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

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

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Abstract

Differences in teacher quality are commonly cited as a key determinant of the huge international student performance gaps. However, convincing evidence on this relationship is still lacking, in part because it is unclear how to measure teacher quality consistently across countries. We use unique international assessment data to investigate the role of teacher cognitive skills as one main dimension of teacher quality in explaining student outcomes. Our main identification strategy exploits exogenous variation in teacher cognitive skills attributable to international differences in relative wages of nonteacher public sector employees. Using student-level test score data, we find that teacher cognitive skills are an important determinant of international differences in student performance. Results are supported by fixed-effects estimation that uses within-country between-subject variation in teacher skills.

Keywords: teacher cognitive skills, student performance, instrumental variable, PIAAC, PISA

JEL classification: I20, H40, H52

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1. Overview

Numerous international assessment tests have shown that the cognitive skills of students differ greatly across countries, including across developed economies. 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 (2012)). 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) Notwithstanding any evidence that these differences explain differences in student outcomes, they 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 to quantify differences in teacher skills in numeracy and literacy across countries. These differences in teacher cognitive skills reflect, as we discuss below, both where teachers are drawn from in each country's skill distribution and the overall level of cognitive skills in each country's population.

Descriptively, we find that teacher cognitive skills differ widely internationally. For example, average numeracy and literacy skills of teachers in the worst-performing countries (Italy and Russia) are similar to the skills of employed adults with just a post-secondary, non-tertiary education in Canada.[1] In contrast, the skills of teachers in the best-performing countries (Japan and Finland) are higher than 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

[1] We use Canada for the 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.

student performance. Specifically, we use country-level measures of subject-specific teacher skills along with 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 three 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, as well as institutional features of the school systems. Controlling for 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, the OLS coefficients on teacher cognitive skills cannot be interpreted causally as the OLS models likely suffer from omitted-variable bias. For instance, the educational attitudes in a country, a country's curriculum, or the nature of teacher preparation may be correlated with both teacher cognitive skills and student performance.

Second, we exploit information about the performance of students and teachers in 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 across-subject model also controls for all differences across countries that are not subject-specific, e.g., general education preferences or the nature of teacher labor markets. However, we worry that these estimates may still be biased by any country differences that are subject-specific; for example, some countries may particularly emphasize math skills while others may attach more importance to reading skills. Moreover, the within-student estimation likely amplifies any attenuation bias resulting from measurement error in our observed teacher cognitive skills.

Our preferred identification strategy draws on quasi-experimental variation in teacher cognitive skills due to differences in wage distributions across countries. Specifically, we use the gross hourly wages provided in the PIAAC micro data to instrument teacher skills with the position of public sector employees in the wage distribution of private sector college graduates, excluding all teaching professionals. The basic idea of the instrument is that countries with relatively high wages for public sector employees are able to recruit individuals with higher skills as teachers (who are predominantly public sector employees in most developed countries). By excluding all persons working in the education sector (teachers, university professors, etc.) when constructing the instrument, we ensure that the instrument does not reflect the education preferences in a country.

Irrespective of the identification strategy employed, results indicate a sizeable impact of teacher cognitive skills on student performance. In our preferred IV estimation, we find that a one-standard-deviation increase in teachers' numeracy skills raises student math performance by 20 percent of an international standard deviation. The teacher-skills effect is about half this magnitude in reading but is also highly statistically significant. We further find that parent cognitive skills are always positively associated with student performance in both math and reading; however, only the association between parent numeracy skills and student math performance is statistically significant. Furthermore, results are robust to different ways of controlling for the general skill level of adults in a country.

We also show that measured cognitive skills of teachers do not just reflect their pedagogical skills. We create coarse measures of teachers' subject-specific pedagogical skills by using student-level information in PISA about the instructional practices of their math and language teachers. Adding these indicators as additional control variables does not change the teacher-skills coefficients.

We also find some evidence for effect heterogeneity, as the impact of teacher cognitive skills is stronger for students with low socioeconomic background than for students with high socioeconomic background. At the same time, parent cognitive skills appear to be more important for students with high socioeconomic background.

Finally, previous studies have relied on measures of teacher salaries as proxies for teacher quality. We show that indeed teacher salaries tend to be higher in countries where the teachers have higher cognitive skills, but of course this labor market reduced form does not indicate how salaries should be structured or how responsive the teacher force would be to increased teacher salaries.

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 strategy. Section 5 reports results on the impact of teacher cognitive skills on student performance in math and reading and provides robustness checks and heterogeneity analyses for various student subsamples. Section 6 analyzes the relationship of teacher wages and teacher cognitive skills. Section 7 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 a wide variety of family background factors, school inputs, and institutional factors. But, while these studies give some guidance, they generally 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, or the overall salary levels for teachers – and do not necessarily give an accurate picture of their impact under differing institutional structures.

There has developed a parallel literature on international differences in achievement that builds on the comparative outcome data in existing international assessments (see Hanushek and Woessmann (2011a)). Perhaps one of the clearest explanatory factors from these international studies has been the role of family background in explaining student achievement.[3] In contrast, specific conclusions about the impact of 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. These include the degree of local decision making, the use of accountability systems, and direct rewards for personnel in the schools.[5]

The most convincing 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 this finding has not been very useful in considering international achievement differences. First, the studies reflect almost exclusively experience in the United States. Second,

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[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).

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

[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)). See the range of institutional studies in Hanushek and Woessmann (2011a).

[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 summary 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 the teacher quality distribution one standard deviation upwards.

they have not reliably described any underlying determinants of teacher value-added – and in particular any determinants that can be consistently measured across countries.

These individual country studies suggest that the consideration of common measures of teacher quality in existing international studies may be incorrect. The detailed within-country studies (going beyond just the value-added studies) have generally shown that the common measures of teacher differences – teacher education and teacher experience levels – are not consistently related to student achievement, raising questions about the reliance on these 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] 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. But these incentives, while suggestive from a policy perspective, do not constitute direct measures of differences among teachers.[8]

This inability to describe what lies behind differences in teacher effectiveness has made it particularly difficult to investigate the role of teachers in determining international differences in student performance.[9] The commonly measured teacher characteristics in international data sets offer little hope of describing how teacher differences may enter into cross-country variations in student outcomes.

While results are not entirely consistent across studies, perhaps the closest proxy of an underlying dimension of teacher quality is the cognitive skill of teachers as measured by scores on achievement tests (see Eide, Goldhaber, and Brewer (2004); Hanushek and Rivkin (2006)).[10] Nonetheless, even if accepted as a general measure, this finding has not been helpful in

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[7] We explore the relationship between teacher skills and teacher wages in Section 6.

