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The Value of Smarter Teachers: International Evidence on Teacher Cognitive Skills and Student Performance

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ABSTRACT

International differences in teacher quality are commonly hypothesized to be a key determinant of the large international student performance gaps, but lack of consistent quality measures has precluded testing this. Using unique assessment data, we construct country-level measures of teacher cognitive skills. We find substantial differences in teacher cognitive skills across countries, and these are strongly related to student performance. Results are supported by fixed-effects estimation exploiting within-country between-subject variation in teacher skills. Observed country variations in teacher cognitive skills are significantly related to differences in women's access to high-skilled occupations outside teaching and to salary premiums for teachers.

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1. Overview

Numerous international assessment tests have shown that the cognitive skills of students differ greatly across developed countries. These differences take on considerable significance because the cognitive skills of the population have been shown to be an important driver of a country’s long-run economic growth (e.g., Hanushek and Woessmann (2015)). But less considered is how the overall skills of a nation feed back into the skills of teachers. This paper investigates whether differences in cognitive skills of teachers across developed countries can help explain international differences in student performance.

Public discussions have emphasized the importance of teacher skills for improving student achievement. For example, a widely-cited McKinsey report on international achievement concludes that “the quality of an educational system cannot exceed the quality of its teachers” and then goes on to assert that “the top-performing systems we studied recruit their teachers from the top third of each cohort graduate from their school system.” (Barber and Mourshed (2007), p. 16) In a follow-on report, Auguste, Kihn, and Miller (2010) note that the school systems in Singapore, Finland, and South Korea “recruit 100% of their teacher corps from the top third of the academic cohort,” which stands in stark contrast to the U.S. where “23% of new teachers come from the top third.” (p. 5) They then recommend a “top third+ strategy” for the U.S. educational system. We investigate the implications for student achievement of focusing policy attention on the cognitive skills of potential teachers.

Our analysis exploits unique data from the Programme for the International Assessment of Adult Competencies (PIAAC), which allow for the first time quantifying differences in teacher skills in numeracy and literacy across countries. These differences in teacher cognitive skills reflect, as we discuss below, both the overall level of cognitive skills of each country’s population and where teachers are drawn from in each country’s skill distribution.

Teacher cognitive skills differ widely internationally. For example, average numeracy and literacy skills of teachers in countries with the lowest measured skills (Italy and Russia) are similar to the skills of employed adults with just vocational education in Canada.[1] In contrast, the skills of teachers in countries with the highest measured skills (Japan and Finland) exceed the skills of adults with a master’s or PhD degree in Canada.

Combining this information on teacher quality with student achievement, we find that differences in teacher cognitive skills are a significant determinant of international differences in student performance. Specifically, we use country-level measures of subject-specific teacher skills along with

[1] We use Canada as a benchmark for the international skill comparison because the Canadian sample is by far the largest among all countries surveyed in PIAAC, allowing for a fine disaggregation of individuals by educational degree.

rich student-level micro data from the Programme for International Student Assessment (PISA) to estimate the impact of teacher cognitive skills on student performance in math and reading across 23 developed economies.

We pursue two different strategies to investigate the impact of teacher cognitive skills. First, we estimate OLS models with extensive sets of control variables, including student and family background, general and subject-specific school inputs, institutional features of the school systems, and cross-country differences in the stage of economic development. Controlling for subject-specific parent cognitive skills, which can be approximated with the PIAAC data, allows us to account for the persistence of skills across generations and to distinguish between smart parents and smart teachers. Nevertheless, as countries may differ from one another in other, hard-to-observe ways, omitted-variable bias is an important concern in the OLS estimation.

To circumvent bias due to unobserved heterogeneity, our second approach exploits the performance of students and teachers across two different subjects. This allows us to identify the effect of teacher cognitive skills using only variation between subjects, which directly controls for unobserved student-specific characteristics that similarly affect math and reading performance (e.g., innate ability or family background). At the same time, this within-student between-subject model also controls for all differences across countries that are not subject-specific, such as general education preferences or the nature of teacher labor markets.

The results indicate a robust impact of teacher cognitive skills on student performance. In the OLS estimation with the full set of controls, we find that a one standard deviation (SD) increase in teacher cognitive skills is associated with about 0.1 SD higher student performance in both math and reading. The between-subject estimates are slightly smaller (0.07 SD), which is consistent with an upward bias due to omitted variables in the OLS estimation but also consistent with an increased impact of measurement error in the teacher cognitive skills measures.

Our results are robust to different ways of controlling for the general skill level of adults in a country. Moreover, adding coarse measures of teachers' subject-specific pedagogical skills does not change the teacher-skills coefficients.

We also provide novel evidence about the determinants of differences in teacher cognitive skills across countries. Existing studies have shown a strong decline in teacher cognitive skills in the U.S. during the past decades. This decline has been explained with improving alternative opportunities for women in the labor market (Bacolod (2007)). Using the PIAAC data, we generalize the U.S. evidence to a broader set of countries, exploiting within-country changes across birth cohorts in the proportion of females working in high-skilled occupations. By observing multiple countries, we can more readily assess how female labor-market opportunities interact with teacher quality.

A higher share of women working in high-skilled occupations other than teaching is significantly related to a lower cognitive skill level of teachers, particularly of female teachers. This suggests that international differences in women's opportunities to enter (other) high-skilled occupations provide part of the explanation for the observed variation in teacher cognitive skills across countries.

The PIAAC micro data also permit looking explicitly at whether teachers in each country tend to be paid above or below what would be expected (given their gender, work experience, and cognitive skills). We find considerable variation in the premiums paid to teachers, with Ireland paying teachers considerably above market and the United States playing teachers considerably below market. Further, these country-specific premiums are directly related to the cognitive skills of teachers.

The paper proceeds as follows. Section 2 considers relevant prior research. Section 3 introduces the datasets and describes the computation of our measures of teacher and parent cognitive skills. Section 4 presents our identification strategies. Section 5 reports results on the impact of teacher cognitive skills on student performance in math and reading and provides robustness checks. Section 6 analyzes possible determinants of the cross-country differences in teacher cognitive skills, focusing on women's access to alternative high-skilled occupations and on teacher salaries. Section 7 considers policy trade-offs more directly, and Section 8 concludes.

2. Relevant Literature

Large numbers of studies investigate the determinants of student achievement within individual countries.[2] The clearest conclusion from this "educational production function" literature is that achievement reflects a combination of family background factors, school inputs, and institutional factors. However, these studies are better suited for within-country analysis and are not structured to explain differences in achievement across countries. In particular, all of these studies consider the impacts of school characteristics within a country's overall institutional structure – such as the amount of local decision-making authority at schools, the requirements for teacher certification, and the overall salary levels for teachers – and do not necessarily give an accurate picture of their impact under differing institutional structures.

A parallel literature on international differences in achievement builds on the comparative outcome data in existing international assessments (see Hanushek and Woessmann (2011)). One of the clearest explanatory factors from these international studies has been the importance of family background in explaining student achievement.[3] In contrast, specific conclusions about the impact of

[2] See, for example, the reviews in Hanushek (2002) and Glewwe et al. (2013).

[3] For example, see the review in Björklund and Salvanes (2011) or the analysis in Woessmann et al. (2009).

school resources have been much more limited. There has, for example, been considerable research on overall educational expenditures and on resource inputs such as class size, but the existing research has not identified these as being strong drivers of international differences in achievement.[4] The lack of findings on resources has led to a different set of international studies that focuses on the effects of institutional features of the school systems such as the degree of local decision making, the use of accountability systems, and direct rewards for personnel in the schools.[5]

The most convincing within-country studies show that teacher impacts on student reading and math performance differ greatly and that there is huge variation in teacher value-added (Hanushek and Rivkin (2012)).[6] But these results have not been very useful in addressing international achievement differences. First, the studies focus almost exclusively on the experience in the United States. Second, they have not reliably described any underlying determinants of teacher value-added – and in particular any determinants that can be consistently measured across countries.

Further, within-country studies (going beyond just the value-added studies) have generally shown that the common measures of teacher differences – education, experience levels, and sources and nature of teacher preparation – are not consistently related to student achievement, raising questions about the reliance on these as indicators of teacher quality in international studies. In a closely related set of within-country and international studies, researchers have used measures of teacher salaries as proxies for teacher quality, implicitly assuming that higher-paid teachers have higher skills or are more motivated. However, the within-country evidence again indicates that teacher salaries are a weak measure of teacher quality (see the overview by Hanushek and Rivkin (2006)).[7]

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[4] See Hanushek (2006) for a review of the effects of school resources and the international evidence in Hanushek and Woessmann (2011).

[5] For example, positive impacts have been estimated for school autonomy (especially in developed countries; cf. Hanushek, Link, and Woessmann (2013)) and for increased competition reflected in the share of privately operated schools (West and Woessmann (2010)). The range of institutional studies is assessed in Hanushek and Woessmann (2011).

[6] For a sample of the research into teacher effectiveness, see Rockoff (2004), Rivkin, Hanushek, and Kain (2005), Kane, Rockoff, and Staiger (2008), Chetty, Friedman, and Rockoff (2014), and the summaries in Hanushek and Rivkin (2010). As an indication of the magnitudes involved, Rivkin, Hanushek, and Kain (2005) estimate that the effect of a costly ten student reduction in class size is smaller than the benefit of moving up the teacher quality distribution by one standard deviation.

[7] Challenging this general conclusion, Britton and Propper (2016) find positive effects of relative teacher pay on school productivity, exploiting regional variation in teachers' relative wages. Loeb and Page (2000) similarly relate regional variation in relative teacher wages to rates of educational attainment but also lack direct measures of teacher quality. We explore the country-level relationship between teacher wage premiums and teacher cognitive skills in Section 6.

One general strand of research, largely focused on entry and exit from teaching, investigates the importance of alternative job opportunities for teacher quality.[8] Although these studies look just within the U.S., they suggest feasible approaches to international comparisons. Nagler, Piopiunik, and West (2015) exploit business cycle conditions at career start as a source of exogenous variation in the outside options of potential teachers, finding that teachers entering the profession during recessions are significantly more effective in raising student test scores than teachers who entered the profession during non-recessionary periods. Other work, which forms an important motivation for our study, focuses on the cognitive skills of teachers over time – a dimension of teacher quality that had received some support in prior estimation of educational production functions.[9] Bacolod (2007) documents a decrease in the academic quality (as measured by standardized test scores and undergraduate institution selectivity) of female teachers in the U.S. during the recent decades that coincided with the expansion of job opportunities for women. Corcoran, Evans, and Schwab (2004a, 2004b) show that the decline in measured teacher skills over the same period has been concentrated in the upper portion of the achievement distribution. Both suggest that women's opportunities to enter high-skilled occupations outside teaching are one determinant of the skill level of teachers in a country.

Two kinds of international studies have expanded on the within-country analysis of teacher effectiveness. Dolton and Marcenaro-Gutierrez (2011) construct a country panel with international student assessment tests in the period 1995–2006, showing that teacher salaries – both measured in absolute terms and relative to the average wages in a country – are positively associated with student performance even after controlling for country fixed effects. Related analysis has looked at the use of performance pay, and the international research has tended to find that pay incentives are effective in improving performance.[10] But these incentives, while suggestive from a policy perspective, do not constitute direct measures of differences among teachers.

[8] Early estimation of outside opportunities on teacher transitions is found in Dolton and van der Klaauw (1999), although the key issues were suggested long before in Kershaw and McKean (1962). An early investigation of how preparation for and entry into teaching are related to cognitive skills is found in Hanushek and Pace (1995).

[9] While not completely consistent, previous research has found cognitive skill of teachers (as measured by scores on achievement tests) to be perhaps the strongest proxy of an underlying dimension of teacher quality (see Eide, Goldhaber, and Brewer (2004); Hanushek and Rivkin (2006), and the summary in Hanushek (2003)). In two unique studies for developing countries, Metzler and Woessmann (2012) and Bietenbeck, Piopiunik, and Wiederhold (2015) show the relevance of teacher subject knowledge using individual-level teacher data. See also Harbison and Hanushek (1992) for the impact of measured teacher math skills on achievement in rural Brazil.

[10] For a review on teacher performance pay, see Leigh (2013). See also the international investigation of performance pay in Woessmann (2011).

3. International Comparative Data

A unique feature of this study is the application of new and consistent international data on cognitive skills of teachers to assess the role of cross-country differences in teacher cognitive skills in explaining student outcomes.

3.1 Teacher Cognitive Skills

Measured cognitive skills of teachers are derived from the Programme for the International Assessment of Adult Competencies (PIAAC) survey. Developed by the Organisation for Economic Co-operation and Development (OECD) and collected in 2011/2012, PIAAC tested various cognitive skill domains of more than 160,000 adults in 24 mostly OECD countries that represent almost 75 percent of the world economy.[11] The target population of PIAAC was the non-institutionalized population aged 16-65 years, and samples included at least 5,000 participants in each country.

The survey was administered by trained interviewers either in the respondent's home or in a location agreed upon between the respondent and interviewer. The standard survey mode was to answer questions on a computer, but respondents without computer experience could opt for a pencil-and-paper interview.[12] The survey provides rich information about demographic, educational, and occupational characteristics for each respondent.

After providing the background information, respondents took a battery of cognitive assessments. PIAAC assessments are designed to be valid cross-culturally and cross-nationally and to provide internationally comparable measures of adult skills. The assessments measure key cognitive and workplace skills needed to advance in the job and to participate in society in three domains: numeracy, literacy, and problem solving in technology-rich environments.[13] The test questions are often framed as real-world problems, such as maintaining a driver's logbook (numeracy domain) or selecting key

[11] We use 23 countries in our analysis: Australia, Austria, Belgium (Flanders), Canada, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), and the United States. Cyprus, while participating in PIAAC, did not participate in PISA. According to OECD (2013), data for the Russian Federation are preliminary, may still be subject to change, and are not representative of the entire Russian population because they do not include the population of the Moscow municipal area. Our results are not sensitive to dropping the Russian Federation from the sample.

[12] On average across countries, 77.5 percent of assessment participants took the computer-based assessment and 22.5 percent took the paper-based assessment. A field test suggests no impact of assessment mode (OECD 2013).

[13] PIAAC tests were conducted in the official language of the country of residence. In some countries, the assessment was also conducted in widely spoken minority or regional languages. Respondents could take as much time as needed to complete the assessment. *Literacy* is defined as the "ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential," and *numeracy* is 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" (see OECD (2013) for more details). Because of our focus on students' reading and math performance, we do not use the PIAAC skills in the domain "problem solving in technology-rich environments." Moreover, four countries surveyed in PIAAC (Cyprus, France, Italy, and Spain) did not administer tests in this optional skill domain.

information from a bibliographic search (literacy domain). PIAAC measures each of the skill domains on a 500-point scale. Inspection of sample items indicates that the skills tested in PIAAC reflect knowledge and competencies that should have been acquired by the end of compulsory schooling, but do not reflect more advanced competencies (e.g., solving differential equations) that are acquired only at college.

We are particularly interested in the skills of teachers in each country. In the Public Use File, information on occupation is available only at the two-digit code in some countries (Germany, Ireland, Sweden, and the United States), while a few other countries (Austria, Canada, Estonia, and Finland) do not publicly report any occupational code. For this study, however, we gained access through the OECD to the four-digit ISCO-08 (International Standard Classification of Occupations) codes for all countries, which allows us to identify teachers in fine categories.

