and Natives in Western Countries

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Abstract

This paper empirically tests diverse theoretical explanations for observed skills disparities between adult immigrants and non-immigrants. Using skills data from 100,000 adults (16-65) in 18 Western countries, we show that in almost all countries, adult immigrants are less numerically skilled than non-immigrants, but that the size of the skills gap varies strongly cross-nationally. Multilevel models reveal that differences related to immigrant populations' composition on demographic and socioeconomic characteristics, employment and countries of birth largely explain these regularities. In addition, countries' religious diversity, immigrants social and educational integration are associated with smaller skills gaps, while labor market protectionism and educational systems' vocational orientation are related to larger gaps. Theoretical and policy implications are discussed.

Introduction

The cognitive ability gap between migrants and non-migrants is a robust empirical regularity. Skills disparities between migrants and natives are consistently observed among school-going children in various countries (*cf.* Levels and Dronkers 2008) and are observed in all stages of the educational career, both in Western Europe (Heath, Rothon and Kilpi 2008) and in the US (Phillips, Crouse and Ralph 1998). Although the achievement gap between immigrants and non-migrants is also observed for adults (Kahn 2004), migration-related skills disparities between adults are scarcely studied. In this paper, we aim to explain why cognitive ability gaps between adult immigrants and natives exist, how the gaps differ cross-nationally, and why this is the case.

Most of what we do know about possible theoretical explanations for disparities between migrants and non-migrants comes from studies of immigrant children. These studies suggest a wide variety of relevant explanations for achievement disparities, such as family structure during childhood (Phillips et al. 1998), cultural differences in the valuation of academic success (Fordham and Ogbu 1986), school characteristics (Cook and Evans, 2000; Dronkers and Levels 2007; Fryer and Levitt 2004) and macro-characteristics of both destination countries and origin countries (Levels, Dronkers and Kraaykamp 2008; Dronkers, van der Velden and Dunne 2012). However, findings from the literature on immigrant children cannot be generalized to explain disparities between native and immigrant adults. First generation adults are more likely to be schooled abroad, and they are more actively involved in the migration decision than first generation children. Second generation adults have usually spent more time in the host country than second generation children, which gives them more time to close the gap.

Studies on skills disparities between *adult* natives and immigrants have three main limitations. First, most studies on the skills gap between adult migrants and non-migrants rely

on indirect measures like occupational attainment (Jasso et al. 2000), educational attainment (Antecol et al. 2003) or wages (Belot and Hatton, 2012). Such proxies are less adequate for measuring skills in cross-national settings. The quality of education within the same level of schooling and the selectivity for a given level differ markedly between countries (*cf.* Schneider 2009), so that the increase in skills with each year of additional schooling also differs per country. Wages and occupational status a only pertain to people with jobs, and are possibly biased due to (origin-related) discrimination of migrants (Heath and Cheung, 2007). We use direct measures of skills. Second, we compare a large number of countries, which allows us to better explore the role of contexts. While researchers have used direct measurements of achievement on literacy tests to study the skills gap (see for example: Kahn 2004), most studies can only focus on a small number of destination countries (Green and Riddel 2003; Kahn 2004). Because of the limited possibility to model cross-level interactions between context and migrant status, the conclusions from designs that rely on few countries can be tentative at best. Third, many papers and official documents (OECD 2006; 2012) disregard that as a consequence of selective migration, the socio-economic, cultural and ethnic composition of migrant populations varies greatly between destination countries. These composition effects might be crucial in explaining cross-national variation of immigrants' skills (Borjas 2003). For a number of observed outcomes, the economic, cultural, educational and institutional differences between birth countries explain a larger part of the variation in performance, behaviour and attitudes of migrants than the economic, cultural and educational differences between destination countries (Dronkers & Vink 2012; Fleischmann and Dronkers 2010). Disregarding them could lead to fallacious conclusions regarding destination country-level effects.

Data from the Programme for the International Assessment of Adult Competencies [PIAAC] by the OECD (2013a) allow us to overcome these problems. The data allow for

robust analyses of the complex explanations of the native-immigrant skills gap in a cross-national setting. PIAAC is a large cross-national survey, conducted among large samples of adults aged 16 to 65 in 24 countries. It measures demographic and socio-economic characteristics of individuals, and provides direct measures of literacy and numeracy. These data hold important information about respondents' migration history. As such, PIAAC provides the most elaborate and complete cross-national evidence base on skills of immigrants and natives to date. We combine the PIAAC data with high-quality macro-level indicators on countries' relevant policies and institutional characteristics, and analyse these pooled data using multivariate (hierarchical) multilevel models (Snijders and Bosker 1999) to test a broad variety of hypotheses on compositional and contextual effects. Our results indicate that that (1) differences related to immigrant populations' composition on demographic and socioeconomic characteristics and employment explain a large part of the cross-national variation of skills gaps between immigrants and non-immigrants. Differences related to birth countries are also important. Furthermore, net of compositional differences, skills gaps are smaller (2) in more religiously diverse countries, (3) in countries where immigrants are more strongly socially integrated, (4) where labor markets are less protected, (5) where education is more strongly suited for educating immigrants, and (6) where the education system is less vocationally oriented. We find no evidence that ethnic diversity, linguistic diversity or the stratification of educational systems of receiving countries are related to the skills gap.

2. Theory and hypotheses

Two types of theoretical explanations for skills disparities between immigrants and non-immigrants can be distinguished. First, explanations that pertain to differences in individuals' characteristics that might plausibly aggregate into compositional differences between groups

of immigrants and natives. If natives and immigrants differ with regard to individual-level characteristics associated with cognitive abilities, these differences are likely to explain some of the observed skills disparities between the groups.

Secondly, explanations may pertain to country-level characteristics. Such macro explanations can relate to contextual characteristics of receiving countries, origin countries, and various combinations thereof (*cf.* Van Tubergen 2006). Contextual effects of receiving countries might be the result of population differences in relevant individual-level characteristics such as the proportion of immigrants in the country, or they might derive from country-level differences that cannot be disaggregated into individual-level characteristics. Examples of such contextual effects include institutional characteristics, or the quality of the educational system.

2.1 Hypotheses on compositional differences

We consider individual effects related to demographic makeup and health, the level educational attainment, socioeconomic class, employment, and other differences related to birth countries between natives and first and second generation immigrants.

Demographics

A number of demographic variables are consistently found to be associated with cognitive skills. First, age is an important predictor of cognitive abilities. Although considerable inter-individual variation exists, cognitive abilities generally increase until around the age of 40, and then begin to decline (Hertzog et al. 2009). The gender composition of immigrant and native groups might also be important. Males outperform females on the PIAAC numeracy tests (OECD 2013c). Family forms and number of children might also be related to skills, although the causal direction is no so clear. Finally, poor health is associated with lower

skills. Here too, causality probably goes both ways. First, more cognitively able people have a higher health literacy, which translates into better health (Gottfredson 2004). Particular types of physical and mental disorders also affect cognitive abilities. If the composition of migrant and native subpopulations differ with regards to these characteristics, these differences might help to explain the observed proficiency gap between immigrants and natives. This leads to Hypotheses 1: the proficiency gap between first and second generation migrants and natives can be explained partly by compositional differences between migrants and natives pertaining to age, gender , family form, the number of children, and health.

Educational attainment

Educational attainment is strongly related to skills. In general, the more educated people are, the higher their proficiency in various domains (OECD 2013c). This is theoretically explained by two mechanisms. First, as predicted by human capital theory (Becker 1964) education inculcates skills and provides students with human capital. More education thus means more skills. Second, educational systems sort children based on cognitive skills, so those with higher skills complete more schooling. Which of these facts best explains the relationship between education and skills is a matter of some controversy. In the context of this paper, it is important that if migrant and native subpopulations differ with regards the achieved level of education, we expect these compositional differences to explain part of the observed proficiency gap between immigrants and natives. In most Western countries, the level of educational attainment of both first and second generation immigrants lags behind that of the overall native-born population. Notable exception to this might be countries where point systems are implemented with the express purpose of selecting educated migrants (e.g. Canada). Hence Hypothesis 2: the proficiency gap between first and second generation

migrants and natives can partly be explained by compositional differences in levels of educational attainment (hypothesis 2).

Social class

Large variation in cognitive skills exists among people with equal educational attainment, and the skills of people with various levels of attainment overlap (OECD 2013). Part of this variation may be linked to social class differences. Net of one's own education, one's class origin is also related to cognitive skills. People from higher socioeconomic backgrounds are likely to be more proficient in math, in reading, and in various other domains of abilities, net of their own years of education (OECD 2013c). Part of the explanation for this is hereditary: smarter parents are more likely to have smarter children (Toga and Thompson 2005). A second explanation points towards a second path (Boudon 1974): children of higher social backgrounds are more likely to make educational choices more strongly directed at achieving higher levels of education. As a result, they might be pressed to study harder for exams (*cf.* Jencks et al. 1979), which would result in higher cognitive skills. A third explanation relies in notions of cultural capital (Bourdieu 1973). Higher status parents endow their children with cultural capital, that in turn positively affects their attitude towards schooling, which would in turn increase their skills return to education. Much migration is an attempt to better oneself economically. In many countries, migrants are more likely to be from lower socioeconomic backgrounds than natives found in countries with large gaps. Hypothesis 3: the proficiency gap between first and second generation migrants and natives can be explained by compositional differences pertaining to different levels of socioeconomic class origins between migrants and natives.