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

[9] See reviews of within-country studies of teacher quality in Hanushek and Rivkin (2006, (2012).

[10] In a unique study for a developing country, Metzler and Woessmann (2012) show the relevance of teacher subject knowledge for student performance. Exploiting within-teacher within-student variation using data from 6th-grade students in Peru (an approach we also employ below), they find a positive impact of teacher subject knowledge on student performance in math. See also Harbison and Hanushek (1992) for the impact of measured teacher math skills on achievement in rural Brazil.

understanding international differences in student performance because data on teacher differences in cognitive skills have been nonexistent. We remedy this data shortcoming with recently available international data on adult skills across countries.

3. International Comparative Data

The unique feature of this study is the application of new and consistent international data on cognitive skills of teachers and parents to explain international student achievement differences. These data provide the first opportunity to assess the role of hypothesized 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. Data included both background and labor-market information and an assessment of cognitive skills for these adult participants.

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 provided information about occupational, educational, and demographic characteristics for each respondent.

After providing the background information, respondents also took a battery of cognitive assessments as described below.[13] PIAAC assessments are designed to be valid cross-culturally and

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[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.

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.[14] The test questions are often framed as real-world problems, such as maintaining a driver's logbook (numeracy 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; still, skills tested in PIAAC can probably be improved by a high-quality college education.

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 report any occupational code. For this study, however, we gained access to the four-digit ISCO-08 (International Standard Classification of Occupations) codes for all countries through the OECD, which allows us to identify teachers in fine categories.[15]

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).[16] 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 this teacher group is more involved with the emotional and social upbringing of children than with rigorously teaching students in reading and math.[17]

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[14] *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.

[15] Australia and Finland report only two-digit occupation codes in PIAAC.

[16] Results are very similar if we drop the category "other teachers." However, we prefer to keep these teachers in the sample to increase sample size.

[17] For Australia and Finland we are not able to exclude pre-kindergarten teachers and university professors/vocational school teachers from our teacher sample. However, based on the 21 countries where teachers are defined using the four-digit code, it turns out 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 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.

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 because the median is more robust to outliers than the mean, something that is particularly relevant in smaller samples.[18] 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.[19] 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 numeracy scores 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. (forthcoming)).[20] Also note that teacher numeracy skills are better than teacher literacy skills in some countries, while the reverse is true in other countries. We will exploit this variation in subject-specific teacher skills in the fixed-effects model that uses only variation within countries across subjects (see Section 5.1). 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 a mean of zero and a standard deviation of 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). We use Canada for this skill comparison because it provides by far the largest country 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 similar skills than adults with a bachelor degree (306 points). The literacy skills of the best-performing teachers (in Japan

[18] 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 5 for a robustness check of our main specification).

[19] The sample size for Canada is substantially larger than for any other country surveyed in PIAAC because Canada decided to oversample to obtain regionally representative adult skills.

[20] 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.

and Finland) are even higher than the skills of Canadian adults with a master or doctoral degree (314 points). This comparison, which looks similar for numeracy skills, underscores 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 that teacher cognitive skills fall at or above the median of the skill distribution of the entire adult population. Across all 23 countries, teacher skills fall at the 68th (70th) percentile of the numeracy (literacy) skill distribution of all adults, ranging from the 53rd to the 80th percentile (see Table 1).

As most teachers are college graduates, 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). The position in the overall skill distribution from which countries recruit their teachers can potentially be influenced by policymakers. We address this issue in Section 6.

From Table 1, teachers in France and Spain are drawn highest up from the country distributions of adult skills in numeracy and literacy, respectively. This is the case even though Finnish teachers have the highest measured cognitive skills, reflecting that the country average of cognitive skills is so high; the median Finnish teacher is at the 60th percentile of the college graduate distribution in numeracy (see Figure 2). Or, harkening back to the argument that 100% of Korean teachers come from the top 30%, the median teacher falls at the 72nd percentile of the overall country distribution and the 52nd percentile of the college graduate distribution in numeracy.[21]

Because the PIAAC tests are new and have not been fully validated, it is useful to compare the PIAAC-based teacher cognitive skills with the numeracy and literacy skills of teachers in larger national datasets. 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

[21] 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).

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 PIAAC (survey year is 2011).[22]

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.[23] 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).[24] 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 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).

Given that the position of teacher cognitive skills in the adult skill distribution as measured in PIAAC is very similar to that in other nationally representative datasets with larger sample sizes, we

[22] 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.

[23] 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 the vast majority of PIAAC participants have already completed their education when being tested.

[24] 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).

are confident that our PIAAC measures are good proxies for the true teacher cognitive skills in a country.

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 compute proxies for the numeracy and literacy skills of PISA parents. We begin with the sample of adult PIAAC participants that could in principle be the parents of PISA students. We then match the numeracy and literacy skills of the PIAAC adults to the actual PISA parents based on several observable characteristics. Specifically, we apply the following procedure. We take all adults in PIAAC aged 35-59 with children. With respect to age, these individuals are potential parents of the 15-year-old PISA students since PIAAC adults were 17–44 years old when PISA students were born. For each country separately, we then regress the numeracy/literacy skills of these adults on three characteristics: gender[25], education (3 categories), and number of books at home (6 categories).[26] Finally, we multiply the estimated coefficients with the same three characteristics (i.e., gender, education, and books at home) of the *actual* PISA parents to obtain predicted numeracy/literacy skills of all PISA parents.[27] In the student-level analysis, we use the average skills of mother and father as a proxy for parent cognitive skills.[28]

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 student's general family background as typically measured by parents' education, parental occupation, and number of books at home. 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.

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[25] 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.

[26] 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 identical in PIAAC and PISA, so this variable was not modified. 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).

[27] 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)).

[28] Results are very similar if we use the maximum skills of mother and father instead.

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. The large variation in parent skills suggests that these measures may capture differences in student performance both across and within countries.

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.[29] 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.[30] The tests emphasize understanding as well as flexible and context-specific application of knowledge, and hence do not test curriculum-specific knowledge. PISA contains both multiple-choice and open-answer questions and provides internationally comparable test scores.

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 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 5.3).

Table A-2 provides summary statistics of student performance and student characteristics.[31] Student performance in math and reading differs significantly across countries. Given that the

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[29] We prefer PISA over the alternative international test of Trends in International Mathematics and Science Study, or TIMSS (see Hanushek and Woessmann (2011a)). Students participating in PISA were tested in both math and reading, while TIMSS only assessed math performance. Note that math scores from TIMSS are strongly correlated with math scores from PISA at the country level.