We define teachers as all PIAAC respondents who report as current four-digit occupation code "primary school teacher", "secondary school teacher", or "other teacher" (which includes, for example, special education teachers and language teachers).[14] We exclude university professors and vocational school teachers since the vast majority of PISA students (15-year-olds) are still in secondary school and have therefore not been taught by these types of teachers. We also exclude pre-kindergarten teachers as the roles of this teacher group depend directly on the institutional structures of individual countries and may or may not be contributors to teaching students reading and math.[15]

PIAAC does not allow us to identify the subject that a teacher is teaching, so we use the numeracy and literacy skills of all teachers tested in PIAAC. We focus on the country-level median of the teacher cognitive skills.[16] We weight individual-level observations with inverse sampling probabilities when computing country-specific teacher cognitive skills.

Table 1 reports summary statistics of the teacher cognitive skills in the 23 countries and in the pooled sample. The number of teachers in the national PIAAC samples ranges from 124 teachers in Italy to 834 teachers in Canada, with 231 teachers per country on average. (The sample size for

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[14] Results are very similar if we drop the category "other teachers." We keep these teachers in the sample to increase sample size.

[15] For Australia and Finland we only have two-digit occupational codes and are unable to exclude pre-kindergarten teachers and university professors/vocational school teachers from our teacher sample. However, analysis of the 21 countries where teachers are defined using the four-digit code indicates that teacher skills based on the four-digit code are very similar to those defined using the two-digit code: The correlation of both skill measures is 0.97 for numeracy and 0.95 for literacy. On average, numeracy (literacy) skills based on the two-digit code are only marginally higher (by 0.5 (0.1) PIAAC points) than the respective skills based on the four-digit codes. The average absolute value of these differences is only 2.1 points in numeracy and 1.9 points in literacy. Moreover, simultaneously excluding Australia and Finland from the analysis does not qualitatively change our results below.

[16] The country-level correlation between teacher median skills and mean skills is 0.97 for both numeracy and literacy. Moreover, all results are robust to using mean teacher skills instead of median teacher skills (see Table 4 for a robustness check of our main specification).

Canada is substantially larger than for any other country surveyed in PIAAC because Canada oversampled in order to obtain regionally representative adult skills). Teachers in Finland and Japan perform best in both numeracy and literacy, while teachers in Italy and Russia perform worst in both domains. The range of average numeracy scores across countries is 44 points, which is about 85 percent of the international individual-level standard deviation (53 points). Teachers in the United States (284 points) perform worse than the average teacher in numeracy (295 points) but are slightly above the international mean in literacy. Interestingly, the country ranking and the cross-country variation in teacher cognitive skills are similar to those of all prime-aged workers with full-time employment (see Table 1 in Hanushek et al. (2015)).[17] Also note that teacher numeracy skills are higher than teacher literacy skills in some countries, while the reverse is true in other countries. We will exploit this variation in domain-specific teacher skills in the fixed-effects model that uses only variation within countries between subjects (see Section 5.3). Furthermore, both numeracy and literacy skills of teachers are completely unrelated to the number of teachers in the national PIAAC samples. For the econometric analysis, we standardize the country-specific teacher cognitive skills across the 23 countries (at the country level) to have mean zero and standard deviation one.

To get some sense of the international variation in teacher cognitive skills, we array the median teacher math and literacy skills across countries against the skills of adults by educational group within Canada (Figure 1), the country with the largest total sample. The literacy skills of the lowest-performing teachers (in Italy and Russia) are similar to the literacy skills of employed Canadian adults with only a vocational degree (278 points). Teachers in Canada, the Netherlands, Norway, and Sweden have skills similar to Canadian adults with a bachelor degree (306 points). The literacy skills of the best-performing teachers (in Japan and Finland) are even higher than the skills of Canadian adults with a master or doctoral degree (314 points). These comparisons, which look similar for numeracy skills, underscore the vast differences in teacher cognitive skills across developed countries.

Variations in teacher cognitive skills reflect both where teachers are drawn from the cognitive skill distribution of the population and where a country's overall cognitive skill level falls in the world distribution. As most teachers have obtained a college degree (88 percent on average across all PIAAC countries), we expect teacher cognitive skills to fall above the median of the skill distribution of the entire adult population. Across all 23 countries, median teacher skills fall at the 68th (70th)

[17] Younger teachers have higher skills than older teachers in almost all countries in our sample. Also, male teachers have higher skills than female teachers, especially in numeracy. These patterns, however, are not specific to teachers, but are very similar among all college graduates in a country. Detailed results are available on request.

percentile of the numeracy (literacy) skill distribution of all adults, ranging from the 53rd to the 80th percentile (see Table 1).

It is also illuminating to compare teacher cognitive skills with the skills of all college graduates in a country (see Figure 2). While median teacher cognitive skills fall in the middle of the 25th–75th percentile skill range of cognitive skills of college graduates in most countries, teachers come from the upper part of the skill distribution in some countries (e.g., Finland and Japan) and from the lower part of the college graduate skill distribution in other countries (e.g., Poland and the Slovak Republic).

From Table 1, teachers in France and Spain are drawn highest up from the country distributions of adult skills in numeracy and literacy, respectively. Despite having the highest measured cognitive skills, Finnish teachers are drawn from a lower part of the country's overall skill distribution, reflecting the fact that average cognitive skills in Finland are considerably larger than in France and Spain. Or, harkening back to the argument that 100% of Korean teachers come from the top third of the academic cohort, the median Korean teacher falls at the 72nd percentile of the overall country distribution and the 52nd percentile of the college graduate distribution in numeracy (see Figure 2).[18]

Because the PIAAC tests are new and have not been fully validated, we have compared the PIAAC-based teacher cognitive skills with the numeracy and literacy skills of teachers in larger national datasets for the United States and Germany. These comparisons, described in Appendix A, support the overall validity of the estimates of teacher cognitive skills that are derived from PIAAC.

3.2 Parent Cognitive Skills

Because the parents of the PISA students (henceforth "PISA parents") are not tested themselves in any skill domain, we use the PIAAC data to impute the numeracy and literacy skills of the PISA parents. We begin with the sample of adult PIAAC participants that could in principle be PISA parents. We then estimate the numeracy and literacy skills of the PISA parents from the PIAAC micro data on the basis of several common observable characteristics. Specifically, separately by country, we regress the numeracy/literacy skills of PIAAC adults aged 35–59 with children[19] on three characteristics: gender[20], education (3 categories), and number of books at home (6 categories).[21] We

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[18] These descriptive statistics indicate that the overall statements about where teachers fall in the skill distribution of different countries (e.g., Barber and Mourshed (2007) and Auguste, Kihn, and Miller (2010)) are not accurate and likely do not adequately indicate the important dimensions of teacher cognitive skills across countries. This point about teacher skills was first made by Schleicher (2013).

[19] Individuals in this age bracket are potential parents of the 15-year-old PISA students since they were 17–44 years old when PISA students were born.

[20] We compute skills separately for PISA mothers and fathers because numeracy/literacy skills of women and men might differ. By predicting gender-specific skills, PISA students with single mothers, for example, are assigned only the skill level of women and not the average skill level of men and women.

[21] We collapsed the original 8 categories of the PIAAC education variable into 3 categories so that the education categories in PIAAC and PISA would exactly match. The 6 categories of the number of books at home variable are

then use these estimated coefficients with the same three characteristics of the PISA parents to obtain predicted numeracy/literacy skills of all PISA parents at the individual family level. In the student-level analysis, we use the maximum skills of mother and father as a proxy for parent cognitive skills, although results are very similar if the average skills of mother and father is used instead.

Although the PIAAC-based parent skills are only coarse proxies for the true skills of PISA parents, controlling for the estimated cognitive skill level of parents allows us to tackle several issues. First, since originally studied in the Coleman Report (Coleman et al. (1966)), it has been clear that the family and education in the home is important. Using parental cognitive skills adds a qualitative dimension to family influences over and above the common measures of the student's general family background. More generally, student performance is likely to be persistent across generations, for example, because the quality of the education system or the valuation of education changes only slowly over time. Second, adding information about parent cognitive skills provides a means of separating teacher cognitive skills from the skills of the country's overall population.

Table A-1 presents summary statistics of parent skills in numeracy and literacy by country. Similar to teacher cognitive skills, parent cognitive skills differ greatly across countries, ranging (in numeracy) from 258 points in Poland to 301 points in Belgium. Also, parent skills differ substantially within countries. On average, the difference between the minimum and maximum skill in a country is 88 points, or 1.7 times the international individual-level standard deviation.

3.3 Student Performance and Further Control Variables

International data on student performance come from the Programme for International Student Assessment (PISA), conducted by the OECD.[22] PISA is a triennial survey that tests math and reading competencies of nationally representative samples of 15-year-old students, an age at which students in most countries are approaching the end of compulsory schooling. PISA contains both multiple-choice and open-answer questions and provides internationally comparable test scores. The tests emphasize understanding as well as flexible and context-specific application of knowledge, and hence they do not test curriculum-specific knowledge.

We use the two PISA cycles 2009 and 2012 because the student cohorts in these two test cycles have largely been taught by the teacher cohorts tested in 2011 and 2012 in PIAAC. Student cohorts

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identical in PIAAC and PISA, so this variable was not modified. We use number of books at home in addition to educational degree, since this variable has been shown to be the single strongest predictor of student test scores (Woessmann (2003)). Sample sizes range from 1,074 adults in the Russian Federation to 11,933 adults in Canada with an average sample size of 2,851 adults per country (see Table A-1).

[22] We rely on the PISA assessments instead of the alternative international test of Trends in International Mathematics and Science Study, or TIMSS (see Hanushek and Woessmann (2011)). PISA covers more PIAAC countries, and students participating in PISA were tested in both math and reading, while TIMSS only assessed math performance. Note, however, that math scores from TIMSS are strongly correlated with math scores from PISA at the country level.

of earlier PISA cycles (2000, 2003, and 2006) have partially been taught by some PIAAC teachers, but teacher turnover would introduce additional error in the teacher skill measures for students in these earlier cycles. Another reason for combining PISA 2009 and 2012 is that students provide information about the instructional practices of their teachers only for the subject that is the focus in each round of PISA testing: reading in 2009 and math in 2012. From the survey information, we can compute country-specific indicators of instructional practice for reading (based on PISA 2009) and for math (based on PISA 2012). These instructional-practice indicators capture subject-specific pedagogical skills of teachers, which might be a potentially important confounding factor for teacher cognitive skills (see Section 5.2).

Table A-2 provides summary statistics of student performance and student characteristics. Student performance in math and reading differs widely across countries. Given that the learning progress in one school year is about 40 PISA points, the difference between the USA and Korea is almost two school years in math and one school year in reading. For the econometric analysis, we standardize student test scores at the student level across the 23 countries and the two PISA assessments to have mean zero and standard deviation one. As we are interested in differences across countries, each country receives the same total weight in each PISA cycle. Student characteristics (e.g., gender and migration status) and information about parents (e.g., education, occupation, and number of books at home) come from student background questionnaires.[23] In addition to parent cognitive skills, we use number of books at home, parents' highest educational degree, and parental occupation to control for family background (see Table A-3).

Based on student information, we can construct measures of weekly instructional time for both language and math classes.[24] Furthermore, school principals provide information on whether the school is public or private, city size, total number of students in the school, the lack of qualified math teachers and language teachers, and different types of autonomy (see Table A-4).

Country characteristics include variables that have been used in previous cross-country analysis, such as cumulative educational expenditure per student between age 6 and 15, GDP per capita, and school starting age (see Table A-5).

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[23] As with all such surveys, the dataset of all students with performance data has missing values for some background questions. Since we consider a large set of explanatory variables and since a portion of these variables is missing for some students, dropping all student observations with any missing value would result in substantial sample reduction. We therefore imputed values for missing control variables by using the country-by-wave means of each. To ensure that imputed data are not driving our results, all our regressions include an indicator for each variable with missing data that equals one for imputed values and zero otherwise.

[24] Following Lavy (2015), we aggregate this information across students to the school level.

4. Estimation Strategy

In the baseline OLS model, we estimate an international education production function of the following form:

$$y_{iksc} = \alpha + \lambda T_{kc} + \boldsymbol{X}_{isc}\boldsymbol{\beta}_1 + \boldsymbol{X}_{sc}\boldsymbol{\beta}_2 + \boldsymbol{X}_c\boldsymbol{\beta}_3 + \boldsymbol{Z}_{iksc}\boldsymbol{\gamma}_1 + \boldsymbol{Z}_{ksc}\boldsymbol{\gamma}_2 + \varepsilon_{iksc}, \qquad (1)$$

where y_{iksc} is the test score of student *i* in subject *k* (math or reading) in school *s* in country *c*. T_{kc} represents the median teacher cognitive skills in subject *k* in country *c*. $\boldsymbol{X}_{isc}$ is a vector of student-level variables measuring student and family background, $\boldsymbol{X}_{sc}$ is a vector of school-level characteristics, and $\boldsymbol{X}_c$ is a vector of country-level control variables. The $\boldsymbol{Z}$ vectors include subject-specific control variables; $\boldsymbol{Z}_{iksc}$ contains student-level variables of parents' numeracy and literacy skills, and $\boldsymbol{Z}_{ksc}$ contains school-level variables measuring the shortage of qualified teachers and weekly instructional time in math and language classes. (See Tables A1-A5 for descriptive statistics for all control variables). ε_{iksc} is an error term, assumed to be mean zero. Throughout, we cluster standard errors at the country level because teacher skills do not vary within countries.[25]

Interpreting the OLS estimate of λ as the causal effect of teacher cognitive skills on student performance is problematic, because of the possibility of omitted variables correlated with both teacher skills and student performance. Such omitted variables could include, for example, the educational attitude in a country: Societies that emphasize the importance of good education may have both teachers with high cognitive skills and parents who strongly support their children's education. Similarly, if the quality of the education system is persistent and not perfectly captured by our measure of parent cognitive skills, then student performance and teacher cognitive skills (who went through the same education system one generation earlier) might be positively correlated even if teacher cognitive skills have no real impact on student performance. On the other hand, sorting of students and teachers within schools and across schools (within countries) – which often plagues micro-level analysis of educational production – is no concern in our study because teacher cognitive skills are aggregated to the country level.

[25] Recent research has shown that clustered standard errors can be biased downward in samples with a small number of clusters (e.g., Donald and Lang (2007); Cameron, Gelbach, and Miller (2008); Angrist and Pischke (2009); Imbens and Kolesar (2012)). Although there is no widely accepted threshold when the number of clusters is "small," the work of Cameron, Gelbach, and Miller (2008), Angrist and Pischke (2009), and Harden (2011) suggests a cutoff of around 40 clusters. To check whether clustering in our cross-country sample with just 23 clusters produces misleading inferences, we use the wild cluster bootstrap procedure suggested by Cameron, Gelbach, and Miller (2008) for improved inference with few clusters (using Stata's *cgmwildboot* command for implementation). All results remain robust when employing the wild bootstrap procedure as an alternative to clustering.

To the extent that omitted variables are not subject-specific, we can circumvent bias by focusing on just within-student variation in teacher skills across math and reading. Within-student effects of teacher cognitive skills on student performance are estimated by adding student fixed effects to Equation (1), implicitly holding constant all factors that do not differ between subjects.[26] These fixed effects capture subject-invariant performance differences across students (e.g., family background, innate ability, and motivation) and across countries (e.g., general educational attitude).[27] The remaining concern is that any subject-specific factors not included in the model would continue to bias the teacher-skills coefficient (e.g., international differences in the valuation of math vs. reading knowledge).