Employment status

There is a strong positive relationship between being employed and being skilled (OECD 2013c). Two theoretical explanations can be offered. First, it could be that more skilled are more likely to get and less likely to lose jobs compared to lower skilled. Secondly, it might also be the case that those who are unemployed lose skills. Theoretically, both causal paths make sense. First, skills are a good predictor of economic productivity (Hanushek and Woessman 2008). Although education and cognitive ability are correlated, they are not to be equated. Employers can use educational credentials as a signal of expected productivity (cf. Spence 1973), but because of the high variation in skills within education levels, they might end up hiring people who are relatively underskilled compared to their evenly educated peers, and less productive than they expected. Analyses of earnings suggest this to be the case (Allen and Van der Velden 2001). If the job market functions well, employers might be more inclined to fire less lower skilled workers. On the other hand: skills are nurtured by using them, and the workplace is the place where most cognitive skills are commonly used. Becoming unemployed is associated with depreciation of human capital (Mincer and Ofek 1982). Both explanations point towards a positive relation between being employed and cognitive abilities. In most Western countries, employment ratios are higher amongst natives than immigrants (Van Tubergen, Maas and Flap 2004). These differences might aggregate into explaining skills disparities. Hypothesis 4: the proficiency gap between first and second generation migrants and natives can be explained partly by compositional differences pertaining to different levels of employment (4a) and work experience (4b).

Migration variables

Some explanations for skills disparities are related to the migration decision itself. For example, immigrants are usually less proficient than natives in the language of their destination countries (Epenshade and Fu 1997; Stevens 1999), and that this lower language

proficiency is correlated with fewer employment possibilities and lower wages (Dustman and Fabri 2003). A second common explanation for skills disparities is that migrants who have obtained their diploma in their birth country have skills that cannot be easily transferred (or certified) in their countries of destination. Immigrants who are schooled abroad lack human capital suited to the labor market of their destination country, which would help explain the often observed earnings disadvantage immigrants have when they arrive in their destination country (Chiswick 1978; Borjas 1985). Hypothesis 5: the proficiency gap between first and second generation migrants and natives can be explained by compositional differences pertaining to different levels of language proficiency (5a) between migrants and natives, and by the fact that migrants are less likely schooled in educational systems that inculcate the kinds of human capital valued in destination countries.

Countries of birth

In addition to the individual-level effects described above, a wide variety of effects related to immigrants' birth countries has been proposed (Kao and Thompson 2004). For example, scholars have argued that cultural differences between ethnic groups can explain differences in educational aspirations, which would in turn translate in differences in cognitive skills (for example: Fordham and Ogbu 1988). In addition to such origin-related compositional differences, proposed macro-level differences relate to contextual characteristics, such as economic development and political stability (Levels et al. 2008), or their religious composition (Dronkers and De Heus 2013). We explore the extent to which such differences contribute to explaining skills disparities with dummies signifying their countries of birth.

2.2 Hypotheses on contextual effects

A large number of societal characteristics might be expected to explain skills disparities between immigrants and natives. Here, we explore the role of countries' culture, their structure (e.g. labor markets) and their institutions (e.g. educational systems)

Cultural hypotheses

Western countries differ markedly in the cultural characteristics of their populations. For example, the extent to which countries are culturally, ethnically, religiously and linguistically diverse might affect the skills gap. It could be argued that in more culturally diverse societies, societal acceptance of non-native cultures should be higher, and, as a consequence, immigrants would face less trouble integrating. For example, cultural acceptance of non-native languages might be higher in more linguistically diverse destination countries, and non-native religions might be more accepted in countries that are already religiously diverse. Finally, in countries that are characterised by higher levels of ethnic diversity, acceptance of immigrants from non-native ethnicity might be higher. Hypothesis 6: skills disparities between natives and first and second generation immigrants are smaller in countries with a higher ethnic (6a), linguistic (6b) and religious (6c) diversity.

Countries' religious histories might also be important. The theoretical reasoning revolves around the assumption that immigrants are more prone to invest in the acquisition of skills if they feel that the returns to this investments are more likely, and that the societal returns are more likely to be higher in societies that are more accepting. Acceptance of non-Christian religions might be higher in countries in which Christian religions are historically less prominent. This would particularly benefit immigrants from non-Christian denominations. Also, acceptance might be higher if other religions are historically more significant. Hypothesis 7: skills disparities between natives and first and second generation immigrants are smaller in countries in which Protestantism (7a) or Catholicism (7b) is historically less

important, and Islam (7c), and other non-Christian religions (7d) are historically more important.

Hypotheses on institutional inclusiveness

Countries differ in the extent to which their societal institutions are open and enable active citizenship, societal participation and labor market integration. In general, the more open countries might be, the more they invite participation, and the more they will provide immigrants with incentives to invest in skills acquisition. First, in countries in which political participation is more open, it is more likely that immigrants will strive to participate, both by seeking office and by voting. This higher political participation probabilities might serve to serve as an incentive for immigrants to invest in education, thereby reducing skills gaps. Furthermore, the level of prejudice against minorities is a trait of destination countries (Portes and Zhou 1993). In Western countries, ethnic and racial discrimination are legally prohibited, but more subtle forms of discrimination still negatively affect immigrants' chances of integration. The extent to which discrimination of immigrants occurs varies cross-nationally and partly depends on laws and policies designed to counter subtle discrimination. Hypothesis 8: skills disparities between natives and first and second generation immigrants are smaller in countries that are more democratic (8a) and countries that have more strongly adopted laws and policies to stimulate the integration of immigrants (8b).

The way labor markets are structured might also provide a critical structural trait of societies. Skills, once learned in education, are nurtured in the labor market, and most informal learning of new skills takes place on the job. Labor market participation of immigrants might be crucial for combating skills disparities between immigrants and natives. Of course, countries differ in the extent to which their labor markets are open for immigrants. Labor market protection often benefits those who already have jobs over those who are trying

to get jobs, as it is often assumed that employers are less willing to hire someone when it is more burdensome to fire them if they do not meet the requirements of the job. Particularly first generation immigrants, who are almost by definition outsiders in their destination countries, might have more difficulties in labor markets if existing workers are more protected. Also, countries differ in the extent to which they allow immigrants to work, and in the extent to which they grant working immigrants the same rights as working natives. Hypothesis 9: skills disparities between natives and first and second generation immigrants are larger in countries with stronger labor market protection of workers (9a), and smaller in countries that have more strongly adopted laws and policies to stimulate the labor market integration of immigrants (9b).

Immigrant children have very specific educational needs: they are generally less proficient in the languages of their destination countries, less familiar with destination countries' school cultures, and often have lower aspirations. Some countries' educational systems are more suited to deal with these specific circumstances, which would help explain skills gaps between immigrants and natives. The extent to which countries' secondary educational systems meet the educational demands of immigrant children will affect the size of the skills gap between immigrant and native children. Furthermore, if the immigrant share of the total population is larger, countries' educational systems are more likely to adapt to cater to the needs of immigrant students. We expect skills disparities between natives and first and second generation adult immigrants to be smaller in countries in which the skills gap between native and immigrant children in secondary education is lower (10a), in countries in which the proportion of immigrant students is higher (10b), and in countries in which a larger part of the student population is in schools with high concentrations of immigrants (10c).

Hypotheses on educational systems

There are large between-country differences in the way education is organized (Shavit and Müller 1998). Countries differ in the number of distinct educational tracks at secondary education, the age at which children are selected into different educational programmes, and the size and content of vocational tracks. All these system traits might be expected to affect skills disparities between immigrants and natives.

Stratification of education systems refers to the extent to which students are divided into separate educational tracks and groups. Vertical stratification refers to the number of grades in standard curricula, and is informative about the number of transitions in standard curricula. Highly horizontally stratified systems have more tracks and track pupils into different types of secondary education at a relatively young age. In addition, pupils can also be grouped according to ability. This is horizontal stratification within schools. Two examples illustrate the distinction. The Dutch education system has high horizontal stratification between schools: it selects relatively early and children can be placed in 7 educational tracks. At first glance the American high school system is much less stratified: it offers the same type of education to all high school pupils. However, the American system is highly focussed on ability grouping. High achievers can be assigned to so-called 'honors' sections of the courses in which they excel, whereas low achievers have to attend 'remedial' sections (Slavin 1990).

The argument behind educational stratification is that the more homogeneous learning environments are, the more focused curricula can be and the more instruction can be tailored to the needs of children. As a consequence, stratification increases the performance of all students (Hanushek and Wössmann 2006). However, this comes at a cost. Evidence suggests that lower class children perform less well in highly stratified systems. Selection into tracks usually takes place at an age are were the decisions are more affected by parental backgrounds than by children's abilities (Mare 1981; Shavit and Blossfeld 1993). Educational aspirations are mainly class driven: most students eventually strive for a level of educational attainment

that prevents downward intergenerational mobility Breen and Yaish (2006). In addition, higher educated parents are more aware of the different educational options and better able to navigate their children successfully through the educational careers (Pfeffer 2008), which is particularly important in highly stratified systems. As a consequence, lower SES pupils and their parents make less ambitious tracking decisions than higher SES pupils, and are overrepresented in schools and tracks with less favourable teaching conditions and less ambitious curricula (Dupriez, Dumay, and Vause 2008).