[30] Since teachers in PIAAC were only tested in the domains numeracy and literacy, we discard the science test scores in PISA.

[31] All statistics are averages across PISA 2009 and PISA 2012. Again, we weight individual-level observations with inverse sampling probabilities.

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 regressions, we normalize test scores at the student level across the 23 countries with a mean of zero and a standard deviation of one, separately for each PISA cycle. 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.[32] 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 also construct measures of weekly instructional time for both language and math classes. As in Lavy (forthcoming), we aggregate this information across students to the school level. Furthermore, school principals provide information on the lack of qualified math teachers and language teachers, whether the school is public or private, city size, total number of students in the school, and about three 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).

4. Estimation Strategies

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

$$y_{iksc} = \alpha + \delta T_{kc} + \boldsymbol{X}_{isc}\boldsymbol{\beta}_1 + \boldsymbol{X}_{sc}\boldsymbol{\beta}_2 + \boldsymbol{X}_{c}\boldsymbol{\beta}_3 + \boldsymbol{Z}_{iksc}\boldsymbol{\gamma}_1 + \boldsymbol{Z}_{ksc}\boldsymbol{\gamma}_2 + \varepsilon_{iksc}, \tag{1}$$

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.[33] The ***Z's*** are also control

[32] 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.

[33] See Tables A-2, A-3, A-4, and A-5 for a complete list of all control variables.

variables, but they vary across subjects. $\boldsymbol{Z}_{iksc}$ is a vector containing student-level variables of parents' numeracy and literacy skills, and $\boldsymbol{Z}_{ksc}$ is a vector containing school-level variables measuring the shortage of qualified teachers and weekly instructional time in math and language classes. ε_{iksc} is an error term with mean zero.

Interpreting an OLS estimate of δ as the causal effect of measured teacher cognitive skills on student performance is problematic, however, because of the possibility of unobserved omitted variables correlated with both teacher cognitive 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 higher cognitive skills and parents who strongly support their child's education (not perfectly captured by our measure of parent cognitive skills). Similarly, if the quality of the education system is persistent and not perfectly captured by our measure of parent cognitive skills, student performance and cognitive skills of teachers (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. Alternatively, subject-specific skills and pedagogical capabilities of teachers might be correlated either because a high-quality teacher education raises both types of skills or simply because of differential self-selection of individuals into the teaching profession. Note that self-selection or sorting of students and teachers across schools (within countries) and within schools is no concern in our study because teacher cognitive skills are measured at the country level. Finally, country-specific teacher cognitive skills are likely measured with error such that OLS estimates are biased toward zero, a subject to which we return below.

We use two independent strategies to address these concerns. The first strategy exploits the fact that both teacher skills and student performance are observed in two distinct subjects. This allows us to exploit within-student variation in teacher skills across math and reading. We investigate whether differences in student performance between math and reading are systematically associated with differences in teacher skills between math and reading.[34] While student characteristics, student ability, family background, and school environment are the same for both subjects, teacher skills can differ between math and reading. Within-student effects of teacher cognitive skills on student performance are estimated by adding student fixed effects in Equation (1). The student fixed effects capture any performance differences between students that are not subject-specific, for instance, due to family background, innate ability, and motivation. Adding student fixed effects also controls for any non-subject-specific differences across schools (and hence across countries) and for

[34] Within-student across-subject variation has already been used in previous research (e.g., Dee (2005), Metzler and Woessmann (2012), Lavy (forthcoming)).

international differences in general pedagogical skills of teachers. Note that all control variables contained in the **X** vectors are absorbed by the student fixed effects, whereas all subject-specific variables contained in the **Z** vectors, such as parent skills in numeracy and literacy, control for differences within students across subjects. Importantly, following Lavy (forthcoming), we control for instructional time in math and language classes at the school level. In contrast to the OLS estimates, the estimated effect of teacher cognitive skills here is "net" of teacher skill spillovers across subjects (for example, if teacher literacy skills affect student math performance).[35]

The student-fixed-effects approach, however, has the disadvantage that it cannot control for unobserved differences across countries that differ across subjects. For example, if societies have both teachers with high numeracy skills and a strong preference for advancing children in math (with parents supporting their children accordingly), then fixed-effects estimates of teacher cognitive skills will still be biased. Furthermore, the coefficient on teacher cognitive skills might still be attenuated in the fixed-effects model if teacher skills are measured with error. In fact, the attenuation bias is likely more severe in the fixed-effects model than in the OLS model (see below).

To address these latter concerns, we employ an alternative identification strategy with instrumental-variable (IV) estimation. We draw on exogenous variation in teacher cognitive skills due to cross-country differences in public sector wages. The basic idea is that countries paying teachers relatively higher wages are more likely to attract and retain individuals with high skills in the teaching profession as teaching becomes more attractive relative to other professions. Instrumenting teacher cognitive skills with relative teacher wages would likely be invalid, however, as high teacher wages might reflect a high preference for children's education. Therefore, we use the PIAAC micro data to compute the wages of public sector employees relative to those paid in the private sector, but always exclude wages of teaching professionals. Specifically, the instrument is constructed as the position (i.e., the percentile rank) of the mean wages of nonteacher public sector employees in the wage distribution of nonteacher private sector college graduates.[36]

Wages of nonteacher public sector employees should be substantially correlated with teacher wages because teachers are predominantly public sector employees themselves (76 percent in our sample). In fact, the correlation between the instrument and the position of teacher wages in the wage distribution of nonteacher private sector college graduates is strong (0.79), but far from unity. At the same time, wages of public sector employees – excluding all persons working in the education sector – are likely uncorrelated with education preferences in a country. One might still

[35] Note that spillover effects are completely eliminated in the student fixed-effects model when cross-subject spillovers are identical in math and reading.

[36] As in Hanushek et al. (forthcoming), we trim the bottom and top one percent of the wage distribution to limit the influence of outliers.

worry that nonteacher wages are influenced by teacher wages if teachers are a dominant group among all public sector employees. This would violate instrument exogeneity if the level of teacher wages would reflect country-specific education preferences. However, teaching professionals represent only a minority among all public sector employees. In the national PIAAC samples, the share of teaching professionals among all public sector employees ranges from 14 to 27 percent, with an average of 18.7 percent. Besides these low shares of teaching professionals, it seems furthermore plausible that fiscal arguments – and not teacher wages – determine the wage bargaining for nonteacher public sector employees.