There is a trade-off, however, because, while the student fixed-effects estimation may alleviate most problems of omitted variables, any attenuation bias due to measurement error in observed teacher cognitive skills is likely to be more severe than in the OLS model.[28] On net, these offsetting effects are likely to lead to teacher-skills estimates in the fixed-effects model that are smaller than in the OLS estimations.

5. Teacher Cognitive Skills and Student Performance

It is easiest to motivate the analysis with simple visual evidence showing that teacher cognitive skills are positively associated with student performance aggregated to the country level. The two upper graphs in Figure 3 show the unconditional cross-country relationship between teacher numeracy skills and student math performance (left panel) and between teacher literacy skills and student reading performance (right panel), respectively. Both numeracy and literacy skills of teachers are clearly positively associated with aggregate student performance. The two bottom graphs in Figure 3 show specifications analogous to those in the upper panel but additionally include country-specific skills of all adults aged 25–65 to net out the skill persistence across generations.[29] Although losing statistical significance, the coefficient on teacher numeracy skills is reduced only modestly, while the coefficient on teacher literacy skills even increases. When Korea, the most obvious outlier,

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[26] Within-student across-subject variation has frequently been used in previous research (e.g., Dee (2005, 2007), Clotfelter, Ladd, and Vigdor (2010), and Lavy (2015)).

[27] In contrast to the OLS estimates, the estimated effect of teacher cognitive skills in the student fixed-effects model is “net” of teacher skill spillovers across subjects (for example, if teacher literacy skills affect student math performance). Spillover effects are completely eliminated when cross-subject spillovers are identical in math and reading.

[28] Our teacher skills are measured with error because we do not observe the skills of individual teachers and because the observed country-level skills are a noisy measure of the true country-level teacher skills. Because true teacher skills are strongly correlated at the country level (the correlation of observed teacher skills across subjects is 0.77), differencing country-level teacher skills likely aggravates any attenuation bias (see Griliches and Hausman (1986)).

[29] The country-level correlations between teacher skills and adult skills are 0.70 for numeracy and 0.77 for literacy. Skills of teachers and adults are substantially correlated since both have been educated in the same education system at about the same time.

is excluded, the coefficient on teacher numeracy skills becomes larger (0.074) and statistically significant at the 10 percent level.[30] Although coarse, these country-level plots indicate that teacher cognitive skills could be a determinant of international differences in student performance.

5.1 Ordinary Least Squares Results

We now more rigorously investigate the relationship between teacher cognitive skills and student performance using student-level test-score data. Table 2 reports results from the least squares estimation of Equation (1). The unconditional correlation between teacher numeracy skills and individual-level student math performance (Column 1) is identical to the country-level estimate presented in Figure 3. The coefficient on teacher numeracy skills remains statistically significant when adding a large set of background factors at the individual, family, school, and country level (Column 2) and when including the numeracy skills of parents of PISA students (Column 3). The estimate in Column 3 implies that a one SD increase in teacher numeracy skills increases student math performance by almost 0.1 SD. Even though various parent characteristics, such as education level and number of books at home, are included, parent numeracy skills are significantly related to student performance, but the coefficient is rather modest in size compared to teacher cognitive skills. Columns 4–6 report results for reading. In the specification with all controls (Column 6), the point estimate on teacher literacy skills is only slightly below the coefficient on teacher numeracy skills and is also highly statistically significant. In contrast to numeracy impacts, parent literacy skills do not appear to be significant for student reading performance.

The estimated coefficients on the other control variables included in Columns 3 and 6 are reported in Appendix Table A-6. All coefficients have the expected signs. For example, girls perform worse in math than boys but perform better in reading; and migrants perform worse than natives in both subjects. Student performance is positively associated with the number of books at home (a proxy for the educational, social, and economic background), parents' education degree, and the skills content of parents' occupation. Students perform better in private schools, in schools with lower shortages of teachers, and in schools with more subject-specific instruction time (only significant for math). Regarding the country-level characteristics, we observe a negative, albeit small, coefficient on GDP per capita and a close-to-zero coefficient on educational expenditure per student. School starting age is positively related to student performance, but significant only for math.

We also find some evidence for heterogeneity of the teacher-skill effect across student subgroups (Table A-7). While the impact is similar for boys and girls in math, it is larger for girls in reading.

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[30] When omitting teacher skills, adult skills and student performance are strongly positively correlated in both math and reading. However, when conditioning on teacher skills, the estimates for adult skills substantially decrease in size and lose statistical significance.

The teacher-skill effect is also somewhat larger for low-SES students, as measured by the PISA index of economic, social, and cultural status (ESCS), as compared to high-SES students (at least in reading) and for migrants relative to natives.[31] In contrast, parent cognitive skills appear to be more important for high-SES students and for natives.

The results indicate that students living in the countries at the top of the PISA rankings perform better in math and reading in part because their teachers have higher numeracy and literacy skills. To gauge the magnitude of our estimates, we use these OLS coefficients to simulate the improved student performance if each country brought its teachers up to the level of Finnish teachers, who are the most skilled teachers by the PIAAC measures (Table 3). For some countries, such as Japan, this is not a huge change, but even Japanese students would improve somewhat (0.05 SD in math and 0.03 SD in reading). But for other countries, the improvements in student performance would be substantial. The U.S. would be expected to improve by roughly 0.26 SD in math; Russia and Italy would be expected to improve by about 0.35 SD in math.

The teacher-skill estimates do not capture the effect of just a single school year but rather reflect the cumulative effect of teacher cognitive skills on student performance over all school years. Thus, these are long-run impacts that presume that the quality of students' teachers in the first ten grades would improve to the level of Finland – something that would take some time and effort to realize.

The baseline OLS model already controls for a multitude of determinants of student performance, including a proxy for the cognitive skills of parents. Still, as teacher skills are measured at the country level, identification also raises particular challenges in this international setting. While we control for cross-country differences in GDP per capita, educational expenditures, and school starting age, countries may also differ from one another in other, hard-to-observe ways. For instance, cultural traits, educational attitudes, and the nature of teacher preparation may be associated with both teacher cognitive skills and student performance. To circumvent potential biases due to unobserved country heterogeneity that is similar across math and reading, we employ a student fixed-effects model in Section 5.3. Before presenting these estimates, however, we first show that the baseline OLS results are robust to alternative ways of measuring teacher or parent cognitive skills and to additionally controlling for country-specific measures of instructional practices.

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[31] Because first-generation migrants might have migrated to the PISA test country shortly before the PISA test, we cannot ascribe their math and reading performance to the skill level of teachers in the test country. Therefore, we use only second-generation migrants in this analysis since these students were born in the PISA test country and have spent their school career in the education system of that country.

5.2 Robustness Checks

Since teacher cognitive skills vary at the country level, our first robustness check replaces the individual-level parent cognitive skills with country-level parent cognitive skills, as measured by the median skills of all PIAAC respondents aged 35–59 with children (i.e., the same PIAAC respondents used to construct the individual-level parent skills). Using country-level parent cognitive skills leaves the teacher numeracy skills coefficient unchanged (Column 2 in Table 4), and even increases the coefficient on teacher literacy skills somewhat (Column 6). We obtain very similar results when we replace the country-specific parent skills with country-specific *adult* skills, as measured by the median skill level of all adults aged 25–65 (Columns 3 and 7). Thus, the impact of teacher cognitive skills remains unchanged when we control in various ways for the general cognitive skill level of the population at the country level, i.e., at the same level where teacher skills are measured. From these results we feel confident that we have separated the effect of teachers from the overall cognitive skill level of parents and the adult population in general. As a final specification check, we use average teacher cognitive skills instead of median skills. The coefficients, reported in Columns 4 and 8, are again very close to the baseline estimates.

Another worry is that our subject-specific teacher-skill measures are confounded by correlated differences in pedagogical skills. To investigate this, we use information from the PISA students about their teachers' activities in language and math classes to construct indicators of subject-specific instructional activities as proxies for teachers' pedagogical skills. We follow the OECD (2010) approach of measuring specific instructional practices through survey responses of students (e.g., how often does a teacher ask questions that make students reflect on a problem), while we aggregate these instructional practices to the school level.[32] As noted in Section 3, instructional practices are asked only for the subject that was the focus in the respective PISA cycle (reading in 2009 and math in 2012). For the PISA cycle when a subject was not the focus, we impute the subject-specific instructional-practice indicator by using the country-level measure from the other PISA survey,

[32] For *reading*, we use the following items (each measured on a 4-point scale ranging from "never or hardly ever" to "in all lessons") to construct the instructional-practice indicator: asking students to explain the meaning of a text; asking questions that challenge students to get a better understanding of a text; giving students enough time to think about their answers; recommending books or author to read; encouraging students to express their opinion about a text; helping students relate the stories they read to their lives; and showing students how the information in texts builds on what they already know. For *math*, we use the following items (each measured on a very similar 4-point scale ranging from "never or rarely" to "almost or almost always"): asking questions that make students reflect on the problem; giving problems that require students to think for an extended time; presenting problems in different contexts so that students know whether they have understood the concepts; helping students to learn from mistakes they have made; asking students to explain how they have solved a problem; and presenting problems that require students to apply what they have learnt to new contexts.

assuming that the instructional practices in a subject have not noticeably changed within a country over the three-year period between 2009 and 2012.[33]

Table 5 reports the results when we augment the baseline model by controls for the instructional practices in math and language classes (the baseline estimates are reported in Column 1 for math and in Column 3 for reading). The instructional-practice indicators are positively related to student performance, although only the coefficient on instructional practices in language classes is both statistically significant and economically meaningful. A one SD increase in the quality of instructional practice is associated with 0.035 SD higher student performance in reading. Importantly, however, when instructional practices are added, the teacher-skill estimates change very little, suggesting that teacher cognitive skills have an independent impact on student performance.[34]

Supporting this, we construct another indicator using information on instructional practices reported by teachers.[35] In line with the results in Table 5, all teacher-reported instructional practices are negatively correlated with teacher cognitive skills, suggesting that, if anything, the impacts of cognitive skills are understated by omitting the pedagogical skills of teachers.[36]

Finally, to address issues of divergent national cultures (in particular, differing educational attitudes) around the world, we show that our results are robust to specifications that include continental fixed effects and that restrict the analysis to just European countries, which makes the sample culturally more homogeneous (Table A-8). Moreover, any analysis that exploits international variation with limited degrees of freedom might suffer from the problem that the results are driven by a few outliers. Therefore, we replicated the baseline OLS specification with all control variables, but excluded each country individually from the sample. The estimated teacher-skill effects are

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[33] To some extent, the country-level instructional-practice indicators just reflect cultural differences in how actively teachers communicate with their students. Therefore, it is understandable that the instructional-practice measure is largest in Anglo-Saxon countries and smallest in Asian countries.

[34] The coefficients on teacher cognitive skills even increase slightly since teacher cognitive skills and instructional practices are negatively correlated at the country level (r=-0.30 in math and r=-0.42 in reading).

[35] Data come from TALIS 2013 (see OECD (2014)) for details). Instructional practices assessed in TALIS include: present a summary of recently learned content; students work in small groups to come up with a joint solution to a problem or task; give different work to the students who have difficulties learning and/or to those who can advance faster; refer to a problem from everyday life or work to demonstrate why new knowledge is useful; let students practice similar tasks until teacher knows that every student has understood the subject matter; check students' exercise books or homework; students work on projects that require at least one week to complete; students use ICT for projects or class work.

[36] We do not use instructional practices from TALIS in the student-level regressions for three reasons. First, four of the 23 countries in our sample (Austria, Germany, Ireland, and the Russian Federation) did not participate in TALIS 2013, which would substantially reduce our sample. Second, at the time of writing, TALIS 2013 micro data were not available, so we would have to rely on the aggregate data published by the OECD. However, the OECD does not provide sufficient information on how the published country-level indicators of instructional practices have been constructed. Third, the OECD only provides instructional practices for all (lower secondary) teachers, which means that the instructional practices in TALIS are *not* subject-specific.

always very close to the baseline coefficients, confirming that the results are not driven by any individual country (results available upon request).

5.3 Student Fixed-Effects Results

While the previous section has shown that our teacher-skill estimates are remarkably robust to different skill measures, additional controls, and various subgroups, we are still concerned about omitted variables that vary at the country level. Thus, we now turn to estimation with student fixed effects. Here, we exploit only within-country variation to identify the effect of teacher cognitive skills on student performance, eliminating any non-subject-specific bias.

Table 6 presents the results of the student fixed-effects specifications that match the OLS specifications except that now performance on both subjects is pooled and control variables that do not differ across subjects are automatically dropped due to their collinearity with the student fixed effects. With all subject-varying controls included, the fixed-effects estimate of teacher cognitive skills is about 25 percent smaller than the corresponding OLS estimate but remains statistically significant (Column 3). This decrease in magnitude might occur for two distinct reasons. First, country-specific omitted variables that are similar across subjects, such as general education preferences – which likely bias the OLS coefficient upward – are taken into account in the fixed-effects model. Second, as discussed in Section 4, attenuation bias becomes more severe as the measurement error in teacher skills likely increases when differencing numeracy and literacy skills.[37] Interestingly, the effect of instructional time on student performance is similar to the effect size in Lavy (2015), who exploits within-student between-subject variation using PISA data from 2006. The coefficient on parent cognitive skills, albeit only slightly smaller than the OLS coefficient for math, is statistically insignificant, likely because of the strong correlation between the numeracy-literacy skill differences of teachers and parents.

The student fixed-effects model assumes that the impact of subject-specific teacher skills is the same in math and reading. To allow for differential effects of teacher numeracy skills and teacher literacy skills, we also included them separately in the model (results not shown). Without imposing the uniformity of effects in the two subjects, we still find very similar coefficients on teachers' numeracy (0.066) and literacy skills (0.077), both significant at the 5 percent level.

[37] It is not surprising that the standard error on the teacher-skill coefficient increases with the addition of parental skills in Column 3. The numeracy-literacy skill *differences* of teachers and parents are more strongly correlated (r=0.77) than the respective skill *levels* (0.34 in math and 0.41 in reading). Therefore, the effect of teacher cognitive skills is identified only from the limited part of the skill variation that is independent of variation in parent skills.

In summary, the estimated impact of teacher cognitive skills on student performance proves highly robust to different ways of measuring teacher or parent cognitive skills, to additional controls, and to other sources of identifying variation.

6. Determinants of Teacher Cognitive Skills

The existing international differences in teacher cognitive skills reflect both where teachers are drawn from in each country's skill distribution and the overall level of cognitive skills in each country's population – and policies to improve the skills of teachers could conceptually focus on either of these dimensions. Increasing the overall achievement of a country's population would of course be highly desirable and would be self-reinforcing through improving the pool of potential teachers. Nonetheless, consideration of potential overall improvement policies, while widely discussed elsewhere, is beyond the scope of this analysis.

We instead focus on the determinants of where teachers are drawn from the overall skill distribution of the population, which as noted above has received relatively little and narrow attention. Our international data permit a much broader investigation of how external forces and policy choices affect the skills of the teaching force. Specifically, we can explore across the broad range of international experiences how improvements in alternative job opportunities for women over time and differences in relative teacher pay have altered the skill levels of teachers.