If this reasoning is applied to the educational careers of immigrants, their skills acquisition is likely to be lower in highly stratified educational systems. As a consequence of their overall lower level of resources and lesser knowledge of educational systems in their destination countries, they are more likely to be selected into lower educational tracks, even if they are L2-proficient. Just as people from lower socioeconomic backgrounds, immigrants and their parents will generally be less informed about the functioning of their destination country's educational system, which is especially disadvantageous in highly differentiated systems. Hypothesis 11: skills disparities between natives and first and second generation immigrants are larger in countries in which the educational system is more strongly stratified vertically (11a), horizontally between schools (11b), and horizontally within school (11c)

Finally, the extent to which educational systems are vocationally oriented is theoretically important. The nature of vocational education differs cross-nationally. In countries like Italy and France, vocational education mainly provides an education for low-ability children, whereas in countries like Sweden it aims to teach general vocational skills (Breen 2005). Immigrant children disproportionately take vocational tracks (Kao and Thompson, 2003), and it is plausible that their skills acquisition is strongly affected by the vocational orientation and vocational specificity of education. In systems were vocational education is more prevalent, vocational tracks might be more acceptable tracks for children

from less disadvantaged backgrounds, which would increase the ability levels of children in vocational education. Immigrant children might benefit from the higher level of their peers. The same can be said for systems that are more vocationally specific. Hypothesis 12: skills disparities between natives and first and second generation immigrants are lower in countries in which the educational system is more strongly vocationally oriented (12a), and more strongly vocationally specific (12b).

3. Data

Testing our hypotheses requires a large dataset with a large number of destination countries and adult respondents from immigrant and non-immigrant backgrounds, as well as direct information about their skills. The 2013 wave of the Programme for the International Assessment of Adult Competencies [PIAAC] survey is the first cross-national dataset that meets these requirements. The OECD collected these data in 2012 and 2013 (OECD 2013a) from over 150,000 respondents in 24 highly industrialized countries. Representative national samples contain over 5,000 adults between the age of 16 and 65. Next to highly detailed information about a wide variety of background variables, the survey uses advanced psychometric tests to provide reliable estimates of adults' proficiency in literacy, numeracy and problem-solving in technology-rich environments. Respondents were asked to complete assessment tests designed that directly measure cognitive abilities on these three domains. All three types of skills are essential for processing information (OECD 2013b). While most PIAAC countries have a sizable proportion of immigrants in their samples, we had to exclude data from Poland, Slovakia, Japan and Korea, as because their samples did not include enough immigrants to allow for reliable comparisons. Other selections were also necessary. Data from Russia are not yet available, and we also excluded data from Australia for technical-administrative reasons. Finally, the original Canadian sample included of some 25,000 cases,

which is about five times larger than samples from the other countries. To make the national sample more comparable in size to the national samples of the other countries, we took a random sample of 20% of the original Canadian sample. Finally, we deleted cases with missing values that could not sensibly be imputed. The total working sample contains N=99,826 respondents from 18 countries: Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden, the United Kingdom, and the United States.

[Table 1 about here]

4. Measurements

4.1 Distinguishing natives and immigrants

PIAAC asked respondents in what country they were born, and whether their parents were born outside the test country. We used this information to distinguish first generation immigrants, second generation immigrants, and natives. Natives are people whose parents were both born in the country were the respondent lived and was tested. By this definition natives are people with no reported cross-national migration history for two generations, plus those born in a foreign country to two natives of the country in which they now live. First generation immigrants are foreign-born respondents with at least one parent born in a country other than the one where they took the PIAAC tests. Second generation immigrants are respondents who were born in the country where they took the PIAAC test, but who have at least one parent born elsewhere. We also include a dummy signifying whether or not people had one parent born in the test country. In the analyses, natives are the omitted reference category. As can be seen in Table 2, a sizable proportion of immigrants from the first and

second generation are sampled in all countries. In total, the data contain information on 19,818 immigrants, of whom 11,255 are first generation and 8,563 are second generation.

4.2 Dependent variable: numeracy skills

Our dependent variable is derived from the PIAAC measurement of competence in numeracy skills. Numeracy is defined as "the ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life." The test has 56 items, that together measure how well respondents can use mathematical information to solve real-life problems (OECD 2013b). To reduce the total time-on-test, respondents were given only with a selection of the items. Item response techniques were then used to compute 10 plausible values for numeracy. The scale ranges from 0 to 467, with an overall average of 269 and a standard deviation of 53.

[Table 2 about here]

4.3 Independent variables

Below, we will discuss the measurement of the independent variables in detail. Descriptive statistics appear in Table 2.

Demographic variables. We include a number of variables pertaining to demographic characteristics of respondents. First, we control for gender, using a dummy that signifies whether respondents were male (1) or female (0). We measure for respondents' *age* in years, and include an additional quadratic term to account for the non-linearity of the relationship between age and skills. The mean age in the entire sample is 41 years. We also include a dummy signifying whether respondents were *living with a spouse or significant other* (1) or not (0). This is the closest we can get to measuring their marital status with these data.

Finally, we also include the number of children respondents have had. This measure ranges from 0 to 25, with an overall mean of 1.4.

Health. The PIAAC survey asks "In general, would you say your health is excellent, very good, good, fair or poor?" This self-assessment is commonly used in international surveys and strongly correlates with objective indicators of health (Idler and Benyamini 1997). We use a dummy distinguishing whether or not respondents were in poor health (1), or in excellent, very good, good, or fair health (0). Missing values are also categorized and added as a dummy.

Educational attainment is the number of years respondents would normally have spent in formal education to achieve the highest credential they have attained. Cross-national comparability is achieved by combining information on respondents answer to the question "which qualification on this card is the highest you have obtained" with the reported highest level of education in national education systems. The information was converted into nominal years of schooling by country experts (OECD 2013b).

Social class. We measure individuals social origin class with two complementary variables. As a measurement of the *level of education of respondents' parents,* we a categorical variable that indicates the level of educational attainment of the highest educated parent. We distinguish whether the highest educated parent was higher educated, medium educated, or lower educated. Respondents with lower educated parents form the reference category. We also add a dummy to account for missing values. As a second indicator of parental socioeconomic status, we use dummies for the number of books in the respondent's home at age 16 (11-25, 26-100, 101-200, 201-500, and more than 500 books). Ten books or fewer are the reference category. An additional dummy indicates missing values.

Work-related variables: we measure the effect of having a job using a dummy variable coded (1) if respondents are *unemployed*, and (0) otherwise. *Work experience* is the total numbers of years respondents reportedly have done paid work during their lifetime.

Speaking a non-native mother tongue: respondents were asked about the languages they had learned as a child and still understood. From this information, the OECD determined the native language of respondents. The variable we use is scored (1) if respondents' native language is different from the language in which the survey was performed, and (0) if it was the same.

Having a diploma from a foreign country: in all countries except the UK and France, respondents were asked in what country they had obtained their diploma. In the UK and France, we used information about the year persons obtained their highest credential and the year they migrated to infer whether they were likely to have obtained their credentials in the test country. This measure is scored (1) if respondents obtained their diploma in the test country, and (0) if it was in a different country.

Birth countries. We control for unobserved heterogeneity due to birth countries by including separate dummies for each of the countries in which respondents were born. Nepal is the reference category. This does imply that second generation immigrants have their destination country as their birth country dummy. Precise information on the birth countries of the parents is not available. This means that the control for the unobserved heterogeneity due to the parental origin countries of the second generation, which can influenced the skills of their children, deviates from the control for unobserved heterogeneity for the first generation.

Cultural country variables. To measure the levels of *ethnic, linguistic and religious diversity,* we use measures devised by Alesina et al (2003). Each measure reflects the probability that two randomly selected people from each destination country will be of a different ethnic,

linguistic or religious group. A higher score on these measures indicates a higher level of diversity. We use the measures as provided by Teorell et al. (2013). The *historical significance of religious denominations* is indicated by the relative size of religious groups in 1980. More specifically, we use the numbers of Catholics, Protestants, Muslims and "other religions" as percentage of countries' total population in 1980. Information was coded by La Porta et al. (1999), and provided by Teorell et al. (2013).