Another worry is that our instrument just reflects a country's preference for public sector provision of goods and services, which may be correlated with preferences for education. However, neither of these conjectures is supported by the data. First, the instrument does not seem to be a proxy for the importance of the public sector in a country; the correlation between the instrument and public expenditure as a percentage of GDP is actually negative (-0.40).[37] Second, the instrument appears to be unrelated to a country's education preferences. The correlations with both cumulative expenditure per student between the age of 6 and 15 normalized with GDP per capita (r=0.04) and with public expenditure on education as a share of total public expenditure (r=0.12) are basically zero.[38] Given these findings, we are confident that the instrument is not correlated with education preferences.

A remaining issue is that countries with high public sector wages also spend more on education simply because they have more resources. Since our standard set of control variables includes cumulative educational expenditure per student between age of 6 and 15 in a country, we directly control for this potentially confounding factor.

We use the wages of college graduates (in the private sector) when constructing the instrument as the vast majority of teachers are college graduates themselves, implying that teachers are recruited mainly from the national pool of college graduates.[39] We use all nonteacher public sector employees when constructing the instrument – instead of restricting ourselves to college graduates

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[37] Data on public expenditure as a share of GDP and public expenditure on education as a share of total public expenditure come from OECD (2014a). Data refer to the year 2011.

[38] Alternative data sources for gauging the importance of education in a country could be the World Value Survey or the European Social Survey. However, there is no adequate question in these datasets that could capture educational preferences in a country.

[39] In the PIAAC data, the share of teachers who are college graduates varies between 67 percent in Austria and 98 percent in Poland. Across the 23 countries in our sample, the mean share is 88 percent.

in the public sector – to ensure a reasonable sample size.[40] Predicted values of teacher cognitive skills are obtained in the following first-stage model:

$$T_{kc} = \alpha + \varphi RelWage_c + \mu CollSkills_{kc} + \boldsymbol{X}_{isc}\boldsymbol{\beta}_4 + \boldsymbol{X}_{sc}\boldsymbol{\beta}_5 + \boldsymbol{X}_c\boldsymbol{\beta}_6 + \boldsymbol{Z}_{iksc}\boldsymbol{\gamma}_3 + \boldsymbol{Z}_{ksc}\boldsymbol{\gamma}_4 + \eta_{iksc}, \tag{2}$$

where teacher cognitive skills in subject *k* in country *c*, T_{kc}, are regressed on the instrument, i.e., the relative wages of nonteacher public sector employees, $RelWage_c$, the median skills of college graduates in subject *k* in country *c*, $CollSkills_{kc}$, and all other control variables from Equation (1). We include the median skills of college graduates in Equation (2) because the instrument is a relative measure that expresses wages of public sector employees relative to a comparison group, namely, college graduates in a country. By controlling for the skill level of the comparison group, the instrument explains deviations of teacher cognitive skills from the country-specific skill level of college graduates.

The instrumental-variable approach uses distributional information on nonteacher wages within countries. The instrument is likely not correlated with subject-specific preferences across countries, thus circumventing the potential bias in the within-student approach. Since the instrument is probably not correlated with the measurement error in the teacher cognitive skills variables, the instrumental-variable approach helps solve potential bias due to measurement error.

Measurement Error

Our country-level teacher cognitive skills are obviously measured with error. First, we do not observe the skills of the individual teachers who teach the students tested in PISA. Second, the observed country-level skills are a noisy measure of the true country-level teacher skills because, for instance, we use the numeracy (literacy) skills of all teachers and not just of math (language) teachers. Suppressing subject and school indices, one can write the population model we would like to estimate as follows:

$$y_{ic} = \alpha + \delta T^*_{ic} + \boldsymbol{X}_{ic}\boldsymbol{\beta} + \varepsilon_{ic}, \tag{3}$$

where T^*_{ic} represents the true skills of student *i*'s teacher (in country *c*).[41] For simplicity, the vector $\boldsymbol{X}_{ic}$ here contains all other control variables. The individual-level teacher cognitive skills, T^*_{ic}, can

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[40] In some countries, the number of nonteacher public sector employees who graduated from college is well below 200. Results are similar if we only use nonteacher public sector college graduates for constructing the instrument.

[41] Conceptually, T^*_{ic} does not represent the skills of a single teacher, but rather a skill average of all the teachers who have taught student *i* in the current and past years, with more recent teachers receiving more weight. To keep language simple, we will refer to T^*_{ic} as representing the skills of a single teacher.

be expressed as follows: $T_{ic}^* = T_c^* + u_{ic}$, where T_c^* represents the true, but unobserved, median skills of teachers in country c (relevant for our PISA student population). The error term u_{ic} is uncorrelated with T_c^* as skills of individual teachers are distributed around the median skill in each country.[42] As T_c^* is unobserved, we can rewrite the last equation as follows:

$$T_{ic}^* = T_c + \omega_c + u_{ic}, \tag{4}$$

where T_c is our observed measure of country-level teacher cognitive skills, and $\omega_c = T_c^* - T_c$ is the difference between true and observed country-level teacher cognitive skills. Substituting (4) into (3) yields:

$$y_{ic} = \alpha + \delta T_c + \boldsymbol{X}_{ic}\boldsymbol{\beta} + (\delta\omega_c + \delta u_{ic} + \varepsilon_{ic}). \tag{5}$$

Assuming that the omitted variables (included in ε) are positively associated with observed teacher cognitive skills, T_c, then δ will be overestimated if the positive omitted-variable bias is larger in magnitude than the attenuation bias due to the measurement error in the country-level teacher cognitive skills. In contrast, δ will be biased downward if the measurement error is more severe than the omitted-variable bias.

Finally, the attenuation bias due to measurement error in the country-level skills is probably exacerbated in the within-student model because differencing cognitive skills is particularly problematic when the (true) numeracy and literacy skills are more strongly correlated than the measurement error in numeracy and literacy skills (Griliches and Hausman (1986)). Because true teacher skills in numeracy and literacy are certainly strongly correlated at the country level (the correlation of *observed* teacher skills across subjects is 0.77), differencing country-level teacher skills likely leads to a more severe attenuation bias.

5. The Impact of Teacher Cognitive Skills on Student Performance

It is easiest to motivate the analysis with simple visual evidence showing that teacher cognitive skills and student performance are positively associated at 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 positively

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[42] Note that using true *country*-level teacher skills, T_c^*, instead of true *individual*-level teacher skills, T_{ic}^*, would still yield consistent estimates of δ. The noisy macro-level measure would, of course, imply less precisely estimated coefficients.

associated with aggregate student performance. The two bottom graphs in Figure 3 show the association between teacher cognitive skills and aggregate student performance after controlling for country-specific skill levels of all adults aged 25-65 to net out the skill persistence across generations.[43] 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, is excluded, the coefficient on teacher numeracy skills becomes larger (0.074) and statistically significant at the 10 percent level.[44]

These simple country-level plots are of course subject to the multitude of potential biases discussed above. In the following student-level analysis, we begin with OLS and student fixed-effects estimates of the impact of teacher skills. We then present the instrumental-variable results, followed by robustness checks and heterogeneity analyses.