6.1 Alternative Professional Opportunities for Women

Changes in the cognitive skills of teachers have been studied in the U.S., where there is general agreement of a decline over time in measured achievement and in other quality indicators (Murnane et al. (1991), Corcoran, Evans, and Schwab (2004a, 2004b), Bacolod (2007)).[38] A common hypothesis is that this decline in teacher cognitive skills in the U.S. during the past decades was the result of improving alternative opportunities for women in the labor market. As more women have access to high-skill, high-wage occupations, fewer high-skilled women choose to become teachers, thus leading to declining average teacher skills.[39] Testing this hypothesis has been difficult, however, because the underlying data on teachers have come from piecing together a limited number of snapshots of skill differences from U.S. surveys conducted at different points in time. The limited

[38] There is a longer investigation of the teaching profession, largely from a sociological perspective, that focuses on the well-being of teachers in terms of their relative status and earnings, as opposed to any aspect of teacher quality or teacher effectiveness. See, for example, Bergmann (1974), Reskin (1984), and Tienda, Smith, and Ortiz (1987). Such analyses have also had an international comparative component as in Charles (1992), Blackburn, Jarman, and Brooks (2000), and Kelleher (2011), but again lacking any attention to the impact on students.

[39] As Bacolod (2007) points out, the opening of alternative high-wage jobs does not necessarily imply declining teacher quality; in a Roy model, it would depend on comparative advantage in different occupations and the correlation of a worker's skills in different occupations.

observations plus incomplete measures of skill demands or rewards in alternative occupations present serious challenges to any analysis.[40]

In the spirit of Bacolod (2007), we relate within-country changes in labor-market choices of females to changes in teacher skills across birth cohorts. However, our analysis differs in two key ways. First, we observe multiple countries, which not only dramatically expands the range of observations we observe but also allows us to account for any general (i.e., non-country-specific) time trends that affect both the nature of female labor-market participation and teacher skills. For example, the teaching profession might have become less attractive relative to other (possibly newly emerging) high-skilled occupations over time, explaining both an increasing share of females in other high-skilled occupations and a decline in average teacher skills. Second, we explicitly consider the human capital intensity of alternative employment opportunities (instead of simply relying on relative average wages in teaching and elsewhere).

We proceed by constructing an indicator of women's access to high-skilled occupations in a country's labor market. For country-cohort cells, we compute the proportion of female teachers relative to females in high-skilled occupations. We use the PIAAC micro data to classify occupations as "high-skilled" by identifying country-specific occupations that employ the most educated males. For two-digit occupations in each country, we calculate the average years of schooling of male employees currently working in each occupation at the time of the PIAAC assessment (i.e., in 2011/2012).[41] Second, ranking occupations in each country by average schooling level and starting with the occupation with the highest level, we define all occupations as "high-skilled" until males working in these occupations comprise 25 percent of all working males in the country.[42] We choose the 25 percent rule to ensure that a similar share of workers is employed in high-skilled occupations in each country; other variants of defining high-skilled occupations led to very uneven shares of males working in high-skilled occupations across countries. To obtain cohorts with sufficient numbers of teachers, we merge 15 adjacent birth years. As birth years of workers in the PIAAC data range from 1946 to 1990 (excluding very young workers who mainly have not completed their university degree), we obtain three birth cohorts per country.

Consistent with the notion that teacher skills are directly affected by competition from other occupations that demand high skills, we expect that higher concentrations of females in teaching lead

[40] Bacolod (2007) expands on the data by using observations for the separate U.S. states.

[41] There are no internationally comparable data that would allow computing these country-by-cohort-specific shares on the basis of historical labor-market records.

[42] Note that teaching is a high-skilled occupation in every country in our sample. Applying an alternative categorization that classifies all occupations contained in the one-digit ISCO codes 1 (Managers) and 2 (Professionals) as high-skilled leads to qualitatively similar results.

to higher cognitive skills of teachers. The test of this exploits changes in the share of female teachers relative to women in all high-skilled occupations over three birth cohorts in 18 countries.[43] Our estimation always includes cohort fixed effects to control for general time trends in women's labor-market opportunities and for skill depreciation across birth cohorts. Moreover, country fixed effects account for cross-country differences in women's labor-market participation and in the average skill level that are constant across birth cohorts.

Table 7 reports the results of estimating the effect of alternative job opportunities for both the skill level of female teachers (Columns 1 to 4) and the skill level of all teachers (Columns 5 to 8). For both numeracy and literacy, we find that a higher share of high-skilled female workers in teaching is positively and statistically significantly related to the cognitive skill level of teachers. As expected, this association is always stronger for the skill level of female teachers than for the skill level of all teachers. The coefficients barely change when we add the average skill level of university graduates in the respective country-cohort cell to account for country-specific skill depreciation.[44]

The estimates are also economically meaningful. An increase in the share of high-skilled female workers in teaching by 10 percentage points leads to a 0.45 SD increase in the numeracy skills of female teachers and to approximately 0.30 SD increase in the numeracy skills of all teachers. (The results are slightly stronger for literacy.) The share of high-skilled female workers in teaching varies between 16 percent in the U.S. and 32 percent in Norway (across all three birth cohorts). Thus, if females in the U.S. had similar employment opportunities as in Norway, average teacher numeracy skills in the U.S. would increase by about 0.45 SD, closing more than half of the gap to the international average in teacher numeracy skills. Across all 18 countries in the sample, the share of high-skilled female workers in teaching decreases from 29 percent in the oldest birth cohort (born 1946–1960) to 23 percent in the youngest cohort (born 1976–1990), reflecting an international improvement of alternative job opportunities for women across birth cohorts. This is associated with a decline of 0.26 SD in the numeracy skills of female teachers and a decline of 0.17 SD in overall teacher numeracy skills.

[43] For this analysis, we exclude the ex-communist countries (the Czech Republic, Estonia, Poland, Russia, and the Slovak Republic) since occupational choices in these countries were less driven by market forces but rather depended on political attitudes. While our results indicate that females' labor-market opportunities affect the level of teacher cognitive skills, the analysis uses only pseudo cohorts based on the cross-sectional PIAAC data. Thus, the validity of our results depends on the assumption that women do not change the type of their occupation (high-skilled vs. low-skilled; teacher vs. nonteacher) in a systematic way over their careers. Furthermore, our approach assumes that the country-specific pattern of skill depreciation across cohorts is similar for teachers and university graduates.

[44] Several studies suggest that losses of skills over the life cycle occur, underlining the importance of controlling for skill depreciation (e.g., Cascio, Clark, and Gordon (2008); Edin and Gustavsson (2008)).

6.2 Teacher Pay

An obvious consideration in looking at the pattern of teacher skills is the pay received by teachers. In fact, the argument that teacher pay is significantly related to teacher quality has been in the heart of much of the debate about educational policy for many years (see, e.g., Dolton and Marcenaro-Gutierrez (2011)). The idea is that countries that pay teachers relatively better are able to recruit teachers from higher up in the skill distribution and also are able to retain teachers in their profession.[45] If this link is present, there would be leverage for policymakers to raise the skills of teachers in the country by paying them higher wages, with commensurate positive effects on student performance.[46]

In order to investigate the salary-skills relationship across countries, we can estimate whether *ceteris paribus* teachers are paid a premium in the labor market. Using the individual-level PIAAC data, we estimate a Mincer earnings equation with log earnings (ln *y*) regressed on gender (*G*), potential work experience (*E*), achievement in numeracy and literacy (*A*), and a teacher indicator (*T*).[47]

$$\ln y = a_0 + a_1 G + a_2 E + a_3 E^2 + a_4 A + \delta T + \varepsilon \qquad (2)$$

The parameter δ is the premium for teachers given their characteristics. We estimate a separate premium for each country, and we find a wide dispersion. Figure 4 shows the estimated teacher premiums across countries, ranging from +45 percent in Ireland to -20 percent in the United States and Sweden.[48] (Table A-9 presents the detailed regression output for each country). While there have been many discussions of the relative pay of teachers in the United States (see Hanushek (2016)), most have ignored the possibility that teachers are systematically different from college graduates

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[45] Raising pay might also provide already-recruited teachers with more incentives to exert higher effort to improve the educational outcomes of the children they teach. The evidence on effort is, however, not very encouraging; see Springer et al. (2010). While much of the policy discussion of performance pay does not distinguish between the effort margin and the selection-retention margin, it is the latter that seems more important. The international studies effectively look at selection and retention, while within-country analyses almost always look at effort; see Woessmann (2011). For developing countries, the evidence on effort is stronger (see Muralidharan and Sundararaman (2011)), but this might not generalize to the developed countries we analyze.

[46] Another channel through which a positive association between teacher pay and teacher skills may materialize (at least in the long run) is that higher salaries for teachers may improve the status of the teaching profession. As a result, more children might want to become teachers in the future, facilitating the recruitment of more able individuals.

[47] This approach follows Hanushek et al. (2015) in estimating an earnings function without years of schooling, which is one of several inputs into cognitive skills. We use the sample of all university graduates surveyed in PIAAC in each country, which are the relevant comparison group for teachers (88 percent of teachers have obtained a college degree). However, results are qualitatively similar when we add years of schooling as an additional control or estimate the Mincer earnings function on the whole population.

[48] It is remarkable that teacher wages premiums are similarly low in the United States and Sweden, since both countries are at opposite extremes of wage inequality (see Table 1 in Hanushek et al. (2015)). In the United States, workers at the 90th percentile of the wage distribution earn 4.5 times as much as workers at the 10th percentile. In Sweden, workers at the 90th percentile earn only twice as much as workers at the 10th percentile.

working in other occupations (e.g., in terms of cognitive skills and gender composition). The estimates here indicate that teachers are paid some 20 percent less than a comparable college graduate elsewhere in the U.S. economy after adjusting for observable characteristics.

Figure 5 puts pay and skills together in an added-variable plot of teacher pay premiums (δ) against the cognitive skills of teachers in the country. Importantly, estimates are conditioned on the cognitive skills of all nonteacher college graduates to account for international differences in overall country skill levels and to allow us to assess how pay relates to the position of teachers in the distribution of the country's skills.[49]

The results indicate that higher relative teacher pay is systematically related to higher teacher skills. The top panel is numeracy skills against the pay premium, while the bottom is literacy skills. The clear conclusion is that countries that pay teachers more for their skills also draw their teachers from higher parts of the skill distribution. In terms of magnitude, a 10 percentage points higher teacher wage premium is associated with an increase in teacher numeracy (literacy) skills of 0.18 (0.16) SD. The coefficient on college graduates' skills equals 1 for both numeracy and literacy (not shown), again suggesting the powerful influence of a country's overall skill level.

These results are also consistent with previous work in the U.S. on pay-skill relationships. Corcoran, Evans, and Schwab (2004b) argue that, while average cognitive skills of teachers have not changed much, there has been a sharper decline in the top deciles of skills. Bacolod (2007) finds larger declines in teacher cognitive skills. Both see the importance of teacher salaries and alternative opportunities for women in the labor market.

The interpretation of these results is, however, important for policy. These estimates are reduced-form estimates that reflect the labor-market equilibrium. They do not, however, indicate what the supply function for higher quality teachers looks like. In other words, they are not causal estimates of how the quality of teachers would change if teacher salaries were raised.[50] Moreover, the estimated relationship relates to the long run after many cohorts of teachers have been recruited. In other words, while making it clear that a more skilled teaching force will require higher salaries, the evidence says

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[49] An alternative approach is to run country-level regressions of teacher skills on relative teacher wages, measured as the percentile rank of country-specific mean teacher wages in the wage distribution of all nonteacher college graduates. This approach yields similar salary-teacher skill results, but it does not allow for any differences in the distribution of earnings characteristics between teachers and nonteachers.

[50] These issues have been part of the policy discussion in the U.S., where questions have arisen about how to attract more effective teachers as measured by teacher value-added. Higher teacher salaries would undoubtedly expand the pool of potential teachers and would also help to cut down on teacher turnover. This evidence does not, however, indicate that more effective teachers will be hired out of the enlarged pool; nor does it indicate that the teachers who are induced to stay in teaching are the more effective teachers. The same holds for changing the cognitive skills of the teaching force.

nothing about either how salaries should be structured or the responsiveness of teachers to higher salary offers.[51]

7. A Larger Policy Perspective

Our results indicate that the overall level of cognitive skills of a country's teacher force directly influences the student achievement levels that a country can expect. The magnitudes are important, however. A one SD improvement in teacher cognitive skills leads to a 0.1 SD improvement in PISA scores. Since PISA scores represent the cumulative learning of 15-year-olds, this suggests an average learning gain of about 0.01 SD per year.

An appropriate comparison for policy purposes would be estimates of the variations in teacher effectiveness derived from value-added models of annual learning gains (Hanushek and Rivkin (2012)). A consensus estimate is that a one SD difference in teacher effectiveness (measured by value-added) relates to a student performance difference of around 0.15 SD per year.[52] These results suggest that a pool of teachers with higher cognitive skills tends to contain more effective teachers, but within that pool there is a wide variation in teacher effectiveness. Thus, knowing a potential teacher's cognitive skills provides some overall indication of potential effectiveness but at the individual teacher level other factors exert greater influence on effectiveness.[53]

We currently have virtually no information about either the supply function of teacher cognitive skills or the supply function of teacher effectiveness. The previous analysis suggests, not surprisingly, that average teacher cognitive skills move with pay premiums in teaching. There is also some indication that teacher effectiveness responds to pay differentials through exit and retention decisions of teachers.[54] These do not provide sufficient information to derive supply elasticities on either

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[51] In a separate analysis, we have investigated whether relative public-sector wages (i.e., mean public-sector wages over mean private-sector wages) affects an individual's decision to enter the teaching profession. Using annual OECD data on public-sector and private-sector wages for multiple countries, we aggregated the data to the same three birth cohorts as in Section 6.1. Controlling for country and birth-cohort fixed effects, we fail to find a robust relationship between teacher cognitive skills and the relative public-sector wages in the years before college graduation. There are several potential reasons for this result. Most importantly, we do not observe teacher wages, but rather rely on coarse measures of average public and private wages. Furthermore, it is unclear at which point in their educational career individuals decide to become teachers. We also made a preliminary investigation of considering economic conditions at the beginning of careers on teacher skills (following Nagler, Piopiunik, and West (2015)), but the small samples when finely disaggregated by age could not support this estimation.

[52] This is a conservative estimate since it is based on just the within-school variance in teacher quality. In terms of total variance that includes any between-school variation in quality, one SD higher teacher effectiveness is related to about 0.2-0.3 SD better student performance.

[53] This interpretation does help to reconcile previous findings about the inconsistent impact of cognitive skills in determining individual teacher effectiveness (Hanushek (2003)). This evidence, all drawn from U.S. experiences, is consistent with individual score test differences being hard to disentangle from variations in overall effectiveness, implying that large samples with good measures of cognitive skills are necessary in order to detect the impacts.

[54] Dee and Wyckoff (2015) investigate the strong effectiveness-related salary system in Washington, DC. Large potential pay incentives encourage highly effective teachers to do even better; a threat of firing poor performers encourages increased exit from the system at the bottom end of performance.

margin, making it impossible to compare directly the achievement implications of alternative pay programs. While this analysis has focused on the achievement effects of altering the average level of cognitive skills of teachers, it is unlikely that the appropriate policy would be simply moving the entire teacher distribution up as opposed to altering the shape of the distribution along with any increase in average salaries (Hanushek (2016)). Nonetheless, how skills and effectiveness might, for example, respond to removing the large discount to teacher salaries in the United States is unknown.