Country variables on institutional inclusiveness. The level of *democratization* is measured by the Van Hanen Index of Democratization (Van Hanen 2011; Teorell et al. 2013), which combines information on the level of political competition and the level of democratic participation. Democratic competition is measured as the percentage of votes not cast for the largest party, multiplied by the percentage of the population who actually voted in the election, divided by 100. The index ranges from 26 to 45.5; a higher score indicates a higher level of democratization. *Countries' social inclusion of immigrants* is measured by the 2010 MIPEX index (British Council and Migration Policy Group 2011). This measures integration policies in all countries in our data. Based on peer-reviewed information from experts on migration laws, education and discrimination, the index uses information from 148 indicators on laws and policies related to immigrant labor market mobility, educational inclusiveness, anti-discrimination regulations, migrants' political participation, becoming a national, laws regulating family reunion and long term residence. *Labor market protectionism* is measured with the Employment Protection Legislation index, developed by the OECD (2012) for the period 1985-2008. We use the index scores from 2008. The EPL index uses the existence of (a) policies to protect workers against dismissal, (b) requirements for collective dismissals and (c) regulations regarding temporary employment. A higher score corresponds to a more protective labor market. Scores range from 0.85 to 3.11. The extent to which countries' *labor markets are open for immigrants* is measured using the

2010 MIPEX index score on labor market mobility (British Council and Migration Policy Group 2011), which combines information on labor market accessibility for migrants, the extent to which migrants have access to general and targeted labor market support, and the extent to which they share the same rights as workers do. We rely on OECD (2013e) for information on the number of immigrant students in each country of destination, and for information on the percentage of children in schools that have over 25% immigrant children.

Educational systems variables. For most variables related to educational systems, we rely on information from the 2012 PISA program (OECD 2013e; 2013f). Our measure of the math gap between 15-year old immigrant and native students is taken from the PISA 2012 results (OECD 2013e). It ranges from -84 to 2; a higher score means a smaller gap. The OECD (2013f) also provides information about the extent to which educational systems are stratified. Our measure of *vertical stratification* is the standardized PISA index that combines information about the variation of grade levels that 15-year old students attend, the variation of entry age into primary schools, and the percentage of students who repeated one or more grades. *Between school horizontal stratification* is measured by a standardized index combining 5 indicators, i.e. the number of educational tracks available to 15 year olds, the percentage of students in pre-vocational or vocational tracks, the age of first selection, the percentage of students in selective schools, and the percentage of schools that transfer low-achieving students to other schools. The standardized index of *horizontal stratification within schools* refers to the percentage of students in schools that group students by math ability. Our measure of educational systems' *vocational orientation* is drawn from Bol and Van der Werfhorst, 2013), and based on the percentage of students enrolled in upper secondary vocational programs (from the OECD and UNESCO). It ranges from -1,82 to 1,84; a higher score means a more vocationally specific system. In order to capture *vocational specificity*, we followed convention and used the percentage of upper secondary

vocational education that takes place in a dual system. Data were provided by (Bol and Van de Werfhorst 2013). The scale ranges from 0-47.7.

[About here Table 3]

5. Analyses and results

5.1 Descriptive analyses

Table 3 presents estimates of the skills gap between natives, second generation migrants and first generation migrants, while controlling for whether or not the migrants had a parent from the destination country. The estimates are the result of separate OLS regression analyses for each participating country. The plausible values on numeracy allow for direct and unbiased estimation of differences in the numeracy proficiency of migrants and natives in various countries (OECD 2013b). We used the analysis module (Version 3.0.55) of the International Association for the Evaluation of Educational Achievement Analyzer and SPSS Version 21 to estimate cross-national differences in the cognitive ability gap between first and second generation immigrants and natives in various OECD countries.

The table suggests two main conclusions. First, in almost all of the countries under examination, significant differences in numeracy skills exist between first and second generation migrants and non-migrants. In most countries, first generation migrants are less proficient in numeracy than natives are. The gap between natives and first-generation migrants is largest in the Sweden, Finland, Norway, and France, with estimated proficiency gaps of over 50 points. In Ireland, first generation migrants are actually slightly more proficient than natives. The smallest gaps can be observed in former socialist countries like Estonia and Czech Republic, as well as in the UK. In Cyprus and Canada, the differences between first generation migrants and natives are not statistically significant.

In most countries, second generation migrants also perform worse than natives, but the gap is usually smaller than the gap between natives and first generation migrants. Notable exceptions are Cyprus, Ireland, Italy and the United States, where no significant skills disparities can be observed between second generation migrants. In Canada, second generation immigrants outperform natives on the numeracy tests by about 20 points.

The second inference we can make from Figure 1 is that considerable cross-national variation exists, both in the numeracy of natives and migrants, and, as a consequence in the size of the proficiency gap between them. For example, the large gap between first generation immigrants and natives in the Nordic is partly explained by the relatively high numeracy scores of natives in these countries. In fact, immigrants in these countries have about comparable numeracy levels as immigrants in other countries. Figure 1 serves to illustrate this important point. The smallest gaps can be observed in former socialist countries like Estonia and Czech Republic, as well as Cyprus and Ireland. Migrants in Italy, Spain and France are least proficient. However, the gaps between immigrants and non-immigrants are relatively small, because of the relatively low numeracy skills of natives in these countries. In fact, natives in these countries are less numeracy proficient than second generation migrants are in most countries for which we have estimates.

[Figure 1 about here]

[Table 4 here]

5.2 Multilevel analyses of compositional effects

We now turn from comparing countries to explaining observed country differences with characteristics of these countries and thus testing our hypotheses. The hierarchical structure of

the PIAAC data demands using multilevel models to generate accurate standard (Snijders and Bosker 1999).[1] We account for unobserved heterogeneity between ethnic groups with birth country fixed effects dummies. This allows us to exclude the possibility that differences between receiving countries can be attributed to selective migration. Note that the cross-national variation of general cognitive abilities observed in Figure 1 is accounted for by a variance component that estimates the variance at the level of countries. In addition to the random intercept, we allow the effects of being a first or second generation migrant to vary between countries by modelling random slopes for these parameters.[2]

Our results are presented in Table 4. Model 1 estimates skills disparities between natives and first and second generation immigrants in a cross-national design. Overall, first generation immigrants are significantly less proficient in numeracy that natives (*b*=-31.967). Second generation immigrants also are less proficient than natives, but the gap is less wide (*b*=-11.529). As can be seen by the significance of the random components, the skills disparities between natives and first (Ω^2_{fg}=348) and second (Ω^2_{sg}=55) generation immigrants do vary between countries. Turning to the random intercept, it can be seen that, as is usual in these analyses, most of the variance is generated between individuals within countries (Ω^2_i= 2495). Only about 7% of the variance is generated at the country level (Ω^2_c=186).

In Model 2, demographic variables are added. The parameters behave as expected. Numeric proficiency rises with age until the average age of (-2.397/(2*-0.034))= 35.25 and then declines. Furthermore, men are more proficient in numeracy then women (*b*=10.981), and those living with a spouse or partner are more proficient than those living alone (*b*=10.090). The number of children one has had is negatively related to numeracy skills (*b*=-3.371). Finally, people of poor health are much less numerically proficient than those with fair health or better (*b*=-29.415). Controlling for these demographic characteristics does little to change the overall gap between first and second generation migrants. If anything, the

estimates of the fixed effects are somewhat higher than those in Model 1. However, compared to Model 1, the cross-country variance of the effect of coming from a second generation is reduced with about one fifth, from Ω^2_{sg}= 55 to Ω^2_{sg}= 44. In other words, demographic differences in the composition of second generation immigrants account for some 20% of the cross-national variation in the skills difference between second generation immigrants and natives. By and large, this supports Hypothesis 1.

In Model 3, we add educational attainment to the equation. It is positively related to skills (*b*=7.709), and it does contribute to interpretation of the overall effects of being a first or second generation migrant (*b*=-31.953 vs. *b*=-11.712), albeit only marginally. However, accounting for educational attainment does reduce the cross-national variation in the effect of being a first generation immigrant with over 30% to 224, and the random component of being a second generation immigrant with 44%, to Ω^2_{sg}= 24. This is consistent with Hypothesis 2.

Model 4 adds social class variables. Over and above one's own education, parental education and the number of books at home are positively related to numeracy. Accounting for social class further reduces the fixed part of the skills gap. It also further reduces the random components. The random slope for first generation immigrants now has a variance of Ω^2_{fg}= 182; for second generation immigrants, the random slope variance is about Ω^2_{sg}= 17. This is consistent with Hypothesis 3.

Model 5 shows that in addition to the variables in the previous model, unemployed are less numerically skilled (*b*=-7.755), and people with longer work experience are more skilled (*b*=0.424). The interpretation of the overall fixed effects is again small but observable. Variance of the random components also falls further, which by and large supports Hypothesis 4. Note that only accounting for variables related to demographics, educational attainment, social class and employment account for over 50% of the total cross-national

variance of the relationship between being a first generation immigrant and numeracy skills, and about two thirds of the original variance in the slope of second generations.

In Model 6, we add variables related to the specific migration history. As expected, those whose native language is not the language of the destination country perform less well on the numeracy tests (*b*=-11.652), and those who have obtained their highest diploma in a foreign country are also less proficient (*b*=-12.192). Adding these variables seriously reduces the overall skills gap. Compared to the previous model, the overall difference between natives and first generation migrants reduces with 36% to *b*=-18.237; the overall difference between natives and second generation migrants reduces with 35% to *b*=-6.242. These variables also contribute to reducing the cross-national variance of the skills gaps, which is in line with Hypothesis 5.