5.1 OLS and Student Fixed-Effects Estimates

OLS Results

Table 2 reports results from the least squares estimation of Equation (1), which serves as a benchmark for the fixed-effects and instrumental-variable estimates. 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).[45] The estimate in Column (3) implies that a one-standard-deviation increase in teacher numeracy skills increases student math performance by almost 10 percent of a standard deviation. 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 are 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 slightly below the coefficient on teacher numeracy skills. In contrast to math, parent literacy skills do not appear to matter for student performance in reading. The estimate is small, albeit positive, and statistically insignificant.

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[43] 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. To some extent, skills are also correlated because teachers are included in the computation of adult skills.

[44] 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.

[45] Table A-6 reports the estimated coefficients on all other control variables of specifications (3) and (6).

Student Fixed-Effects Results

Our simple OLS estimation is prone to bias due to omitted variables. Because many of the omitted variables we are concerned about vary at the country level, one strategy to overcome these problems is to use only within-country variation to identify the effect of teacher cognitive skills on student performance. Having test scores in two different subjects for students and teachers, as well as substantial variation in teacher skills across subjects,[46] we implement the fixed-effects model by regressing the difference in student performance (math minus reading test score) on the difference in teacher skills (numeracy minus literacy), thereby eliminating any non-subject-specific bias due to student, school, and country heterogeneity.

Table 3 presents the results of the student fixed-effects estimates. The specifications are the same as in Table 2, except that control variables that do not differ across subjects are dropped. With full controls, the fixed-effects estimate on teacher cognitive skills is about 40 percent smaller than the corresponding OLS estimate, but is still statistically significant (Column 3). This decrease in coefficient magnitude might occur for three 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 controlled for in the fixed-effects model. Second, as discussed above, the attenuation bias becomes more severe as the measurement error in teacher skills very likely becomes larger when differencing numeracy and literacy skills. Third, the numeracy-literacy skill differences of teachers and parents are strongly correlated (r=0.77); unsurprisingly, the drop in the teacher coefficient occurs when parent cognitive skills are included (Column 3).[47] Hence, the effect of teacher cognitive skills is identified only from the limited part of the skill variation that is independent of variation in parent cognitive skills.

The within-student model assumes that the effect of teacher numeracy skills on student math performance is identical to the effect of teacher literacy skills on student reading performance (e.g., Lavy (forthcoming)). To allow for differential effects of teacher numeracy and literacy skills, we also included them separately in the estimation equation (not shown). Without imposing the uniformity of effects in the two subjects, we still find very similar coefficients on teachers' numeracy (0.052) and literacy skills (0.058), both significant at the 10 percent level.

Two other results are worth mentioning. The coefficient on parent cognitive skills in Column (3) is slightly larger than in the OLS model for math and almost statistically significant at the 10 percent level (p=0.1002). Interestingly, the effect of instructional time on student performance is

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[46] The country-level correlation between teachers' numeracy skills and literacy skills is 0.77, and thus far below 1.

[47] The *levels* of teacher and parent cognitive skills are much less correlated (0.34 in math and 0.41 in reading).

similar to the effect size in Lavy (forthcoming), who exploits within-student between-subject variation using PISA data from 2006.

5.2 Instrumental-Variable Results

While both OLS and student fixed-effects results suggest a positive impact of teacher cognitive skills on student performance, we are still concerned about making a causal interpretation. Most importantly, if unobserved country-level determinants of student performance are subject specific, then the fixed-effects coefficients would still be biased. For example, the attitude toward education in a country may not be similar for both subjects, but knowledge and skills might be valued higher in one subject than in the other. Furthermore, the fixed-effects estimates are likely biased towards zero as we difference two variables that are measured with error. To address these concerns, we employ an instrumental-variable approach that exploits arguably exogenous variation in teacher cognitive skills across countries.

Specifically, we instrument the country-specific teacher cognitive skills with the relative wages of nonteacher public sector employees in a country. The basic idea is that countries with high wages for public sector employees are able to attract higher-skilled college graduates into the teaching profession (and retain them in the job). Controlling for the direct effect of well-endowed public sectors on student performance through higher education expenditure, the instrument exploits variation in teacher skills that is unlikely to be correlated with a country's (subject-specific) preference for education or other omitted variables simultaneously affecting teacher cognitive skills and student performance. Thus, we estimate the impact of teacher cognitive skills using the variation in skills related to the attractiveness of the public sector in each country.

Table 4 reports results from the IV regressions. The first-stage results in the bottom panel show that the relative wage of nonteacher public sector employees is a strong predictor of teacher cognitive skills. In the model with all controls (Column (3) for math and Column (6) for reading), we find that an increase in the wage position of public sector employees by 25 percentile ranks (e.g., a move from the 25th percentile to the median in the wage distribution) is associated with an increase in teacher skills of approximately 77 (85) percent of an international standard deviation in numeracy (literacy). The F-statistic of the instrument far exceeds 10 in all models, suggesting that our estimation does not suffer from a weak-instrument problem.[48] As expected, IV standard errors are substantially larger than those in the OLS models.

[48] Weak instruments can lead to inconsistencies in the IV estimates (Bound, Jaeger, and Baker (1995)). Moreover, if instruments are weak, the conventional asymptotic approximations used for hypothesis tests and confidence intervals will usually be unreliable (Stock, Wright, and Yogo (2002)).

Since identification relies on only 23 independent observations at the country level, one potential worry is that the positive association between the instrument and teacher cognitive skills is driven by a few outliers. An added-variable plot of the first-stage relationship that includes all control variables indicates that this is not the case (see Figure 4). To construct this graph, we have aggregated the residuals of the student-level regressions to the country level, the level where the instrument and teacher cognitive skills vary. We observe a clear positive relationship between the relative wages of nonteacher public sector employees and teacher cognitive skills, as indicated by the solid regression lines. Excluding the three outliers (Finland, Italy, and Japan) leads to similar regression lines, with even slightly larger slopes. Therefore, the correlation between instrument and teacher cognitive skills in the first-stage estimation is not driven by outliers.[49]

The second-stage results of the IV estimations are reported in the upper panel of Table 4. Higher teacher numeracy skills significantly increase student math performance (Columns 1-3). In the preferred specification in Column (3) which controls for the skills of parents of PISA students to net out the intergenerational persistence in skills, we find that a one-standard-deviation increase in teacher numeracy skills increases student math performance by 20 percent of an international standard deviation.