8. Conclusions

We use newly available data from the Programme for the International Assessment of Adult Competencies (PIAAC) to provide a novel description of the skills of teachers in numeracy and literacy in 23 developed economies. These teacher cognitive skills differ substantially across countries. We then combine the country-level measures of teacher cognitive skills with micro data on student performance from PISA to estimate international education production functions that extensively control for student, school, and country background factors, including coarse measures of the cognitive skills of the parents of PISA students. In addition to OLS models, we estimate the impact of teacher cognitive skills using student fixed-effects models, which exploit between-subject variation and account for omitted (non-subject-specific) country-level factors.

With both approaches, we find a positive relationship between teacher cognitive skills and student performance. In terms of magnitude, in both math and reading, a one SD increase in teacher cognitive skills is associated with an increase in student performance by about 0.1 SD (0.07 SD in the fixed-effects model). This effect reflects, however, the cumulative impact of having better teachers through age 15. Additional specifications that control for the general skill level in a country in various ways confirm that the teacher-skill effects do not just reflect the intergenerational persistence in skills. Neither is the estimated impact of teacher cognitive skills confounded by teacher pedagogical skills.

We then consider possible determinants of teacher cognitive skills. First, we investigate whether women's opportunities to enter alternative high-skilled occupations affect the skill level of teachers in a country. Exploiting within-country changes in the share of women working in high-skilled occupations outside teaching across three birth cohorts in 18 countries, we find that a higher share of women in high-skilled jobs other than teaching is significantly related to a lower cognitive skill level of teachers, particularly of female teachers. This indicates that differences in women's access to high-skilled occupations represent one determinant of the observed international differences in teacher cognitive skills and of the time pattern of changing teacher skills. We also show that wage premiums paid to teachers (given their gender, work experience, and cognitive skills) are directly related to teacher cognitive skills in a country. Note though that the key is whether teachers are paid a premium, because wages in all occupations, not just teaching, respond to higher cognitive skills (Hanushek et al. (2013)).

Within-country evidence, primarily from the United States, has highlighted the importance of teacher quality for student achievement. But the research behind this has been largely unable to identify any characteristics or behavior of teachers that systematically lead to higher effectiveness. By considering international differences in student performance, the analysis here is able to identify an important role for better cognitive skill of teachers as an ingredient into teacher effectiveness. Simply put: Smarter teachers produce smarter students.

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Appendix A. Validation of PIAAC Cognitive Skills Data with External Sources

The PIAAC data on teacher cognitive skills raise two potential concerns. First, the teacher skill measures are derived from relatively small samples.Second, they rely on a new battery of achievement tests. In order to validate these measures, we compare them with estimates from larger national surveys in the United States and Germany.

We first look at the U.S. National Longitudinal Survey of Youth (NLSY79 and NLSY97). The NLSY79 is a nationally representative sample of 6,111 young men and women who were born between 1957 and 1964. The NLSY97 is a nationally representative sample of 6,748 individuals born between 1980 and 1984. (Note that these age cohorts partly overlap with the age range of the PIAAC participants.) We measure NLSY79 respondents' occupation (using four-digit Census codes) in 2010 (last available year) and NLSY97 respondents' occupation in 2011 to make this sample as comparable as possible to the PIAAC survey in 2011.[55]

We take the mathematics and language skills tested in the four AFQT subtests which are part of the Armed Services Vocational Aptitude Battery (ASVAB). The ASVAB was administered to 94 percent of NLSY79 respondents in 1980 and to 81 percent of NLYS97 respondents in 1997. We combine the scores from the mathematical knowledge and arithmetic reasoning tests into a numeracy skills measure and the scores from the word knowledge and paragraph comprehension tests into a literacy skills measure.[56] Based on these measures, teacher skills fall at the 67th (64th) percentile in the adult skill distribution in numeracy (literacy). This is quite close to the position of teacher skills in the PIAAC data for the USA (see Table 1): 70th (71st) percentile in numeracy (literacy).

We also compare teacher cognitive skills from PIAAC with those from Germany's adult cohort of the National Educational Panel Study (NEPS).[57] This dataset is a nationally representative dataset of 9,352 adults born between 1944 and 1986. NEPS has several advantages for our purpose. First, similar to PIAAC, the competency tests in NEPS aim at measuring numeracy and literacy skills in real-life situations which are relevant for labor market success and participation in society. Second, NEPS tested skills at about the same time (in 2010/2011) as PIAAC did. Third, almost the same age

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[55] Teachers are defined as in PIAAC (i.e., excluding pre-kindergarten teachers and university professors/vocational education teachers). We weight individual-level observations with the cross-sectional weights taken from the year in which the occupation is measured, giving each NLSY survey the same total weight.

[56] As respondents were born in different years, we take out age effects by regressing test scores on year of birth dummies first (separately for NLSY79 and NYS97). We control for age effects in the NLSY data because participants were still children or adolescents at the time of testing. In contrast, we do not take out age effects in the PIAAC data because most PIAAC participants have already completed their education when tested.

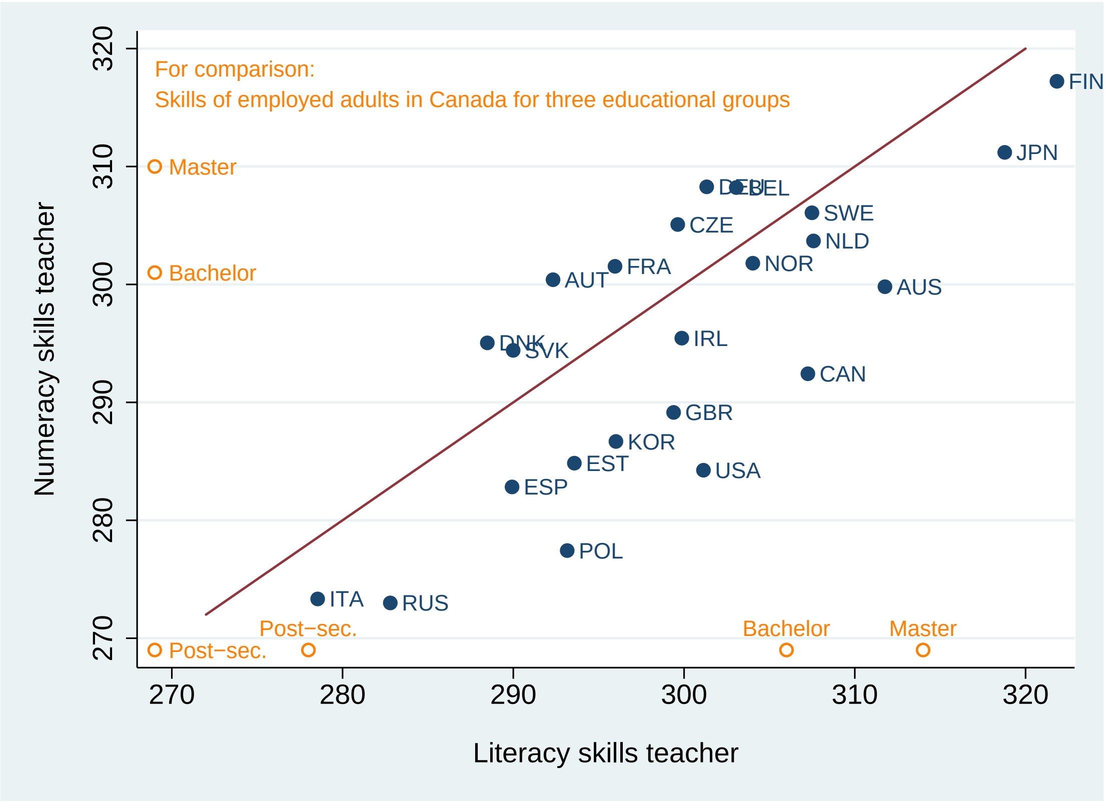
[57] This paper uses data from the National Educational Panel Study (NEPS): Starting Cohort 6 – Adults, doi:10.5157/NEPS:SC6:3.0.1. From 2008 to 2013, NEPS data were collected as part of the Framework Programme for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, the NEPS survey is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg in cooperation with a nationwide network. See Blossfeld, Roßbach, and Maurice (2011).

cohorts were tested in NEPS and PIAAC. Similar to PIAAC, we keep all adults aged 25–65 and identify teachers based on the four-digit ISCO-88 occupation codes, where occupation is measured in 2010/2011. Teacher skills in NEPS fall at the 68th (76th) percentile among the adult skill distribution in numeracy (literacy). Again, this is similar to the respective positions of teachers in the PIAAC sample for Germany: 72th (74th) percentile in numeracy (literacy).

The similarity of teacher cognitive skills in the adult skill distribution found in PIAAC and in these nationally representative datasets with larger sample sizes supports using the PIAAC scores as measures of the teacher cognitive skills in each country.

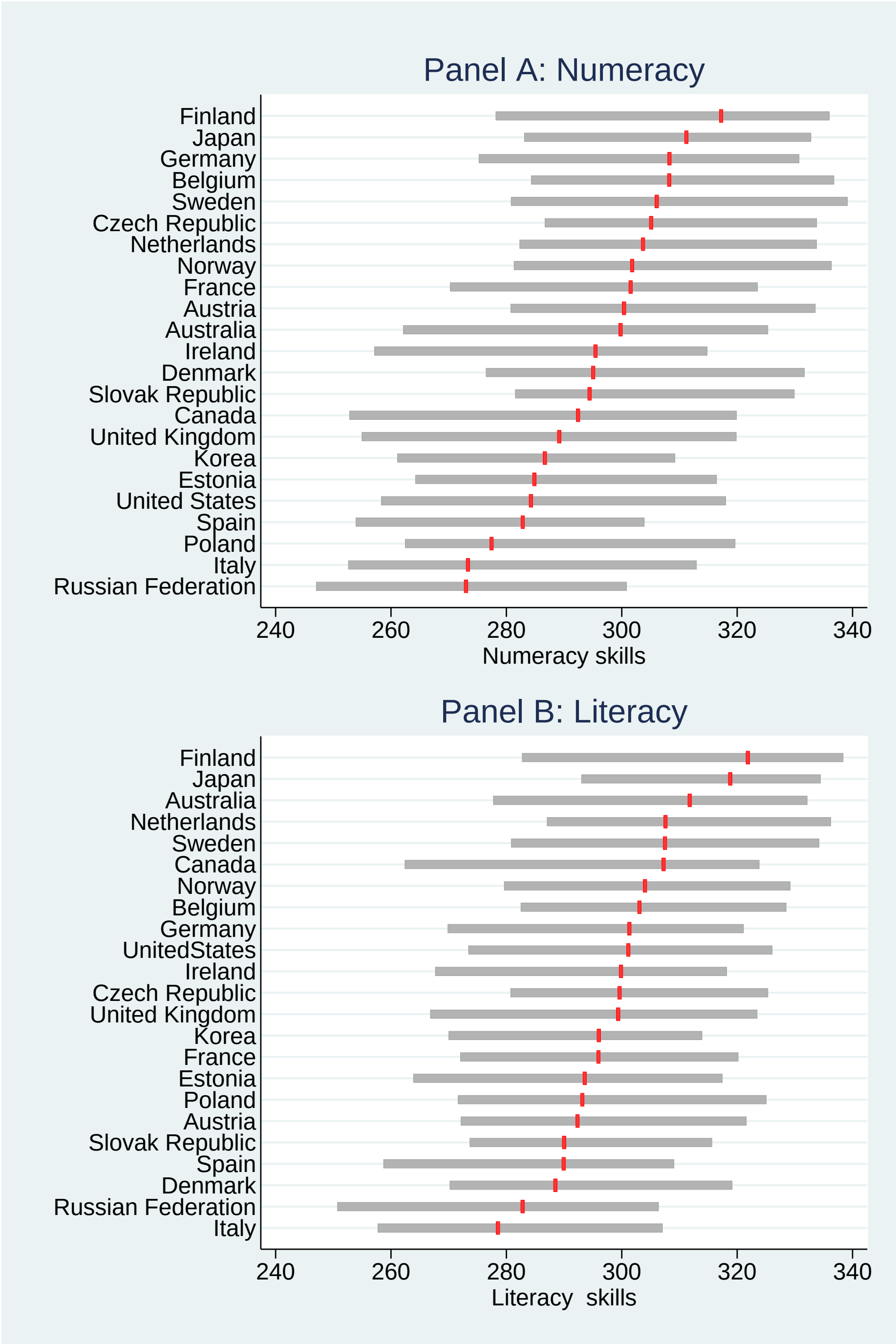
Figures and Tables

Figure 1: Teacher Cognitive Skills
Compared to Canadian Workers with Varying Education Levels



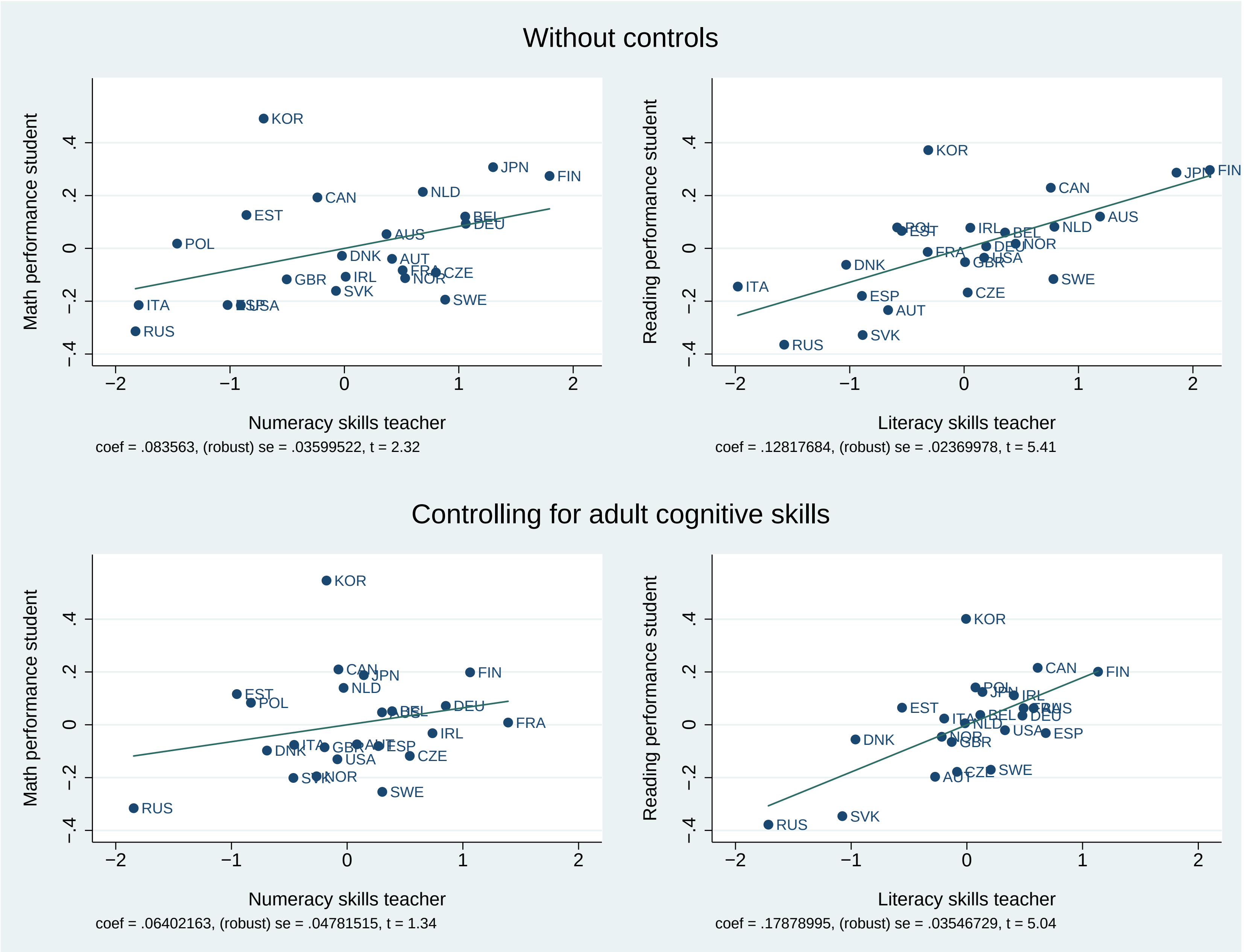
Note: The blue dots indicate country-specific teacher skills in numeracy and literacy (see text for construction of teacher cognitive skills). The orange circles indicate the median cognitive skills for three educational groups of employed adults aged 25–65 years in Canada (the largest national sample in PIAAC). *Post-sec.* includes individuals with vocational education (post-secondary, non-tertiary) as highest degree (2,434 observations); *Bachelor* includes individuals with bachelor degree (3,671 observations); *Master* includes individuals with a master or doctoral degree (1,052 observations). *Data source*: PIAAC.