In Model 7, we control for the unequal distribution of migrants from different countries of birth to different destinations, by including birth country dummies. Adding these dummies does little to interpret the relationship of the other fixed variables with skills. However, accounting for origin differences fully interprets the overall gap between first generation immigrants and natives (*b*=-2.528), and, although random variance remains, it also interprets the better part of the variance of the random slope (of which Ω^2_{fg}= 49 remains).

5.3 Multilevel analyses of contextual effects

We now turn to testing hypotheses on contextual effects on the skills gap. To do so, we start with Model 7 and, in subsequent steps, add country level variables and their interactions with first and second generation immigrants. We can explore whether the immigrant gradients are affected by the country-level characteristic. In general, we would interpret significant fixed cross-level interactions as supporting evidence of the relevance of the macro-level indicator for explaining skills gaps. The random slopes are informative on the extent to which the

inclusion of the cross-level interactions in the models help to explain cross-national differences in the skills disparities between natives and immigrants. The results are presented in Tables 5-7. All the models control for compositional differences and birth country dummies account for all variation related to origin groups. We also add a control for countries' average score on the PIAAC numeracy index, to parsimoniously control the models for variation caused by unobserved country-level variables that explain general country differences in numerical literacy.

Table 5 shows scores on the cultural variables. With hypothesis 6, we expected that skills disparities between natives and first and second generation immigrants would be smaller in countries with a higher ethnic (6a), linguistic (6b) and religious (6c) diversity. The results in Models 8-10 show that these expectations are partly merited. We find some evidence that the gap between second generation immigrants and comparable natives is smaller in more ethnically diverse countries (b=9,161), although it should be noted that the effect is not highly significant. Also, the skills gap between first generation migrants and natives is smaller in countries that are more religiously diverse (b=23,228), which supports hypothesis 6c. Accounting for religious diversity does help to explain cross-national differences in the gap between first generation migrants and natives, but the coefficient of Ω^2_{fg}= 39 remains significant. The skills gap between immigrants and natives remains generally unaffected by the level of linguistic diversity of countries. We also expected that skills disparities between natives and first and second generation immigrants might be smaller in countries in which Protestantism (7a) and Catholicism (7b) are historically less important, and Islam (7c), and other non-Christian religions (7d) are historically more important. Models 11-14 clearly refute these assertions. The first and second generation gradients remain negative and significant, and no significant interactions can be observed.

Moving to institutional explanations for skills disparities in Table 6, we expected that skills gaps between natives and first and second generation immigrants might be smaller in countries that are more democratic (8a). We do indeed find some support for this, in the sense that the skills disparities between first and second generation immigrants disappear after taking this variable into account. However, the random slope remains significant Ω^2_{fg}= 51. Surprisingly, we find some evidence that second generation immigrants fare worse in more democratic societies (*b*=-0,326), but here, the effect is only weakly significant. Model 16 shows that the skills gap between first generation migrants and natives disappears after taking the level of societal integration into account, partly supporting our hypothesis (8b) on the influence of laws and policies to stimulate the integration of immigrants. However, the gap remains significant for second generation immigrants (*b*=13,175). We also expected that skills disparities between natives and first and second generation immigrants would be larger in countries with a stronger labor market protection of workers (9a). Model 17 supports this hypothesis. While the main effects of first and second generation immigrants are non-significant, the negative interaction effects (*b*=-8.194 and *b*=-3.704, respectively) suggest that migrant-native skills disparities are larger in countries with more protective labor markets. Model 18 suggests that only the skills of first generation migrants profit from laws that are specifically targeted at improving the labor market integration, as the second generation skills gradient remains significant (*b*=-10.122) and no interaction effects can be observed. Finally, we expected that skills disparities between natives and first and second generation immigrants would be smaller in countries in which the skills gap between native and immigrant children in secondary education is lower (10a), in countries in which the proportion of immigrant students is higher (10b), and in countries in which a larger part of the student population is in schools with high concentrations of immigrants (10c). The positive interaction effects in Models 19-21 strongly support these expectations.

In Table 7, we focus on general traits of educational systems. We hypothesized that native-migrant skills disparities should be larger in countries in which the educational system is more strongly stratified vertically (11a), horizontally between schools (11b), and horizontally within school (11c). Although we do find a positive interaction effect between ability grouping and first generation migrants (*b*=3.311), this effect is only weakly significant; on the whole we would argue that we find no evidence in support of the hypotheses linking educational stratification to migrant-non-migrant skills gaps. The level of vocational orientation does affect the skills gaps, but not in the hypothesized direction. We hypothesized that skills disparities between natives and first and second generation immigrants should be smaller in countries in which the educational system is more strongly vocationally oriented (12a) and more strongly vocationally specific (12b). In Model 25, it becomes apparent that skills disparities are generally larger in more vocationally oriented systems, as the interactions between vocational orientations and first (*b*=-5.149) and second generation migrant (*b*=-2.617) are strong and negative. This clearly opposes our expectations. Model 26shows that there is no relation between the level of vocational specificity and skills gaps.

Finally, it should be noted from the random coefficients that none of the variables we tested is able to explain away the cross-national differences in skills disparities, as the random slopes, although mostly interpreted to some extent, remain significant in all models. Of all the tested variables, religious diversity (Ω^2_{fg}=39), labor market protectionism (Ω^2_{fg}= 40) , the immigrant-native gap in secondary education (Ω^2_{fg}= 29) and the vocational orientation (Ω^2_{fg}=41) provide the best explanation for cross-national variation in skills gaps between first generation migrants and natives. For second generation migrants, the best explanations for cross-national variation are the level of vocational orientation (Ω^2_{sg}= 8), labor market protectionism (Ω^2_{sg}=10), the percentage of immigrant students (Ω^2_{sg}= 8) and the percentage of students in schools with high concentrations of immigrants. (Ω^2_{sg}=9).

Limitations of the current study

Our study has limitations, that future research needs to address. First, although a number of data collections are being undertaken in order to gather time-varying macro-data, these are not yet sufficiently detailed or comparable to be used in cross-national analyses. Since longitudinal macro-data on the development of countries' institutional, cultural and structural makeup are still missing, we had to resort to well-chosen time-invariant macro-data instead. This is merited because of two reasons. First, while institutional and cultural variation did take place, the countries we study showed no dramatic changes in rank order on the institutional and structural variation. Macro-variation is mostly a slow process. Secondly, we tested the robustness of our model for time-variation empirically. More specifically, we performed robustness checks (See Appendix) to see if our conclusions would change if we would just analyse the older cohort. Our conclusions remain generally the same. Nonetheless, although our study represent the best of what can be done given the state-of-the art of available macro-indicators, our analyses need to be confirmed by future studies that rely on time-variant macro-indicators.

A second limitation is associated with the way we control for countries of birth. By the standard definition, second generation immigrants are born in the country of destination, and we control for unobserved characteristics of their birth countries accordingly. The large majority of their parents are born in a different country, and some of the unobserved characteristics related to their parents' birth countries are transferred by the socialization of their children. As the data do not hold information on parents' birth country, our analyses cannot control for this origin heterogeneity, as is done in the analyses of PISA data (Levels et al. 2008; Dronkers and De Heus 2013). So, although our analyses do capture many of the observable variables that mediate the relationship between parental birth country and skills,

we might still underestimate the variance due to parental origin for second generation immigrants in contrast with the first generation. In order to ensure the validity of our findings in light of this knowledge, we ran alternative analyses without second generation immigrants (Appendix). Results remain generally comparable, but future research and improved data collection might aim to progress on this point.

Conclusions

Understanding how skills disparities between migrants and non-migrants come into being is highly important. Findings from studies on achievement gaps in the US and Canada suggest that ethnic and racial wage disparities can be attributed largely to differences in observed skills (Freyer and Levitt 2004; Ferrer et al. 2006). In the US debate on the black-white skills gap, it has been argued that "reducing the black-white test score gap would do more to promote racial equality than any other strategy…" (Jencks and Phillips 1998). Robust income differences between migrants and natives are also observable in most Western countries, and it is highly plausible that reducing the skills gap is necessary (albeit perhaps not sufficient) for reducing such wage inequalities. This importance notwithstanding, the poor availability of cross-national data with direct measures of skills disparities between migrants and non-migrants has long hampered our understanding of the reasons behind observed skills disparities.

In this contribution, we empirically tested a wide variety of theoretical explanations for observed skills disparities between adult immigrants and non-immigrants. We used cross-national assessment data with direct measurements of numeracy skills from almost 100,000 adults aged 16-65 to show that adult immigrants are indeed less numerically skilled than non-immigrants in almost all of the Western countries we examined. The skills gap between natives and first-generation migrants is largest in the Nordic countries and France, with

estimated proficiency gaps of over 50 points. We observed the smallest gaps in former socialist countries and the UK. In Cyprus and Canada, no differences between first generation migrants and natives exist, and in Ireland, first generation migrants are slightly more proficient than natives. Adult second generation migrants also usually perform worse than natives, but the gap is smaller than the gap between natives and first generation migrants. In Cyprus, Ireland, Italy and the United States, no significant skills disparities can be observed between natives and second generation migrants, and in Canada, second generation immigrants outperform natives.