It is important to note that this estimate does not capture the effect of just a single school year, but rather reflects the cumulative effect of teacher cognitive skills on student performance over all school years. (While many of the PIAAC teachers will be representative of the set of teachers that the 15-year-olds in PISA had, there obviously is teacher turnover. The interpretation assumes stability in teacher corps skills for the student cohorts tested in PISA.)[50]

The IV coefficient on teacher numeracy skills indicates a sizable impact of a country's teacher cognitive skills on student performance. Moreover, the IV estimate in the last specification is about twice as large as the corresponding OLS estimate. This increase in magnitude likely reflects the elimination of the attenuation bias due to measurement error in the teacher-skill variable (see discussion in Section 4).

Our other main control variable, parent cognitive skills, also enters positively and significantly in the second stage for math. However, the coefficient on parent skills decreases somewhat in magnitude compared to the OLS specifications and captures less of the estimated impact of teacher cognitive skills. (The coefficient on teacher cognitive skills decreases by only 7 percent in the IV

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[49] In Section 5.3, we additionally provide a robustness check that excludes the three outlier countries from the sample.

[50] The average teacher age in our sample is 42.2 years.

regressions between Columns 2 and 3, but decreases by 18 percent in the corresponding OLS models).

A similar pattern holds for reading (Columns 4-6). Better teacher cognitive skills lead to improved student performance, irrespective of the included control variables. In the specification with all controls (Column 6), an increase in teacher literacy skills by one standard deviation improves student performance by about 10 percent of an international standard deviation. This effect size is only half of that in math, indicating that subject-specific teacher skills are more important for math than for reading.[51]

In contrast to the numeracy results, the IV estimate of teachers' literacy skills is very close to the OLS estimate. A potential explanation for this finding is that attenuation bias due to measurement error is less severe for literacy skills than it is for numeracy skills of teachers.

5.3 Robustness, Specification Checks, and Effect Heterogeneity

In this section, we show that our main results reported in Table 4 are robust to alternative specifications and samples. We also explore whether the impact of teacher cognitive skills differs by gender, socioeconomic background, or migrant status of students.

Robustness Checks

Since teacher cognitive skills vary across countries, our first robustness check replaces 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 increases the coefficients on teacher cognitive skills slightly (Columns (1) and (5) in Table 5). 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 2 and 6). These findings show that the impact of teacher cognitive skills remains unchanged even if we control for the general cognitive skill level of the population at the country level (the level where teacher cognitive skills vary). From these results we feel confident that we have separated the effect of teachers from the overall cognitive skill level of parents and of the country.

Any strategy that exploits international variation with limited degrees of freedom might suffer from the problem that the results are driven by a few outlier countries. Therefore, we replicate the

[51] This finding is consistent with individual-level evidence provided in Metzler and Woessmann (2012) for Peruvian students.

main specifications, but exclude the three countries that are outliers in the first-stage regressions (see Figure 4). Even without the outlier countries, teacher cognitive skills enter significantly in the second-stage regressions, and first-stage results still indicate that the instrument is strong (Columns 3 and 7). As we exclude these three countries from the sample, the impact of teacher cognitive skills gets even larger, especially in math. Due to large standard errors, however, the increase is not statistically significant. We also excluded each country individually from the sample (results available upon request). The estimated teacher-skill effects are always close to the baseline coefficients, confirming that the results are not driven by an individual country.

As a final specification check, we use average teacher cognitive skills instead of median teacher cognitive skills. The coefficients, reported in Columns (4) and (8), are very close to the baseline estimates.[52]

Instructional Practices

One worry is that our subject-specific teacher-skill measures reflect differences in pedagogical approaches or pedagogical skills. To investigate whether pedagogical skills indeed confound the teacher-skill effects, we use information from the PISA students about their teachers' activities in language and math classes to construct indicators of subject-specific instructional activities – which can also be interpreted as measures 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.[53] As noted in Section 3, instructional practices are asked only for the subject that was the focus in the respective PISA cycle (language in PISA 2009 and math in 2012). For the PISA cycle when a subject (math or language) was not the focus, we "impute" the subject-specific instructional-practice indicator by using the country-level instructional practice from the other PISA survey, assuming that the instructional practices in the same subject are highly correlated at the country level across the three-year period.

[52] Although the first-stage F statistic in the reading regression decreases compared to the analogous result in Table 4, it is still sizeable, and the point estimate in the second stage is practically identical.

[53] 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.

Table 6 reports the instrumental-variable results when we take into account the instructional practices in math and language classes. For comparison, we report the baseline results for math in Column (1) and for reading in Column (3). When instructional practice is added to the model, the coefficients on teacher cognitive skills change only little, suggesting that the subject-specific teacher skills have a strong independent impact on student performance. In fact, the coefficients on teacher cognitive skills even increase slightly when instructional practice is included since teacher cognitive skills and instructional practice are negatively correlated at the country level (r=-0.30 in math and r=-0.42 in reading). As expected, the instructional-practice indicators are positively related to student performance, although only the instructional practice in language classes captures statistical significance. The magnitude of the language instructional practice is sizeable; there is a 0.036 SD improvement in student reading performance for a one SD increase in (country-level) instructional practice.

One potential problem that these instructional-practice estimates suffer from is that the country-level instructional-practice indicators likely reflect cultural differences, partly just capturing how actively teachers communicate with their students. Therefore, it does not come as a surprise that the instructional-practice indicator is largest in Anglo-Saxon countries, but smallest in Asian countries.

To gain confidence that the negative correlation between subject-specific teacher skills and instructional practice is neither an artifact of the construction of this particular instructional-practice indicator nor driven by systematic misreporting by students, we have additionally looked at country-level information on instructional practices from TALIS 2013 (see OECD (2014b)) for details). In contrast to PISA, TALIS asks teachers to report their own instructional practices.[54] In line with the PISA-based instructional-practice results, all instructional practices surveyed in TALIS are negatively correlated with teacher cognitive skills.[55] Thus, our results consistently indicate that the impact of the subject-specific teacher cognitive skills does not merely (or even mainly) reflect better pedagogical skills of teachers.

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[54] 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.

[55] 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.

Effect Heterogeneity

The effect of teacher cognitive skills was so far estimated for the entire student sample, yielding the impact for the average student. In Table 7, we explore whether the impact of teacher cognitive skills differs across various student subgroups. Panel A reports results for math and Panel B for reading, and all specifications include the full set of control variables. When we stratify the sample by student gender, we find identical teacher effect sizes in reading, but a larger effect of teacher cognitive skills for girls in math. Due to the large standard errors, however, this gender difference is not statistically significant.