Figure 2: Position of Teacher Cognitive Skills in the Skill Distribution of College Graduates



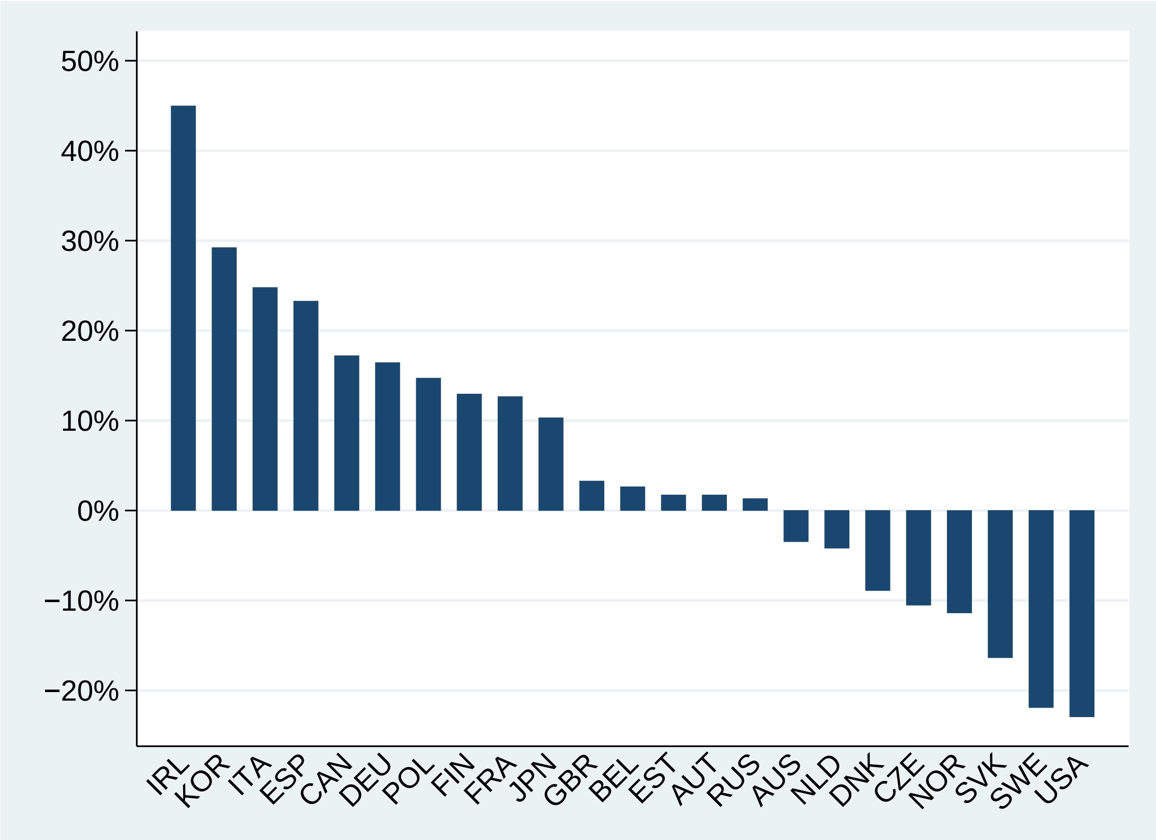
Note: Modified figure from Schleicher (2013). Vertical bars indicate median cognitive skills of teachers in a country. Horizontal bars show the interval of cognitive skill levels of all college graduates (including teachers) between the 25th and 75th percentile. Countries are ranked by the median teacher skills in numeracy and literacy, respectively. *Data source*: PIAAC.

Figure 3: Student Performance and Teacher Cognitive Skills



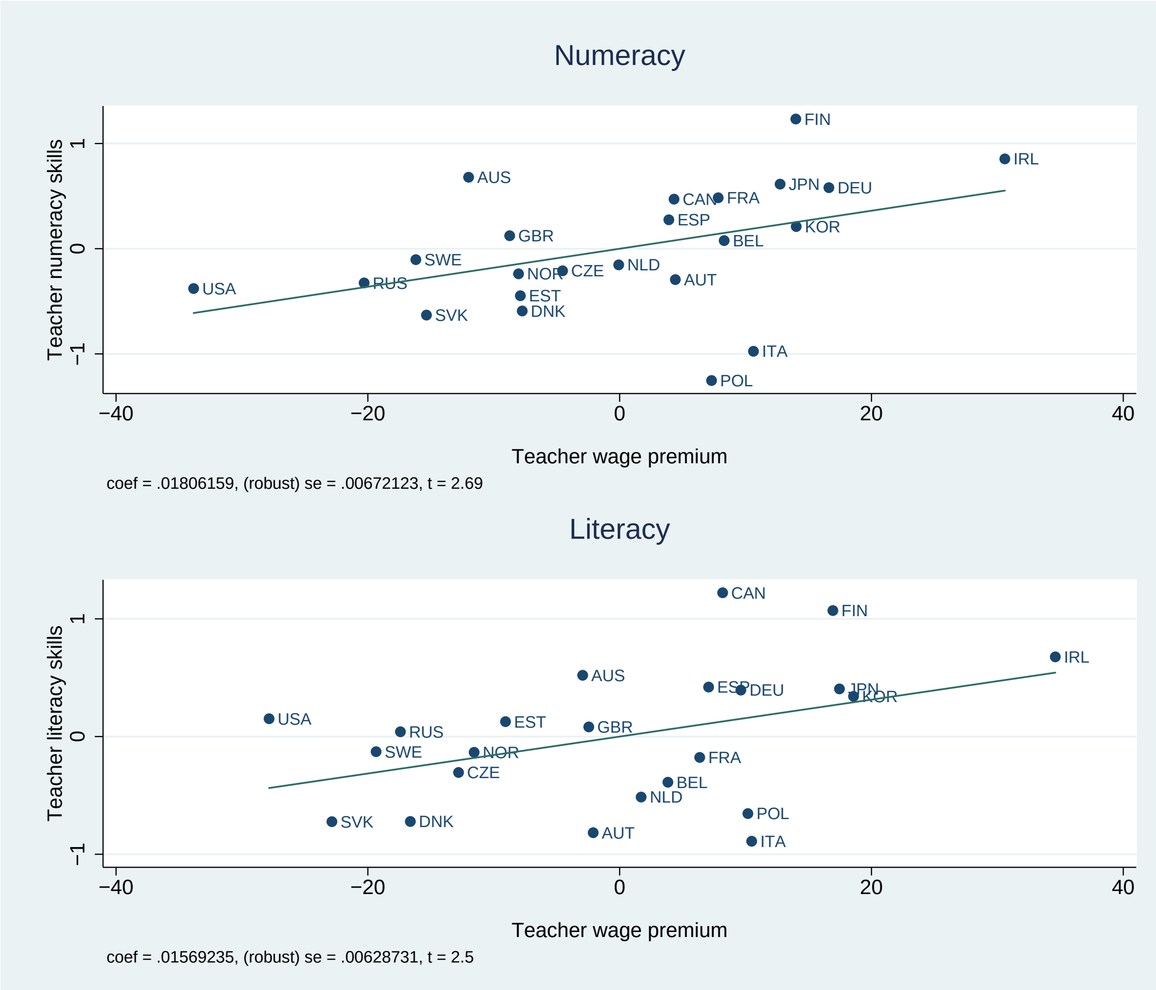
Note: The two graphs in the top panel do not include any controls. The two graphs in bottom panel are added-variable plots that control for country-specific average skills in numeracy and literacy, respectively, of all adults aged 25–65. Scales are deviations from country mean in standard deviations. *Data sources*: PISA 2009 and 2012, PIAAC.

Figure 4: Teacher Wage Premiums around the World



Notes: Bars indicate the percentage difference in gross hourly earnings of teachers with a college degree as compared to all college graduates in a country. Estimates condition on gender, a quadratic polynomial in potential work experience (age − years of schooling − 6), and numeracy and literacy skills. *Data source:* PIAAC.

Figure 5: Teacher Wage Premiums and Teacher Cognitive Skills



Notes: Graphs show added-variable plots that control for country-specific numeracy skills (upper panel) and literacy skills (lower panel) of all college graduates (without teachers). Teacher wage premiums are the percentage difference in gross hourly earnings of teachers with a college degree as compared to all college graduates in a country, conditional on gender, quadratic polynomial in potential work experience, and numeracy and literacy skills (see also Figure 4 and Table A-9). *Data source:* PIAAC.

Table 1: Teacher Cognitive Skills by Country

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
Numeracy	295	300	300	308	292	305	295	285	317	302	308	295
Literacy	299	312	292	303	307	300	288	294	322	296	301	300
Difference	-4	-12	8	5	-15	5	7	-9	-5	6	7	-4
Numeracy rank	68	71	69	68	67	73	56	60	73	80	72	75
Literacy rank	70	75	70	71	72	77	60	69	74	77	74	74
Observations	5,322	248	188	215	834	141	413	188	221	163	127	180
	Italy	Japan	Korea	Netherl.	Norway	Poland	Russia	Slovak R.	Spain	Sweden	U.K.	U.S.
Numeracy	273	311	287	304	302	277	273	294	283	306	289	284
Literacy	279	319	296	308	304	293	283	290	290	307	299	301
Difference	-5	-8	-9	-4	-2	-16	-10	4	-7	-1	-10	-17
Numeracy rank	67	70	72	63	65	64	53	66	75	62	65	70
Literacy rank	73	67	74	67	68	73	54	60	80	65	67	71
Observations	124	147	217	197	279	199	137	133	183	147	310	132

Notes: Teacher cognitive skills are country-specific average cognitive skills of primary school teachers, secondary school teachers, and "other" teachers (including, e.g., special education teachers and language teachers). Because occupation in these countries is reported only at the two-digit level, teachers in Australia and Finland include all "teaching professionals" (ISCO-08 code 23), i.e., additionally include pre-kindergarten teachers and university professors. All skill measures are rounded to the nearest integer. Rank refers to the position of average cognitive skills of teachers in the cognitive skill distribution of all adults aged 25–65 excluding teachers. Individuals are weighted with PIAAC final sample weights. Observations refer to the number of teachers used to construct country-specific teacher skills. *Data source:* PIAAC.

Table 2: Student Performance and Teacher Cognitive Skills (OLS)

	Student Math Performance			Student Reading Performance		
	(1)	(2)	(3)	(4)	(5)	(6)
Teacher cognitive skills	0.083**	0.117***	0.096***	0.128***	0.086***	0.086***
	(0.035)	(0.021)	(0.021)	(0.023)	(0.020)	(0.021)
Parent cognitive skills			0.033***			–0.001
			(0.011)			(0.009)
Student characteristics		X	X		X	X
Parent characteristics		X	X		X	X
School characteristics		X	X		X	X
Country characteristics		X	X		X	X
Students	406,564	406,564	406,564	406,564	406,564	406,564
Countries	23	23	23	23	23	23
Adj. R2	0.01	0.26	0.26	0.02	0.29	0.29

Notes: Least squares regressions weighted by students' inverse sampling probability, giving each country the same weight. Dependent variable: student PISA test score in math (Columns (1–3) and in reading (Columns 4–6), respectively. Student test scores are z-standardized at the individual level across countries. Country-level teacher cognitive skills refer to numeracy in Columns 1–3 and to literacy in Columns 4–6. Teacher skills are z-standardized across countries. Parent cognitive skills are computed as the mean of mother's and father's skills in numeracy (Columns 1–3) or literacy (Columns 4–6). Parent cognitive skills are standardized using teacher cognitive skills as "numeraire" scale. Student characteristics are age, gender, migrant status (first-generation or second-generation), and language spoken at home. Parent characteristics include parents' educational degree, number of books at home, and type of occupation. School characteristics include school location, number of students per school, and three autonomy measures. Country characteristics are expenditures per student, GDP per capita, and school starting age (Table A-1 reports results for all control variables). All regressions include controls for respective imputation dummies and a dummy indicating the PISA wave. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* OECD, PIAAC, PISA 2009 and 2012.

Table 3: Simulation Analysis: Raising Teacher Cognitive Skills to Finnish Level

	Teacher Numeracy Skills		Teacher Literacy Skills	
	Difference from Finnish teachers (in PIAAC points)	Student perf. increase (in % of internat. SD)	Difference from Finnish teachers (in PIAAC points)	Student perf. increase (in % of internat. SD)
	(1)	(2)	(3)	(4)
Australia	17	13.7	10	8.3
Austria	17	13.2	30	24.3
Belgium	9	7.1	19	15.5
Canada	25	19.5	15	12.0
Czech R.	12	9.6	22	18.3
Denmark	22	17.5	33	27.5
Estonia	32	25.5	28	23.3
France	16	12.4	26	21.3
Germany	9	7.0	21	16.9
Ireland	22	17.1	22	18.1
Italy	44	34.6	43	35.7
Japan	6	4.7	3	2.5
Korea	31	24.0	26	21.3
Netherl.	14	10.7	14	11.7
Norway	15	12.1	18	14.7
Poland	40	31.3	29	23.6
Russia	44	34.8	39	32.2
Slovak R.	23	18.0	32	26.2
Spain	34	27.1	32	26.3
Sweden	11	8.8	14	11.8
U.K.	28	22.1	22	18.5
U.S.	33	26.0	21	17.0

Notes: This table shows by how much student performance would increase if teacher skills in numeracy and literacy, respectively, were at the levels in Finland (i.e., the country with highest teacher skills in both numeracy and literacy). Estimation based on Columns 3 or 6 of Table 2. Columns 1 and 3 show difference in teacher skills to Finland. *Data sources:* PIAAC, PISA 2009 and 2012.