Compositional differences explain much of the skills gaps between immigrants and natives. Population differences regarding demographic makeup, migrants' educational attainment, their social class, and their employment account for over half of the total cross-national variation of skills disparities between first generation immigrants and natives, and about two thirds of the variation of the gap between natives and second generations. Migration-specific circumstances and birth country-related differences explain the gap even further. But they cannot explain all of the observed skills disparities, and we find that net of these compositional differences, contextual effects are also highly relevant. Controlling for compositional differences and unobserved heterogeneity caused by origin differences, skills gaps are smaller in more religiously diverse countries, in countries where immigrants are more strongly socially integrated, where labor markets are less protected, where education is more strongly suited for educating immigrants, and where the education system is less vocationally oriented. Of all the tested variables, religious diversity, labor market protectionism, the immigrant-native gap and the vocational orientation in secondary education provide the best explanation for cross-national variation in skills gaps between first generation migrants and natives. For second generation migrants, the best explanations are the level of vocational orientation, labor market protectionism, the percentage of immigrant students and

the percentage of students in schools with high concentrations of immigrants. We found no evidence that ethnic diversity, linguistic diversity or the stratification of educational systems of receiving countries are related to the skills gap.

Our findings have two main implications for policies aimed at reducing inequalities between migrants and non-migrants. First, selective immigration policies go a long way in reducing skills gaps in the long run. The importance of compositional differences for explaining differences in the size of the skills gaps between countries, suggests that selecting migrants based on their educational attainment, demographic qualities, and their employability will serve to reduce aggregate inequalities. However, these policies will do little to affect inequalities between natives and migrants that are already part of society. It seems that skills disparities are smaller in countries that are better equipped to deal with (religious) diversity, and in which immigrants are more strongly integrated. These societal properties are however not easily affected by policies. Skills gaps do seem smaller in countries with less protected labor markets. However, education seems paramount. Educational stratification does not seem related to skills disparities between natives and first and second generation immigrants, but our analyses clearly show that the gaps are much smaller in countries in which the skills gap between 15-year old native and immigrant children in secondary education is lower, in countries in which the proportion of immigrant students is higher, and in countries in which a larger part of the student population is in schools with high concentrations of immigrants. In other words, countries in which the educational system is more effective in dealing with the particulars of educating immigrant children, inequalities between adult migrants and non-migrants are much smaller.

Notes

1 The number of origin groups within destination countries is relatively large (N=196), but the groups themselves are mostly very small in size, often not containing more than 5 persons. This implies that the PIAAC data cannot be analyzed using the double comparative design that has become an important design for quantitatively studying cross-national differences in immigrant skills (Van Tubergen, 2006; Levels et al., 2008). Furthermore, the countries of birth of respondents' parents are unknown, making it impossible to determine the ethnic origin of second generation immigrants.

2 Additional analyses (available from authors) show that the slopes and intercepts do not covary. For reasons of parsimony, we have restricted the covariance parameters to zero.

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Table 1: Numbers of natives, first and second generation immigrants in destination countries

	Native born	First generation immigrants	Second generation immigrants	Total
Austria	3769	660	538	4967
Belgium	4210	346	353	4909
Canada	3810	914	504	5228
Czech Republic	5288	195	508	5991
Denmark	5443	1428	293	7164
Estonia	5031	859	1580	7470
Finland	5110	180	114	5404
France	5202	706	835	6743
Germany	3713	638	944	5295
Ireland	4587	970	341	5898
Italy	4096	326	110	4532
Netherlands	4260	419	332	5011
Norway	4019	588	260	4867
Spain	5048	694	139	5881
Sweden	3252	693	449	4394
United Kingdom	5995	747	772	7514
United States	3333	535	350	4218
Total	80008	11255	8563	99826

Source: PIAAC 2013, authors' computations

Table 2: Descriptive statistics

	Minimu	Maximum	Mean	Std.
Numeracy	0	467	269	53
Individual variables				
First generation	0	1	0.113	0.316
Second generation	0	1	0.086	0.280
One parent native born	0	1	0.069	0.253
Male	0	1	0.474	0.499
Living with spouse or partner	0	1	0.608	0.488
Living situation unknown	0	1	0.000	0.016
Number of children	0	25	1.405	1.395
Age	16	65	40.936	14.207
Poor health	0	1	0.036	0.185
Health unknown	0	1	0.001	0.026
Educational attainment	3	22	12.697	3.117
Parents middle educated	0	1	0.339	0.473
Parents higher educated	0	1	0.242	0.428
Parental education unknown	0	1	0.056	0.231
11to25 books	0	1	0.146	0.353
26to100 books	0	1	0.308	0.461
101to200 books	0	1	0.174	0.379
201to500 books	0	1	0.145	0.352
More than 500 books	0	1	0.080	0.272
Number of books unknown	0	1	0.006	0.078
Unemployed	0	1	0.058	0.234
Total work experience	0	55	17.977	13.559
Non-native mother tongue	0	1	0.093	0.290
Native language unknown	0	1	0.002	0.046
Foreign highest credential	0	1	0.021	0.144
Country variables				
Ethnic diversity	0.06	0.71	0.244	0.200
Language diversity	0.03	0.58	0.247	0.183
Religious diversity	0.16	0.82	0.450	0.209
Percentage Protestants	0.10	97.80	36.229	35.661
Percentage Catholics	0.10	96.90	42.275	36.765
Percentage Muslims	0.00	3.00	0.562	0.812
Percentage Other religions	1.80	69.40	20.934	19.861
Democratic openness	26.00	45.50	35.066	5.945
Societal inclusion of immigrants	41.00	83.00	58.379	10.350
Labor market protectionism	0.85	3.11	2.149	0.662
Labor market inclusion of immigrants	39.00	100.00	66.807	14.669
Immigrant-native math gap at 15	-84.00	2.00	-36.447	23.799
Percentage of immigrant students	3.00	29.00	11.636	6.128
Percentage in black schools	1.00	43.00	14.216	10.588
Vertical stratification	-0.89	1.01	0.073	0.585
Horizontal stratification between schools	-0.98	2.23	-0.117	0.916
Horizontal stratification within schools	-1.55	1.82	-0.023	1.092
Vocational orientation	-1.82	1.84	0.368	0.988
Vocational specificity	0.00	47.70	16.116	16.729
Average score on PIAAC	243.00	285.00	268.603	12.487

Source: PIAAC 2013, authors' computations

Table 3: OLS estimation of the skills disparities between natives and first and second generation immigrants in 18 countries of destination

	Austria	Belgium	Canada	Cyprus	Czech Republic	Denmark	Estonia	Finland	France
Natives	283.997 ***	283.583 ***	259.763 ***	263.025 ***	277.657 ***	284.193 ***	276.699 ***	287.433 ***	263.055 ***
	0.768	*0.772*	*0.881*	*0.768*	*0.591*	*0.678*	*0.628*	*0.680*	*0.754*
First generation immigrants	-35.558 ***	-45.626 ***	-3.338	-0.703	-22.013 ***	-43.765 ***	-18.678 ***	-60.266 ***	-52.837 ***
	2.004	*2.833*	*2.009*	*2.866*	*3.229*	*1.517*	*1.662*	*3.790*	*2.197*
Second generation immigrants	-23.651 ***	-33.142 ***	19.098 ***	-5.771	-20.179 ***	-26.793 ***	-11.677 ***	-52.664 ***	-13.865 ***
	3.490	*4.529*	*3.782*	*6.950*	*3.962*	*4.408*	*1.734*	*10.844*	*2.826*
One native born parent	19.882 ***	30.226 ***	-0.558	12.538 *	11.535 **	30.784 ***	1.140	48.581 ***	14.191 ***
	3.847	*5.033*	*4.416*	*6.007*	*4.189*	*4.150*	*2.038*	*10.559*	*3.398*
Adjusted R^2	0.061	0.054	0.011	0.001	0.012	0.105	0.022	0.045	0.079
N	4967	4909	5228	4340	5991	7164	7470	5404	6743

	Germany	Ireland	Italy	Netherlands	Norway	Spain	Sweden	United Kingdom	United States
Natives	281.159 ***	256.296 ***	252.424 ***	285.694 ***	288.680 ***	246.866 ***	291.276 ***	270.542 ***	258.114 ***
	0.819	*0.782*	*0.777*	*0.729*	*0.800*	*0.732*	*0.905*	*0.630*	*0.974*
First generation immigrants	-37.744 ***	5.811 **	-24.340 ***	-47.886 ***	-53.324 ***	-33.758 ***	-61.744 ***	-22.058 ***	-25.820 ***
	2.156	*1.976*	*3.048*	*2.494*	*2.287*	*2.191*	*2.177*	*1.924*	*2.639*
Second generation immigrants	-11.436 ***	7.107	-13.895	-15.472 ***	-38.512 ***	-19.168 **	-8.291 *	-14.507 ***	0.091
	2.683	*4.696*	*7.755*	*4.203*	*5.451*	*6.125*	*3.992*	*2.826*	*4.141*
One native born parent	10.611 **	0.657	28.670 ***	18.235 ***	38.269 ***	17.575 **	7.277	15.165 ***	-0.247
	3.047	*4.147*	*6.831*	*4.498*	*5.447*	*5.385*	*4.390*	*3.129*	*5.149*
Adjusted R^2	0.054	0.002	0.015	0.068	0.101	0.039	0.156	0.018	0.022
N	5295	5898	4532	5011	4867	5881	4394	7514	4218