Next, we split the sample by students' socioeconomic background, as 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. Using the country-specific median ESCS scores to split the sample, we find that the effect of teacher cognitive skills on student performance is substantially larger for students with low socioeconomic background. The results furthermore suggest that higher teacher literacy skills (at least when measured at the country level) do not improve the reading performance of high-SES students (while the effect in math is sizeable). Interestingly, parent cognitive skills seem to be more important for high-SES students than for low-SES students. A one-standard-deviation increase in parent numeracy skills is associated with an increase in math performance of high-SES students of 0.045 SD; the corresponding estimate for low-SES students is only about half the size. In reading, parent literacy skills are also significantly positive for high-SES students (zero for low-SES students).

Finally, we estimate teacher-skill effects separately for natives and migrants.[56] The pattern is less conclusive here. Teacher cognitive skills seem somewhat more important for migrants in math and for natives in reading. However, the differences of the point estimates are not statistically significant for either math or reading. Moreover, a cautious interpretation of the results for migrants is in order given the limited sample size and the unequal distribution of migrants across countries.

6. Improving Teacher Cognitive Skills

Our analysis consistently indicates 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. It is useful to understand what the estimates say about the impact of raising

[56] Because first-generation migrants might have migrated into the PISA test country just shortly before the PISA test, we can hardly ascribe their math and reading performance to the skill level of teachers in the test country. Therefore, we use only second-generation migrants here since these students were born in the PISA test country and have spent their school career in the education system of the test country.

teacher cognitive skills. When we look across our 23 sampled countries, we see that Finland does in fact have the most skilled teachers by the PIAAC measures. Table 8 uses the estimated achievement models to simulate the improved student performance if each country brought its teachers up to the level of Finnish teachers. For some, such as Japan, this is not a huge change, but even Japanese schools would improve noticeably (0.10 SD in mathematics and 0.03 SD in reading). But for other countries, the improvements in student achievement would be dramatic. The U.S. would be expected to improve by roughly 0.55 SD in student math achievement; Russia and Italy would be expected to improve by almost 0.75 SD in math. Of course, these are long-run impacts since they 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.

One approach to increase teacher cognitive skills, which has other advantages for a country, is to increase the overall achievement of its population. Of course, this is not easy, and considerable controversy surrounds the best way to do this. The clearest policy direction, however, appears to be improving the incentives for higher achievement (e.g., see Hanushek and Woessmann (2011b)). While beyond the scope of this paper, this approach would, by available evidence, rely on strong accountability of achievement, parental choice of schools, and rewards to students and teachers for performance.

Another option for policymakers is to try to attract better performers out of the existing skill distribution of the country. One way to do this may be to raise teacher wages to attract better-skilled individuals into the teaching profession. In fact, the argument that teacher pay is significantly related to teacher quality has been in the heart 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 recruit teachers from a higher part of the skill distribution and also manage to retain teachers in their profession.[57] If this link was present, there would be leverage for policymakers to raise the skills of teachers in the country by paying them higher wages, with positive effects on student performance.[58]

In Table 9, we investigate whether teacher cognitive skills are indeed higher in countries that pay teachers (relatively) higher wages. Based on the PIAAC data, we run country-level regressions

[57] Raising pay might 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 analyzes almost always look at effort; see Woessmann (2011). For developing countries, the evidence on effort is stronger, but this might not generalize to the developed countries we analyze; see Muralidharan and Sundararaman (2011).

[58] 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.

of teacher skills (separately for numeracy and literacy) on relative teacher wages, measured as the percentile rank of country-specific mean teacher wages in the wage distribution of all nonteacher college graduates. Importantly, estimates are conditioned on the skill level of all nonteacher college graduates to account for the differences in skill levels among countries. The results indicate that higher relative teacher pay is systematically related to higher teacher skills. For example, controlling for the wage level of college graduates (Columns 3 and 6), we find that one standard deviation higher relative teacher salaries (i.e., 15 percentile ranks) is associated with higher teacher skills in numeracy (literacy) of about 40 percent (30 percent) of an international standard deviation. The coefficient on college graduates' skills is always close to unity, reflecting the fact that most teachers are college graduates themselves.[59]

The interpretation of these results is, however, important for policy. These estimates are reduced-form estimates that reflect the labor-market equilibrium. Consistent with the strong relationship between wages and skills for the entire labor market (Hanushek et al. (forthcoming)), these results indicate that individuals with higher cognitive skills are paid more whether in the teaching profession or elsewhere in society. These estimates 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.[60] 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 nothing about either how salaries should be structured or the responsiveness of teachers to higher salary offers.

7. Conclusion

We use newly available data from the Programme for the International Assessment of Adult Competencies (PIAAC) to calculate country-level measures of teacher skills in numeracy and literacy in 23 developed economies. We first show that teacher cognitive skills differ substantially across countries. We then combine teacher cognitive skills with micro data on student performance

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[59] These results are also consistent with previous work in the U.S. on pay-skill relationships. Corcoran, Evans, and Schwab (2004) argue that, while average cognitive skills 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.

[60] 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.

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 PISA students' parents.

We estimate the impact of teacher cognitive skills in several different ways including – in addition to OLS models – the use of student fixed effects (exploiting only between-subject variation) and an instrumental-variable approach using variation in teacher cognitive skills attributable to international differences in relative wages of public sector employees outside the teaching profession. These two approaches deal with omitted country-level factors, but we prefer the instrumental-variable estimation because it circumvents the bias from omitted variables that are subject specific and alleviates the potential influence of measurement error. Nonetheless, the alternative designs yield qualitatively similar results: Higher levels of teacher cognitive skills lead to better student outcomes.

Our preferred instrumental-variable approach indicates that a one-standard-deviation increase in teacher numeracy skills raises student performance in math by 20 percent of an international standard deviation in test scores. The effect in reading is 10 percent of a standard deviation and also highly statistically significant.

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. Moreover, while the results are robust in most sub-populations, we also find interesting evidence of effect heterogeneity depending on students' socioeconomic background. Our results suggest that the benefits of better cognitive skills of teachers mainly accrue to students with low socioeconomic background, while parental skills are more important for students with high socioeconomic background.