Table 4: Student Performance and Teacher Cognitive Skills (Robustness)

	Student Math Performance				Student Reading Performance			
	Baseline	Parent skills	Adult skills	Mean teacher skills	Baseline	Parent skills	Adult skills	Mean teacher skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Teacher cognitive skills	0.096***	0.097***	0.085**	0.092***	0.086***	0.117***	0.123***	0.082***
	(0.021)	(0.032)	(0.033)	(0.019)	(0.021)	(0.032)	(0.038)	(0.023)
Parent cognitive skills	0.033***			0.034***	–0.001			0.001
	(0.011)			(0.009)	(0.009)			(0.008)
Parent cognitive skills (country level)		0.026				–0.038		
		(0.027)				(0.035)		
Adult cognitive skills (country level)			0.043				–0.045	
			(0.031)				(0.043)	
Student characteristics	X	X	X	X	X	X	X	X
Parent characteristics	X	X	X	X	X	X	X	X
School characteristics	X	X	X	X	X	X	X	X
Country characteristics	X	X	X	X	X	X	X	X
Students	406,564	406,564	406,564	406,564	406,564	406,564	406,564	406,564
Countries	23	23	23	23	23	23	23	23
Adj. R2	0.26	0.26	0.26	0.26	0.29	0.30	0.30	0.29

Notes: Robustness checks of the baseline least squares regressions. Dependent variable: standardized student PISA test score in math (Columns 1–4) and reading (Columns 5–8), respectively. All skill measures in Columns 1–4 (5–8) refer to numeracy (literacy). Columns 1 and 5 replicate the baseline models from Columns 3 and 6 in Table 2. In Columns 2 and 6, we replace individual-level parent cognitive skills by the country-specific median cognitive skill level of PIAAC respondents aged 35–59 with children. In Columns 3 and 7, we use median cognitive skill level of all PIAAC respondents aged 25–65 instead of individual parent cognitive skills. In Columns 4 and 8, we use mean teacher cognitive skills instead of median cognitive skills. Student, parent, school, and country characteristics are the same as in the baseline least squares models (see Table 2). All regressions include controls for imputation dummies and the PISA wave. Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* OECD, PIAAC, PISA 2009 and 2012.

Table 5: Student Performance and Teacher Cognitive Skills with Instructional Practices (OLS)

	Student Math Performance		Student Reading Performance	
	(1)	(2)	(3)	(4)
Teacher cognitive skills	0.096***	0.099***	0.086***	0.099***
	(0.021)	(0.022)	(0.021)	(0.023)
Parent cognitive skills	0.033***	0.033***	–0.001	–0.003
	(0.011)	(0.011)	(0.009)	(0.009)
Instructional practices		0.068		0.350**
		(0.111)		(0.147)
Student characteristics	X	X	X	X
Parent characteristics	X	X	X	X
School characteristics	X	X	X	X
Country characteristics	X	X	X	X
Students	406,564	406,564	406,564	406,564
Countries	23	23	23	23
Adj. R2	0.26	0.26	0.29	0.30

Notes: Dependent variable: standardized student PISA test score in math (Columns 1–2) and reading (Columns 3–4), respectively. All skill measures in Columns 1–2 (3–4) refer to numeracy (literacy). Indicator for teacher instructional practices is based on the PISA data. See text for details on the construction of the instructional practices indicator. All control variables are the same as in the baseline least squares models (see Table 2). Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* OECD, PIAAC, PISA 2009 and 2012.

Table 6: Student Performance and Teacher Cognitive Skills (Student FE)

	Student performance		
	(1)	(2)	(3)
Teacher cognitive skills	0.075***	0.086***	0.068**
	(0.024)	(0.023)	(0.028)
Parent cognitive skills			0.027
			(0.026)
Instruction time		0.061***	0.064***
		(0.017)	(0.017)
Shortage of teachers		–0.004	–0.004
		(0.007)	(0.007)
Student fixed effects	X	X	X
Students	406,564	406,564	406,564
Countries	23	23	23
Adj. R2	0.01	0.01	0.01

Notes: Fixed-effects regressions weighted by students' inverse sampling probability, giving each country the same weight. Dependent variable: student performance in math and reading. All regressions include subject fixed effects and imputation dummies. Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* PIAAC, PISA 2009 and 2012.

Table 7: Determinants of Teacher Skills: Females in High-Skilled Occupations

	Skills of female teachers				Skills of all teachers			
	Numeracy		Literacy		Numeracy		Literacy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share: female teachers/females in high-skilled occ. (×10)	0.450**	0.443**	0.413**	0.461*	0.286*	0.280	0.343*	0.382*
	(0.172)	(0.195)	(0.192)	(0.227)	(0.154)	(0.163)	(0.184)	(0.214)
Numeracy skills college graduates (w/o teachers)		0.544*				0.532**		
		(0.260)				(0.226)		
Literacy skills college graduates (w/o teachers)				0.819**				0.665*
				(0.368)				(0.320)
Country fixed effects	X	X	X	X	X	X	X	X
Cohort fixed effects	X	X	X	X	X	X	X	X
Observations	54	54	54	54	54	54	54	54
Countries	18	18	18	18	18	18	18	18
R2 (within country)	0.56	0.60	0.47	0.56	0.59	0.63	0.55	0.61

Notes: Dependent variable: cognitive skills of female teachers (Columns 1–4) and skills of all teachers (Columns 5–8). Teacher skills are standardized using the standard deviation from the full sample (23 countries) as "numeraire" scale, such that magnitudes are comparable to the main analysis; cognitive skills of college graduates are standardized similarly. *Share: female teachers/females in high-skilled occ.* is the share of female teachers in a country-cohort cell over all females working in high-skilled occupations. Each cohort covers 15 adjacent birth years (ranging from 1946–1990). Occupations are classified as high-skilled applying the following procedure in PIAAC: First, for each two-digit occupation in each country, we calculate average years of schooling of males currently working in these occupations. Second, ranking occupations by average schooling level and starting from the occupation with the highest level, we define occupations as high-skilled until males working in these occupations comprise 25 percent of all males currently working in that country. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data source:* PIAAC.

Table A-1: Parent Cognitive Skills by Country

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
					Numeracy							
Mean	279	287	280	301	282	267	293	264	299	275	289	275
Std. Dev.	23	21	15	22	20	17	21	11	18	26	21	22
Max – Min	88	128	50	108	120	51	141	40	102	132	126	96
					Literacy							
Mean	277	293	268	289	284	261	278	262	297	272	279	280
Std. Dev.	20	19	15	20	18	12	20	12	17	21	19	18
Max – Min	80	113	47	96	116	37	148	39	101	106	109	86
Observations	65,576	3,137	2,231	2,251	11,933	2,105	3,352	3,463	2,252	3,086	2,293	2,371

	Italy	Japan	Korea	Netherl.	Norway	Poland	Russia	Slovak R.	Spain	Sweden	U.K.	U.S.
					Numeracy							
Mean	267	295	276	295	277	258	266	274	265	275	281	267
Std. Dev.	19	7	17	22	16	12	7	19	22	20	20	32
Max – Min	104	26	85	120	62	43	26	61	94	78	109	135
					Literacy							
Mean	264	294	281	293	273	259	276	270	266	272	285	277
Std. Dev.	16	6	15	21	15	10	9	15	21	19	18	27
Max – Min	86	22	76	109	51	36	34	48	87	71	95	122
Observations	1,789	2,103	3,361	2,276	2,228	1,793	1,074	2,442	2,614	1,864	3,578	1,980

Notes: Summary statistics of parents' cognitive skills (average skill of mother and father) based on actual parents of PISA students. See text for computation of parent cognitive skills. *Max-Min* indicates the difference between the maximum and minimum parent cognitive skills within a country. *Observations* refer to the number of adults in the PIAAC samples used for computing parents' skills. *Data sources:* PIAAC, PISA 2009 and 2012.

Table A-2: Summary Statistics for Student Performance and Student Characteristics

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
Math performance	504	509	500	515	522	496	502	516	530	496	513	494
	(93)	(95)	(94)	(103)	(88)	(94)	(84)	(81)	(85)	(100)	(97)	(86)
Reading performance	502	513	480	508	524	486	496	508	530	501	503	509
	(96)	(98)	(96)	(102)	(91)	(91)	(84)	(82)	(91)	(108)	(93)	(92)
Age (in years)	15.8	15.8	15.8	15.8	15.8	15.8	15.7	15.8	15.7	15.9	15.8	15.7
Female	0.49	0.50	0.51	0.49	0.50	0.48	0.50	0.49	0.49	0.51	0.49	0.49
First-gen. migrant	0.05	0.12	0.06	0.09	0.13	0.02	0.04	0.01	0.02	0.05	0.05	0.12
Second-gen. migrant	0.06	0.12	0.11	0.08	0.15	0.01	0.06	0.07	0.01	0.10	0.11	0.02
Other language	0.08	0.09	0.11	0.22	0.16	0.02	0.05	0.04	0.04	0.08	0.09	0.05
Observations	406,564	28,732	11,345	17,098	44,751	11,391	13,405	9,506	14,639	8,911	9,980	8,953

	Italy	Japan	Korea	Netherl.	Norway	Poland	Russia	Slovak R.	Spain	Sweden	U.K.	U.S.
Math performance	484	533	550	524	494	506	475	489	484	486	493	484
	(93)	(94)	(94)	(90)	(88)	(90)	(86)	(99)	(89)	(93)	(91)	(90)
Reading performance	488	529	537	510	503	509	467	470	485	491	497	498
	(96)	(100)	(83)	(91)	(96)	(89)	(90)	(98)	(90)	(103)	(96)	(94)
Age (in years)	15.7	15.8	15.7	15.7	15.8	15.7	15.8	15.8	15.9	15.7	15.7	15.8
Female	0.48	0.48	0.47	0.50	0.49	0.51	0.50	0.49	0.49	0.49	0.51	0.49
First-gen. migrant	0.06	0.00	0.00	0.04	0.05	0.00	0.05	0.01	0.10	0.06	0.07	0.07
Second-gen. migrant	0.02	0.00	0.00	0.08	0.04	0.00	0.07	0.00	0.01	0.08	0.05	0.13
Other language	0.14	0.00	0.00	0.06	0.07	0.01	0.09	0.06	0.18	0.09	0.07	0.14
Observations	61,978	12,439	10,022	9,220	9,346	9,524	10,539	9,233	51,200	9,303	24,838	10,211

Notes: Means and standard deviations (in parentheses) reported. *Other language* indicates a student who speaks a foreign language at home. *Observations* refer to the number of students in both PISA cycles. Statistics are based on student-level observations weighted with inverse sampling probabilities, giving each PISA cycle the same total weight. *Data sources:* PISA 2009 and 2012.

Table A-3: Summary Statistics for Parent Characteristics

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
Number of books at home												
0-10 books	0.12	0.09	0.13	0.16	0.10	0.10	0.13	0.07	0.07	0.16	0.11	0.14
11-25 books	0.15	0.12	0.16	0.17	0.14	0.14	0.16	0.14	0.12	0.17	0.13	0.15
26-100 books	0.31	0.30	0.31	0.29	0.31	0.35	0.32	0.31	0.34	0.29	0.29	0.30
101-200 books	0.19	0.21	0.17	0.17	0.21	0.19	0.18	0.21	0.22	0.17	0.20	0.19
201-500 books	0.15	0.18	0.14	0.13	0.16	0.15	0.14	0.17	0.18	0.13	0.17	0.15
More than 500 books	0.08	0.10	0.09	0.08	0.08	0.07	0.07	0.09	0.06	0.07	0.10	0.07
Highest educational degree												
ISCED 0	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00
ISCED 1	0.01	0.01	0.01	0.02	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.02
ISCED 2	0.06	0.05	0.04	0.03	0.02	0.01	0.05	0.03	0.02	0.09	0.15	0.07
ISCED 3B,C	0.09	0.07	0.29	0.05	0.00	0.18	0.13	0.02	0.08	0.19	0.12	0.02
ISCED 3A,4	0.28	0.32	0.18	0.28	0.25	0.49	0.15	0.38	0.09	0.19	0.23	0.35
ISCED 5B	0.21	0.13	0.28	0.22	0.24	0.09	0.41	0.22	0.27	0.22	0.18	0.18
ISCED 5A,6	0.35	0.42	0.20	0.40	0.48	0.23	0.24	0.35	0.53	0.30	0.30	0.35
Highest occupational status												
Blue collar-low skilled	0.06	0.05	0.05	0.09	0.06	0.07	0.05	0.06	0.03	0.07	0.06	0.05
Blue collar-high skilled	0.10	0.08	0.14	0.10	0.07	0.13	0.07	0.14	0.07	0.11	0.10	0.09
White collar-low skilled	0.25	0.17	0.26	0.23	0.21	0.27	0.25	0.23	0.20	0.26	0.29	0.26
White collar-high skilled	0.57	0.68	0.53	0.56	0.64	0.52	0.62	0.55	0.69	0.54	0.53	0.58

Table A-3: Summary Statistics for Parent Characteristics (continued)

	Italy	Japan	Korea	Netherl.	Norway	Poland	Russia	Slovak R.	Spain	Sweden	U.K.	U.S.
Number of books at home												
0-10 books	0.12	0.09	0.05	0.16	0.08	0.11	0.09	0.15	0.09	0.09	0.14	0.21
11-25 books	0.19	0.13	0.09	0.18	0.11	0.20	0.19	0.17	0.15	0.11	0.16	0.18
26-100 books	0.08	0.09	0.10	0.07	0.11	0.07	0.08	0.05	0.09	0.11	0.08	0.05
101-200 books	0.30	0.35	0.29	0.30	0.30	0.34	0.34	0.37	0.32	0.30	0.29	0.29
201-500 books	0.18	0.19	0.23	0.15	0.22	0.17	0.17	0.17	0.21	0.20	0.18	0.15
More than 500 books	0.13	0.15	0.24	0.13	0.19	0.11	0.13	0.10	0.15	0.19	0.15	0.11
Highest educational degree												
ISCED 0	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.01
ISCED 1	0.01	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.07	0.01	0.00	0.02
ISCED 2	0.21	0.02	0.04	0.04	0.02	0.04	0.01	0.02	0.18	0.04	0.03	0.05
ISCED 3B,C	0.06	0.06	0.07	0.00	0.03	0.39	0.01	0.14	0.02	0.07	0.20	0.00
ISCED 3A,4	0.37	0.30	0.34	0.32	0.25	0.33	0.08	0.54	0.25	0.18	0.18	0.34
ISCED 5B	0.07	0.15	0.06	0.39	0.39	0.00	0.44	0.06	0.14	0.21	0.23	0.15
ISCED 5A,6	0.28	0.47	0.48	0.21	0.30	0.24	0.46	0.23	0.33	0.48	0.36	0.43
Highest occupational status												
Blue collar-low skilled	0.07	0.07	0.04	0.04	0.03	0.07	0.06	0.11	0.09	0.05	0.05	0.07
Blue collar-high skilled	0.17	0.08	0.06	0.06	0.04	0.27	0.11	0.16	0.18	0.05	0.05	0.06
White collar-low skilled	0.28	0.36	0.29	0.20	0.16	0.23	0.26	0.31	0.29	0.24	0.26	0.21
White collar-high skilled	0.45	0.48	0.59	0.68	0.75	0.43	0.54	0.40	0.43	0.65	0.62	0.64

Notes: Mean shares reported. Statistics are based on student-level observations weighted with inverse sampling probabilities, giving each PISA cycle the same total weight. *Highest educational degree* includes the following categories: *ISCED 0:* no educational degree; *ISCED 1:* primary education; *ISCED 2:* lower secondary; *ISCED 3B,C:* vocational/pre-vocational upper secondary; *ISCED 3A,4:* upper secondary or non-tertiary post-secondary; *ISCED 5B:* vocational tertiary; and *ISCED 5A,6:* theoretically oriented tertiary and post-graduate. *Data sources:* PISA 2009 and 2012.