Notes: presented estimates are country-specific OLS regression coefficients , standard errors in italic
*** p <.000 ** p<.001 * p < .05
Source: PIAAC 2013, authors' computations

Table 4: Multilevel regression of explanatory variables on numeracy

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Fixed parameters														
Intercept	272.806	***	233.728	***	188.960	***	177.473	***	185.479	***	185.285	***	137.626	***
	3.221		*3.450*		*3.359*		*2.889*		*2.842*		*2.833*		*6.940*	
First generation	-31.967	***	-33.232	***	-31.953	***	-29.712	***	-28.459	***	-18.237	***	-2.528	
	4.436		*4.266*		*3.560*		*3.216*		*3.117*		*2.818*		*1.985*	
Second generation	-11.529	***	-12.262	***	-11.712	***	-10.038	***	-9.588	***	-6.242	***	-5.832	***
	2.004		*1.830*		*1.421*		*1.272*		*1.248*		*1.248*		*1.237*	
One native born parent	12.291	***	12.951	***	11.034	***	8.107	***	7.685	***	4.743	***	3.476	***
	0.952		*0.915*		*0.817*		*0.796*		*0.793*		*0.806*		*0.805*	
Male			10.981	***	12.906	***	13.207	***	11.859	***	11.888	***	12.032	***
			0.306		*0.274*		*0.266*		*0.272*		*0.272*		*0.270*	
Living with partner, spouse			10.090	***	6.163	***	6.436	***	5.877	***	5.967	***	5.933	***
			0.364		*0.326*		*0.317*		*0.316*		*0.316*		*0.314*	
Marital state unknown			-10.102		-15.581		-3.281		-3.686		-0.596		0.378	
			9.422		*8.421*		*8.192*		*8.164*		*8.153*		*8.097*	
Number of children			-3.371	***	-0.662	***	-0.396	**	-0.231		-0.205		-0.091	
			0.135		*0.122*		*0.119*		*0.118*		*0.118*		*0.118*	
Age			2.397	***	-0.556	***	-0.193	**	-0.511	***	-0.476	***	-0.430	***
			0.073		*0.068*		*0.067*		*0.068*		*0.068*		*0.067*	
Age^2			-0.034	***	0.000		-0.002		-0.002		-0.003	***	-0.003	***
			0.001		*0.001*		*0.001*		*0.001*		*0.001*		*0.001*	
Good, very good and excellent health			-		-		-		-		-		-	
Poort health			-29.415	***	-17.134	***	-15.960	***	-14.277	***	-14.167	***	-14.080	***
			0.832		*0.748*		*0.727*		*0.728*		*0.727*		*0.722*	
Educational attainment					7.709	***	6.198	***	6.166	***	6.172	***	6.123	***
					0.049		*0.051*		*0.051*		*0.051*		*0.051*	
Parents lower educated							-		-		-		-	
Parents middle educated							3.420	***	3.399	***	3.278	***	3.041	***
							0.368		*0.367*		*0.366*		*0.364*	
Parents higher educated							9.742	***	10.025	***	9.931	***	9.945	***
							0.439		*0.438*		*0.437*		*0.435*	
10 books or less at home							-		-		-		-	
11 to 25 books at home							7.682	***	7.175	***	6.972	***	6.552	***
							0.501		*0.500*		*0.499*		*0.496*	
26 to 100 books at home							15.820	***	15.201	***	14.944	***	14.181	***
							0.456		*0.455*		*0.454*		*0.452*	
101 to 200 books at home							22.733	***	22.176	***	21.871	***	20.902	***
							0.524		*0.523*		*0.522*		*0.520*	
201 to 500 books at home							27.682	***	27.250	***	26.987	***	25.812	***
							0.566		*0.565*		*0.564*		*0.562*	
more than 500 books at home							27.975	***	27.673	***	27.430	***	26.023	***
							0.665		*0.663*		*0.662*		*0.660*	
Unemployed (vs employed)									-7.755	***	-7.730	***	-7.295	***
									0.572		*0.571*		*0.567*	
Total life work experience									0.424	***	0.408	***	0.380	***
									0.019		*0.019*		*0.019*	
Non-native mother tongue											-11.652	***	-7.704	***
											0.693		*0.724*	
Foreign highest credential											-12.192	***	-10.795	***
											1.174		*1.173*	
Origin country dummies included?	No		No		No		No		No		No		Yes[a]	

Table 4: Multilevel regression of explanatory variables on numeracy (continued)

Random parameters													
Individuals	2494.66	***	2307.60	***	1843.31	***	1738.71	***	1726.61	***	1719.25	***	1692.55	***
	11.17		*10.33*		*8.25*		*7.79*		*7.73*		*7.70*		*7.58*	
Countries	186.22	**	181.63	**	175.54	**	122.03	**	115.57	**	114.74	**	54.11	*
	62.27		*60.73*		*58.67*		*40.82*		*38.67*		*38.39*		*22.41*	
First generation	348.20	**	322.06	**	223.71	**	181.96	**	170.58	**	134.18	**	49.26	*
	117.97		*109.16*		*76.14*		*62.23*		*58.44*		*46.29*		*22.67*	
Second generation	54.89	**	44.22	*	23.73	*	17.39	*	16.40	*	15.86	*	15.48	*
	21.00		*17.17*		*9.77*		*7.73*		*7.39*		*7.22*		*7.01*	
Model information														
$N_{countries}$	18		18		18		18		18		18		18	
$N_{individuals}$	99826		99826		99826		99826		99826		99826		99826	
-2*LL*	1064347		1056565		1034134		1028291		1027591		1027119		1025526	

Notes: presented estimates are multilevel regression coefficients, standard errors in italic

*** p <.000; ** p<.001; * p < .05; [a] coefficients of origin fixed effects in Appendix

Source: PIAAC 2013, authors' computations

Table 5: Random slope multilevel regression of cultural macro variables on numeracy, including cross-level interactions with first and second generation immigrants

	Model 8	*Model 9*	*Model10*	*Model 11*	*Model 12*	*Model 13*	*Model 14*
Parameter	Ethnic diversity	Language diversity	Religious diversity	Percentage Protestants	Percentage Catholics	Percentage Muslims	Percentage other religions
Intercept	106.437 *	129.660 **	127.667 **	84.383	112.388 †	118.607 *	121.175 *
	44.528	*41.245*	*47.315*	*50.883*	*53.949*	*45.281*	*43.456*
First generation main effect	-9.445 *	-8.768 *	-18.579 ***	-5.965 †	-10.101 **	-7.324 *	-9.701 **
	3.347	*3.575*	*4.175*	*3.026*	*3.312*	*2.658*	*3.111*
Second generation main effect	-10.082 ***	-9.399 ***	-11.134 ***	-7.049 ***	-8.238 ***	-7.595 ***	-8.338 ***
	1.656	*1.892*	*2.546*	*1.676*	*1.792*	*1.478*	*1.745*
Country variable main effect	16.105	20.546 †	-1.219	-0.104	0.033	2.848	0.140
	10.478	*10.820*	*10.011*	*0.072*	*0.068*	*2.706*	*0.108*
Country variable*first generation	4.627	1.984	23.228 *	-0.063	0.042	-1.621	0.078
	10.805	*11.753*	*8.369*	*0.060*	*0.058*	*2.761*	*0.113*
Country variable*second generation	9.161 †	6.372	7.212	-0.020	0.011	-0.302	0.026
	4.733	*5.701*	*4.814*	*0.032*	*0.031*	*1.373*	*0.058*
Controls							
Individual predictors [a]	Y	Y	Y	Y	Y	Y	Y
Average PIAAC in countries	Y	Y	Y	Y	Y	Y	Y
Origin fixed effects	Y	Y	Y	Y	Y	Y	Y
Variance components							
Individuals	1689.96 ***	1689.96 ***	1689.94 ***	1689.94 ***	1689.93 ***	1689.94 ***	1689.95 ***
	7.74	*7.74*	*7.74*	*7.74*	*7.74*	*7.74*	*7.74*
Countries	53.58 *	50.18 *	64.31 *	53.64 *	62.62 *	59.25 *	55.88 *
	22.89	*21.64*	*26.37*	*22.64*	*26.00*	*25.40*	*23.98*
Random slope first generation	60.09 *	59.68 *	39.48 *	56.59 *	59.98 *	61.74 *	58.88 *
	26.35	*26.14*	*18.43*	*25.34*	*26.63*	*27.14*	*25.85*
Random slope second generation	11.04 *	13.41 *	12.83 *	14.86 *	15.03 *	15.06 *	15.14 *
	5.62	*6.45*	*6.14*	*6.83*	*6.94*	*6.98*	*6.92*

Notes: presented estimates are multilevel regression coefficients, standard errors in italic