Table A-4: Summary Statistics for School Characteristics

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
Instructional time math	3.5	4.0	2.6	3.5	5.3	3.1	3.7	3.7	2.9	3.5	3.3	3.1
Instructional time reading	3.6	3.9	2.4	3.6	5.3	3.0	5.2	3.3	2.5	3.7	3.1	3.0
Shortage math teachers	1.47	1.89	1.33	1.92	1.44	1.25	1.23	1.45	1.16	1.35	1.78	1.40
Shortage language teachers	1.34	1.53	1.36	1.54	1.26	1.12	1.17	1.30	1.10	1.36	1.46	1.16
Private school	0.21	0.41	0.11	0.69	0.08	0.06	0.24	0.04	0.04	0.20	0.06	0.60
Students per school	706	981	558	718	1032	450	480	557	429	822	702	593
Content autonomy	0.68	0.71	0.58	0.56	0.37	0.88	0.68	0.77	0.64	0.64	0.63	0.69
Personnel autonomy	0.43	0.39	0.08	0.38	0.30	0.88	0.58	0.54	0.24	0.05	0.15	0.34
Budget autonomy	0.83	0.93	0.86	0.69	0.75	0.79	0.96	0.84	0.92	0.97	0.88	0.87

	Italy	Japan	Korea	Netherl.	Norway	Poland	Russia	Slovak R.	Spain	Sweden	U.K.	U.S.
Instructional time math	3.8	3.9	3.6	2.8	3.2	3.4	3.6	3.0	3.5	3.1	3.7	4.3
Instructional time reading	4.7	3.5	3.5	2.8	3.8	3.7	3.1	3.0	3.4	3.0	3.8	4.4
Shortage math teachers	1.69	1.27	1.57	2.10	1.73	1.03	1.71	1.13	1.09	1.35	1.64	1.37
Shortage language teachers	1.64	1.21	1.57	1.74	1.70	1.01	1.63	1.10	1.08	1.19	1.38	1.20
Private school	0.06	0.30	0.42	0.67	0.02	0.03	0.00	0.09	0.33	0.12	0.26	0.08
Students per school	752	750	1116	1023	340	324	566	480	701	420	1062	1381
Content autonomy	0.72	0.92	0.89	0.93	0.49	0.75	0.59	0.59	0.53	0.63	0.89	0.48
Personnel autonomy	0.05	0.32	0.23	0.89	0.42	0.46	0.65	0.70	0.18	0.72	0.75	0.66
Budget autonomy	0.84	0.90	0.85	0.99	0.88	0.26	0.58	0.72	0.94	0.93	0.96	0.76

Notes: Country means reported. Student-level information on *instructional time* is aggregated to the school level for both math and reading (see also Lavy (2015)). *Shortage math/language teachers* is based on the following school principal question: "Is your school's capacity to provide instruction hindered by any of the following issues? A lack of qualified mathematics/test language teachers" Possible answer categories are: not at all (1), very little (2), to some extent (3), a lot (4). School autonomy measures are binary. *Data sources:* PISA 2009 and 2012.

Table A-5: Summary Statistics for Country Characteristics

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland
Expenditure per student	77	85	107	89	80	50	99	49	79	79	72	85
GDP per capita	34	39	39	36	38	25	38	20	36	33	36	43
School starting age	6.06	5	6	6	5	6	7	7	7	6	6	4
Instruction practice math	0.60	0.66	0.57	0.56	0.70	0.62	0.64	0.59	0.58	0.59	0.64	0.69
Instruction practice reading	0.49	0.53	0.41	0.43	0.56	0.44	0.57	0.50	0.37	0.52	0.44	0.51

	Italy	Japan	Korea	Netherl.	Norway	Poland	Russia	Slovak R.	Spain	Sweden	U.K.	U.S.
Expenditure per student	81	84	65	88	112	49	12	43	78	89	91	111
GDP per capita	32	34	28	41	49	18	21	22	32	38	35	46
School starting age	6	6	6	6	6	7	7	6	6	7	5	6
Instruction practice math	0.59	0.46	0.38	0.57	0.52	0.60	0.69	0.54	0.64	0.51	0.73	0.72
Instruction practice reading	0.49	0.44	0.34	0.37	0.37	0.59	0.80	0.47	0.44	0.42	0.54	0.61

Notes: Only country-level characteristics reported. The *instruction practice* indicators are based on student information provided in PISA; in 2009 for language teachers and in 2012 for math teachers. See text for details on the construction of the instruction practice indicators. The remaining country characteristics come from OECD statistics. Expenditure per student and GDP per capita are expressed in 1,000 PPP-US-$. *Data sources:* PISA 2009 and 2012, OECD.

Table A-6: Student Performance and Teacher Cognitive Skills from OLS Estimation: Results on All Covariates not Reported in Table 2

Dependent variable: student performance	Math	Reading
Student characteristics		
Age	0.139***	0.139***
	(0.019)	(0.014)
Female	–0.155***	0.349***
	(0.012)	(0.016)
First-generation migrant	–0.145***	–0.124**
	(0.050)	(0.049)
Second-generation migrant	–0.097*	–0.032
	(0.050)	(0.043)
Other language at home	–0.092**	–0.177***
	(0.033)	(0.036)
Family background		
11-25 books	0.213***	0.261***
	(0.024)	(0.021)
26-100 books	0.448***	0.524***
	(0.037)	(0.035)
101-200 books	0.627***	0.722***
	(0.048)	(0.043)
201-500 books	0.830***	0.911***
	(0.053)	(0.050)
More than 500 books	0.855***	0.912***
	(0.057)	(0.053)
ISCED 1	0.106*	0.164**
	(0.052)	(0.078)
ISCED 2	0.115*	0.240***
	(0.066)	(0.063)
ISCED 3B,C	0.219***	0.335***
	(0.074)	(0.071)
ISCED 3A, 4	0.264***	0.374***
	(0.071)	(0.070)
ISCED 5B	0.221**	0.384***
	(0.079)	(0.067)
ISCED 5A, 6	0.296***	0.450***
	(0.079)	(0.064)
Blue collar-high skilled	0.113***	0.094***
	(0.013)	(0.016)
White collar-low skilled	0.181***	0.177***
	(0.017)	(0.017)
White collar-high skilled	0.401***	0.400***
	(0.022)	(0.021)

(continued on next page)

Table A-6 (continued)

Dependent variable: student performance	Math	Reading
School characteristics		
Small Town	–0.005	0.022
	(0.025)	(0.024)
Town	0.004	0.052*
	(0.028)	(0.029)
City	–0.001	0.063*
	(0.031)	(0.032)
Large City	0.019	0.089*
	(0.040)	(0.044)
Private school	0.188***	0.168***
	(0.028)	(0.032)
No. students per school (in 1000)	0.292***	0.249***
	(0.062)	(0.055)
Content autonomy	0.056	0.020
	(0.038)	(0.030)
Personnel autonomy	–0.162***	–0.160***
	(0.042)	(0.035)
Budget autonomy	0.031	0.029
	(0.040)	(0.040)
Shortage math teacher	–0.034**	
	(0.013)	
Shortage language teacher		–0.046***
		(0.016)
Weekly hours math classes	0.060**	
	(0.029)	
Weekly hours language classes		0.005
		(0.022)
Country-level measures		
Educational expenditure per student	0.001	0.003
	(0.002)	(0.002)
GDP per capita	–0.012**	–0.010*
	(0.005)	(0.006)
School starting age	0.079*	0.028
	(0.042)	(0.046)
Students	406,564	406,564
Countries	23	23
Adj. R2	0.26	0.29

Notes: The table reports results on all further covariates of the ordinary least squares estimations with the full set of control variables, corresponding to Column 3 (math) and Column 6 (reading) in Table 2. Omitted categories of family background and school characteristics: *0-10 books*; *parents have no educational degree*; *blue collar-low skilled*; and *village*. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* OECD, PIAAC, PISA 2009 and 2012.

Table A-7: Student Performance and Teacher Cognitive Skills (Heterogeneity)

	Gender		Parental background		Natives vs. Migrants	
	Boys	Girls	High SES	Low SES	Natives	Migrants
Panel A: Student Math Performance						
Teacher cognitive skills	0.091***	0.103***	0.107***	0.084***	0.090***	0.109***
	(0.021)	(0.022)	(0.022)	(0.026)	(0.021)	(0.030)
Parent cognitive skills	0.039***	0.026**	0.054***	0.021*	0.040***	0.005
	(0.012)	(0.011)	(0.015)	(0.011)	(0.012)	(0.014)
Panel B: Student Reading Performance						
Teacher cognitive skills	0.070***	0.105***	0.080***	0.101***	0.074***	0.108**
	(0.021)	(0.024)	(0.021)	(0.025)	(0.022)	(0.038)
Parent cognitive skills	0.005	–0.008	0.016	–0.010	0.004	–0.011
	(0.009)	(0.010)	(0.013)	(0.009)	(0.010)	(0.012)
Students	204,424	202,140	207,914	198,650	350,912	20,433
Countries	23	23	23	23	23	22
Additional controls in Panels A + B						
Student characteristics	X	X	X	X	X	X
Parent characteristics	X	X	X	X	X	X
School characteristics	X	X	X	X	X	X
Country characteristics	X	X	X	X	X	X

Notes: Table reports estimates of the effect of teacher cognitive skills on student performance for the following subsamples: boys, girls, student with a high socioeconomic background, students with as low socioeconomic background, natives, and second-generation immigrants. Dependent variable: standardized student PISA test score in math (Panel A) and reading (Panel B), respectively. Socioeconomic background is measured by the PISA index of economic, social and cultural status (ESCS). This index captures a range of aspects of a student's family and home background that combines information on parents' education, occupations, and home possessions. To account for the unequal distribution of migrants across countries, we re-weight regressions based on the sample of natives and migrants, respectively, giving equal weight to each country within each subsample. Korea has no second-generation migrants and thus drop out from the subsample of migrants. All skill measures in the upper (lower) part in the table refer to numeracy (literacy). Student, parent, school, and country characteristics are the same as in the least squares models (see Table 2). All regressions include controls for respective imputation dummies and a dummy indicating the PISA wave. Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* OECD, PIAAC, PISA 2009 and 2012.

Table A-8: Student Performance and Teacher Cognitive Skills with Continental Fixed Effects and in Restricted Sample (OLS)

	Student Math Performance			Student Reading Performance		
	Baseline	Continental FE	Europe only	Baseline	Continental FE	Europe only
	(1)	(2)	(3)	(4)	(5)	(6)
Teacher cognitive skills	0.096***	0.094***	0.076***	0.086***	0.100***	0.082**
	(0.021)	(0.021)	(0.022)	(0.021)	(0.021)	(0.033)
Parent cognitive skills	0.033***	0.033***	0.033**	–0.001	0.000	–0.001
	(0.011)	(0.011)	(0.012)	(0.009)	(0.009)	(0.010)
Continental fixed effects		X			X	
Student characteristics	X	X	X	X	X	X
Parent characteristics	X	X	X	X	X	X
School characteristics	X	X	X	X	X	X
Country characteristics	X	X	X	X	X	X
Students	406,564	406,564	300,409	406,564	406,564	300,409
Countries	23	23	18	23	23	18
Adj. R2	0.26	0.26	0.27	0.29	0.30	0.31

Notes: Dependent variable: standardized student PISA test score in math (Columns 1–3) and reading (Columns 4–6), respectively. All skill measures in Columns 1–3 (4–6) refer to numeracy (literacy). Columns 1 and 4 replicate the baseline least squares models from Columns 3 and 6 in Table 2. Student, parent, school, and country characteristics are the same as in the baseline least squares models (see Table 2). All regressions include controls for imputation dummies and the PISA wave. Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* OECD, PIAAC, PISA 2009 and 2012.

Table A-9: Teacher Wage Premiums around the World: Regression Output

	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	France	Germany	Ireland	Italy
Teacher	–0.035	0.017	0.026	0.172***	–0.105**	–0.089***	0.017	0.129***	0.127***	0.164***	0.450***	0.248***
	(0.031)	(0.033)	(0.023)	(0.020)	(0.047)	(0.015)	(0.036)	(0.021)	(0.027)	(0.045)	(0.039)	(0.052)
Numeracy	0.097***	0.019	0.066***	0.089***	0.003	0.067***	0.118***	0.096***	0.083***	0.063*	0.107***	0.100***
	(0.028)	(0.031)	(0.020)	(0.018)	(0.054)	(0.019)	(0.024)	(0.024)	(0.021)	(0.036)	(0.032)	(0.035)
Literacy	0.017	0.094***	0.019	0.064***	0.093	0.019	0.034	–0.005	0.007	0.073**	0.022	0.005
	(0.030)	(0.033)	(0.022)	(0.018)	(0.057)	(0.018)	(0.025)	(0.023)	(0.020)	(0.034)	(0.030)	(0.035)
Female	–0.121***	–0.111***	–0.037*	–0.111***	–0.155**	–0.107***	–0.288***	–0.167***	–0.061***	–0.167***	0.002	–0.131***
	(0.020)	(0.028)	(0.020)	(0.016)	(0.063)	(0.014)	(0.026)	(0.019)	(0.018)	(0.028)	(0.030)	(0.042)
Potential experience	0.037***	0.028***	0.026***	0.040****	0.012	0.026***	0.017***	0.025***	0.032***	0.046***	0.051***	0.038***
	(0.003)	(0.007)	(0.003)	(0.003)	(0.008)	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.007)
Potential experience^2	–0.001***	–0.000**	–0.000***	–0.001***	–0.000	–0.000***	–0.001***	–0.000***	–0.000***	–0.001***	–0.001***	–0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

	Japan	Korea	Netherl.	Norway	Poland	Russia	Slovak R.	Spain	Sweden	U.K.	U.S.
Teacher	0.103**	0.292***	–0.042	–0.114***	0.147***	0.013	–0.164***	0.233***	–0.219***	0.033	–0.229***
	(0.041)	(0.050)	(0.026)	(0.015)	(0.040)	(0.116)	(0.044)	(0.032)	(0.021)	(0.036)	(0.040)
Numeracy	0.205***	0.051	0.046	0.069***	0.077**	0.088	0.120**	0.084**	0.030*	0.106***	0.082**
	(0.039)	(0.048)	(0.033)	(0.017)	(0.032)	(0.069)	(0.047)	(0.035)	(0.018)	(0.038)	(0.039)
Literacy	–0.047	0.107**	0.058**	0.009	0.040	0.007	0.003	0.032	0.032*	0.067*	0.102***
	(0.041)	(0.047)	(0.029)	(0.019)	(0.032)	(0.047)	(0.052)	(0.031)	(0.017)	(0.037)	(0.039)
Female	–0.343***	–0.204***	–0.072***	–0.112***	–0.133***	–0.167	–0.179***	–0.110***	–0.107***	–0.130***	–0.115***
	(0.026)	(0.036)	(0.024)	(0.015)	(0.037)	(0.114)	(0.043)	(0.027)	(0.016)	(0.028)	(0.037)
Potential experience	0.038***	0.025***	0.042***	0.030***	0.044***	–0.006	0.023***	0.037***	0.024***	0.043***	0.049***
	(0.004)	(0.006)	(0.003)	(0.002)	(0.005)	(0.012)	(0.008)	(0.005)	(0.003)	(0.004)	(0.006)
Potential experience^2	–0.001***	–0.000	–0.001***	–0.001***	–0.001***	0.000	–0.000**	–0.001***	–0.000***	–0.001***	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Least squares regressions (weighted by sampling weights). Dependent variable: log gross hourly wage. All country samples include workers with a college degree. Numeracy and literacy scores are standardized with std. dev. 1 across countries. *Potential experience* is age − years of schooling − 6. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data source:* PIAAC.