*** p <.000; ** p<.001; * p < .05 ; † p < .10 [a] Individual composition with regards to having one parent from destination country, gender, marital state, educational attainment, parental educational attainment, number of books at home, health, parity, employment status, work experience, proficiency in destination countries' language, and whether or not the educational credential was obtained abroad. Coefficients available on request. Source: PIAAC 2013, authors' computations

Table 6: Random slope multilevel regression of institutional macro variables on numeracy, including cross-level interactions with first and second generation immigrants

	Model 15	*Model 16*	*Model 17*	*Model 18*	*Model 19*	*Model 20*	*Model 21*
Parameter	Level of democratic openness	Societal inclusion of immigrants	Protectionist labor market institutions	Labor market accessibility to immigrants	Immigrant-native math gap at 15	Percentage of immigrant students	Percentage in schools with high number of immigrants
Intercept	124.139 *	136.322 **	128.871 **	129.443 **	145.377 *	138.987 *	127.153 *
	49.172	*42.508*	*42.933*	*44.308*	*58.624*	*55.306*	*55.975*
First generation main effect	12.440	8.001	9.068	-5.895	2.562	-15.758 **	-12.965 **
	12.326	*11.711*	*6.082*	*9.883*	*3.163*	*4.777*	*3.680*
Second generation main effect	3.684	-13.175 *	0.142	-10.122 †	-3.504 †	-13.180 ***	-11.531 ***
	5.840	*5.795*	*3.179*	*4.957*	*1.905*	*2.162*	*1.795*
Country variable main effect	0.080	-0.248	6.811 *	-0.147	-0.151	-0.541	-0.166
	0.468	*0.197*	*3.074*	*0.140*	*0.113*	*0.385*	*0.223*
Country variable*first generation	-0.586	-0.272	-8.104 **	-0.035	0.281 **	0.677 †	0.358 †
	0.345	*0.193*	*2.721*	*0.142*	*0.073*	*0.356*	*0.202*
Country variable*second generation	-0.326 †	0.092	-3.704 *	0.035	0.115 *	0.449 **	0.249 *
	0.163	*0.097*	*1.410*	*0.071*	*0.043*	*0.146*	*0.086*
Controls							
Individual predictors [a]	Y	Y	Y	Y	Y	Y	Y
Average PIAAC in countries	Y	Y	Y	Y	Y	Y	Y
Origin fixed effects	Y	Y	Y	Y	Y	Y	Y
Variance components							
Individuals	1689.93 ***	1689.97 ***	1689.89 ***	1689.93 ***	1683.01 ***	1683.00 ***	1682.99 ***
	7.74	*7.74*	*7.74*	*7.74*	*7.99*	*7.99*	*7.99*
Countries	64.95 *	53.95 *	56.23 *	60.07 *	70.06 *	68.55 *	73.43 *
	26.89	*22.60*	*23.56*	*25.01* *	*29.24*	*29.20*	*30.99*
Random slope first generation	51.35 *	50.43 *	40.21 *	62.12 *	29.26 †	54.80 *	55.66 *
	23.38	*23.24*	*19.74*	*27.32*	*16.45*	*25.87*	*26.15*
Random slope second generation	11.54 *	13.71 *	9.95 *	14.65 *	10.46 *	8.39 †	9.02 †
	5.57	*6.62*	*4.85*	*6.91*	*5.23*	*4.79*	*5.02*

Notes: presented estimates are multilevel regression coefficients, standard errors in italic

*** p <.000; ** p<.001; * p < .05 ; † p < .10 [a] Individual composition with regards to having one parent from destination country, gender, marital state, educational attainment, parental educational attainment, number of books at home, health, parity, employment status, work experience, proficiency in destination countries' language, and whether or not the educational credential was obtained abroad. Coefficients available on request. Source: PIAAC 2013, authors' computations

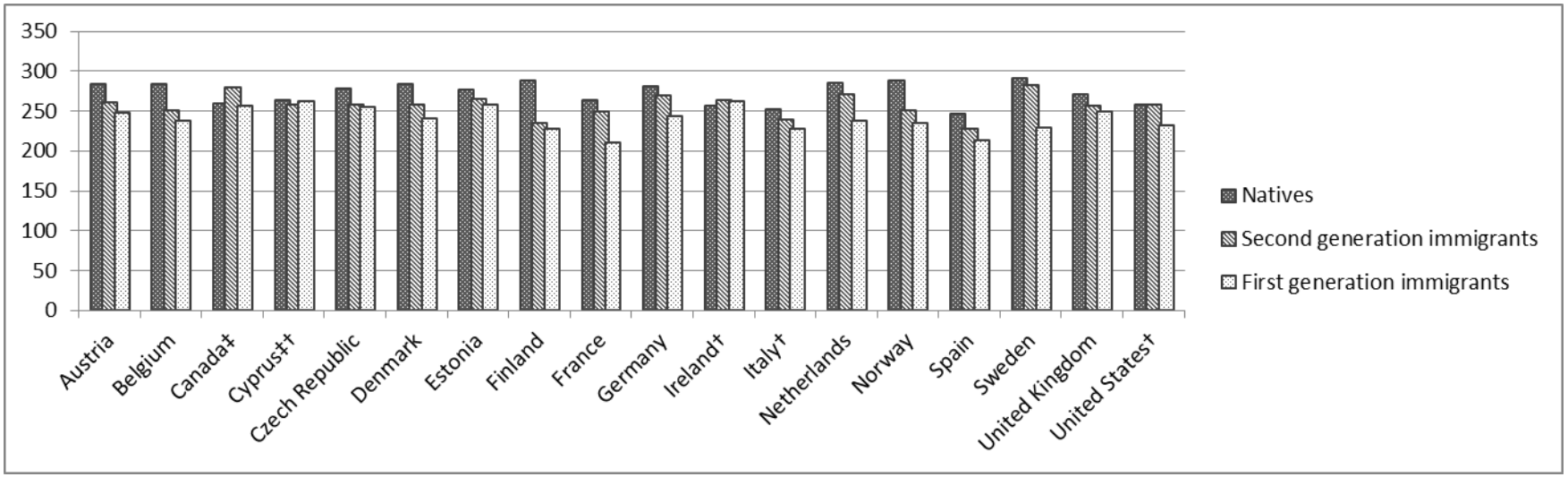
Table 7: Random slope multilevel regression of educational system variables on numeracy, including cross-level interactions with first and second generation immigrants

	Model 22	*Model 23*	*Model 24*	*Model 25*	*Model 26*
Parameter	Vertical stratification	Horizontal stratification between schools	Horizontal stratification within schools	Vocational orientation	Vocational specificity
Intercept	126.362 *	145.559 **	159.000 **	184.813 **	145.596 **
	49.333	*43.695*	*42.114*	*52.675*	*49.696*
First generation main effect	-8.584 **	-7.949 **	-8.688 **	-6.511 **	-9.234 **
	2.151	*2.076*	*2.069*	*1.965*	*2.851*
Second generation main effect	-7.986 ***	-7.784 ***	-7.734 ***	-6.783 ***	-6.848 ***
	1.214	*1.234*	*1.196*	*1.068*	*1.594*
Country variable main effect	-0.114	2.810	-4.820 *	5.354 *	0.099
	3.937	*2.318*	*1.841*	*2.512*	*0.146*
Country variable*first generation	3.532	2.523	3.311 †	-5.149 *	0.069
	3.539	*2.275*	*1.896*	*1.862*	*0.130*
Country variable*second generation	2.013	-0.193	1.166	-2.617 **	-0.057
	1.800	*1.155*	*0.971*	*0.817*	*0.064*
Controls					
Individual predictors [a]	Y	Y	Y	Y	Y
Average PIAAC in countries	Y	Y	Y	Y	Y
Origin fixed effects	Y	Y	Y	Y	Y
Variance components					
Individuals	1689.94 ***	1689.97 ***	1689.93 ***	1689.94 ***	1689.94 ***
	7.74	*7.74*	*7.74*	*7.74*	*7.74*
Countries	63.53 *	54.69 *	47.08 *	54.09 *	61.94 *
	26.51	*23.13*	*20.35*	*23.38*	*25.75*
Random slope first generation	57.61 *	52.88 *	53.38 *	40.90 *	59.48 *
	25.87	*24.27*	*23.96*	*20.29*	*26.33*
Random slope second generation	13.61 *	15.03 *	13.54 *	7.64 †	14.25 *
	6.49	*6.97*	*6.40*	*4.19*	*6.65*

Notes: presented estimates are multilevel regression coefficients, standard errors in italic

*** p <.000; ** p<.001; * p < .05 ; † p < .10 [a] Individual composition with regards to having one parent from destination country, gender, marital state, educational attainment, parental educational attainment, number of books at home, health, parity, employment status, work experience, proficiency in destination countries' language, and whether or not the educational credential was obtained abroad. Coefficients available on request. Source: PIAAC 2013, authors' computations

Figure 1 Numeracy skills disparities between natives and first and second generation immigrants in 18 OECD countries



Notes: ‡differences between natives and first generation immigrants not significant; †differences between natives and second generation immigrants not significant. Source: PIAAC, own computations.