These results offer new insights into measures of teacher effectiveness that have previously been unavailable. 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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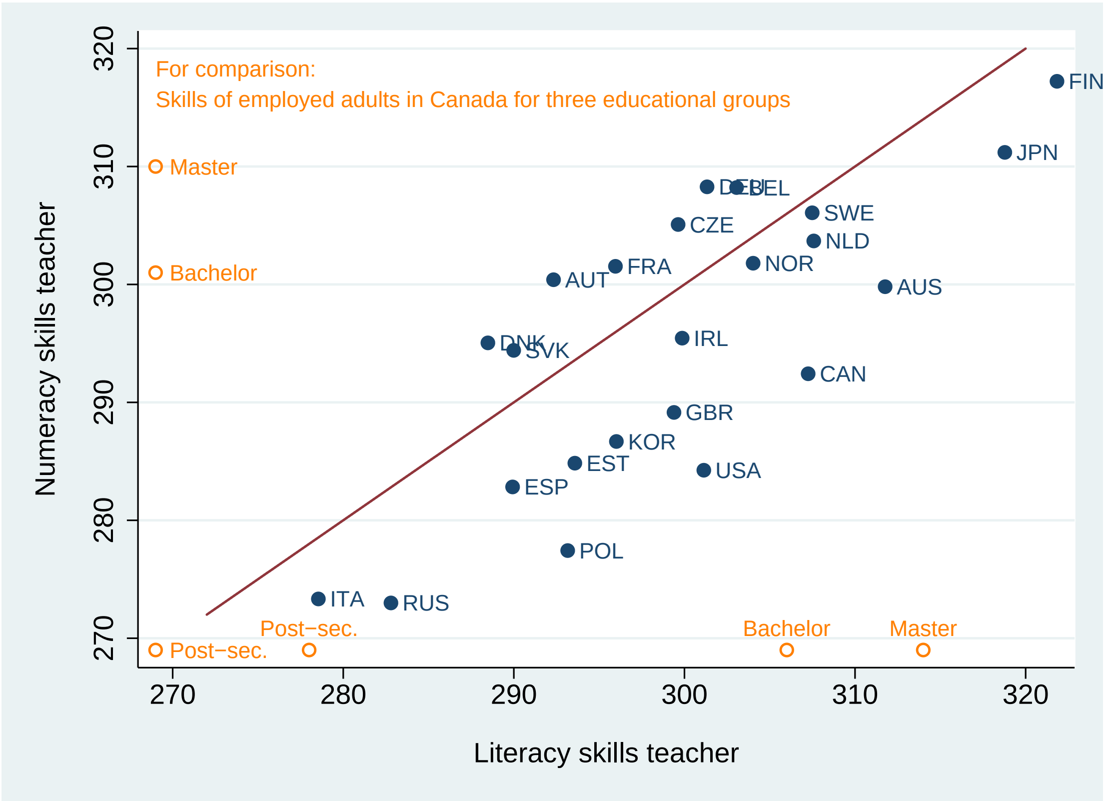
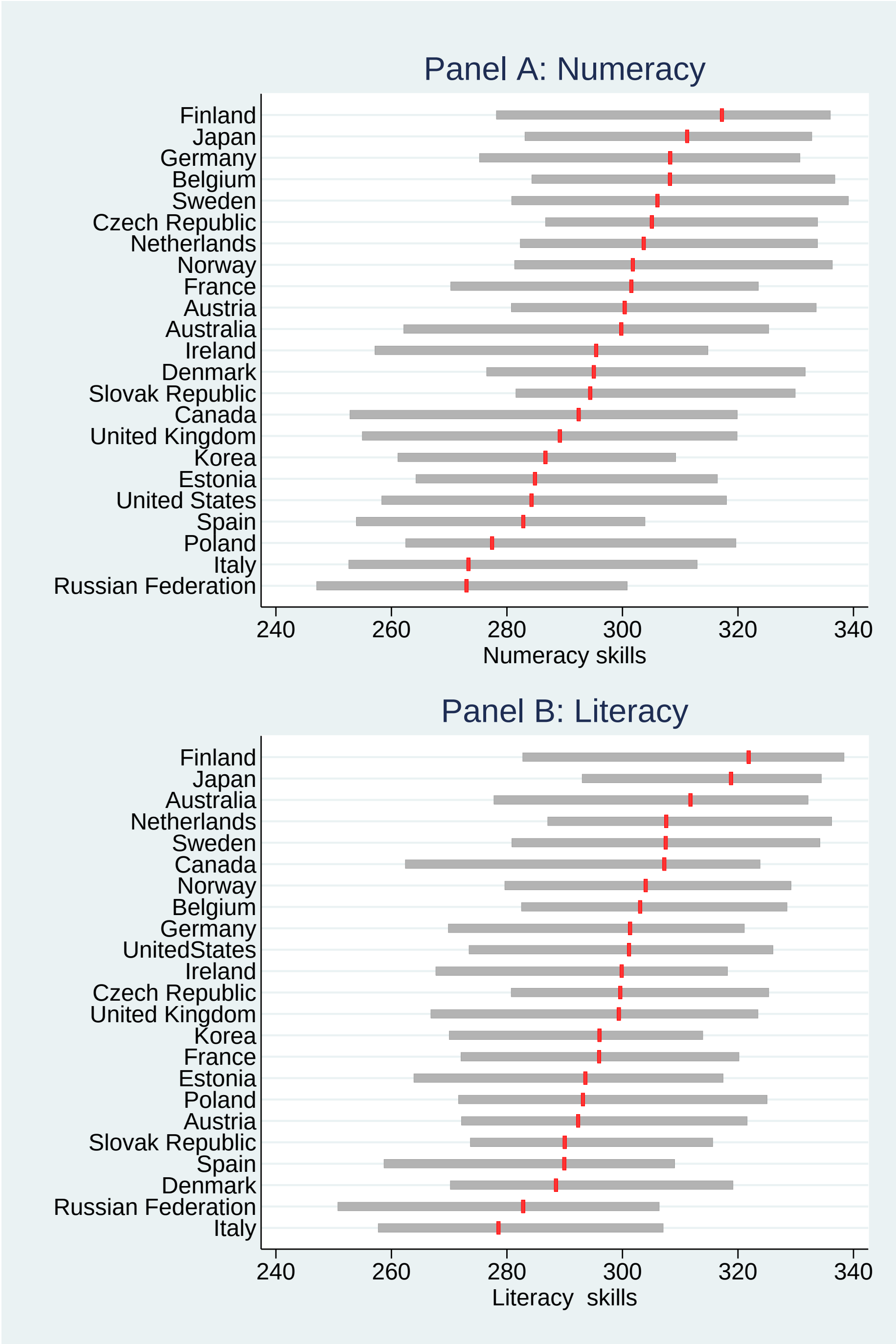
Figures and Tables

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



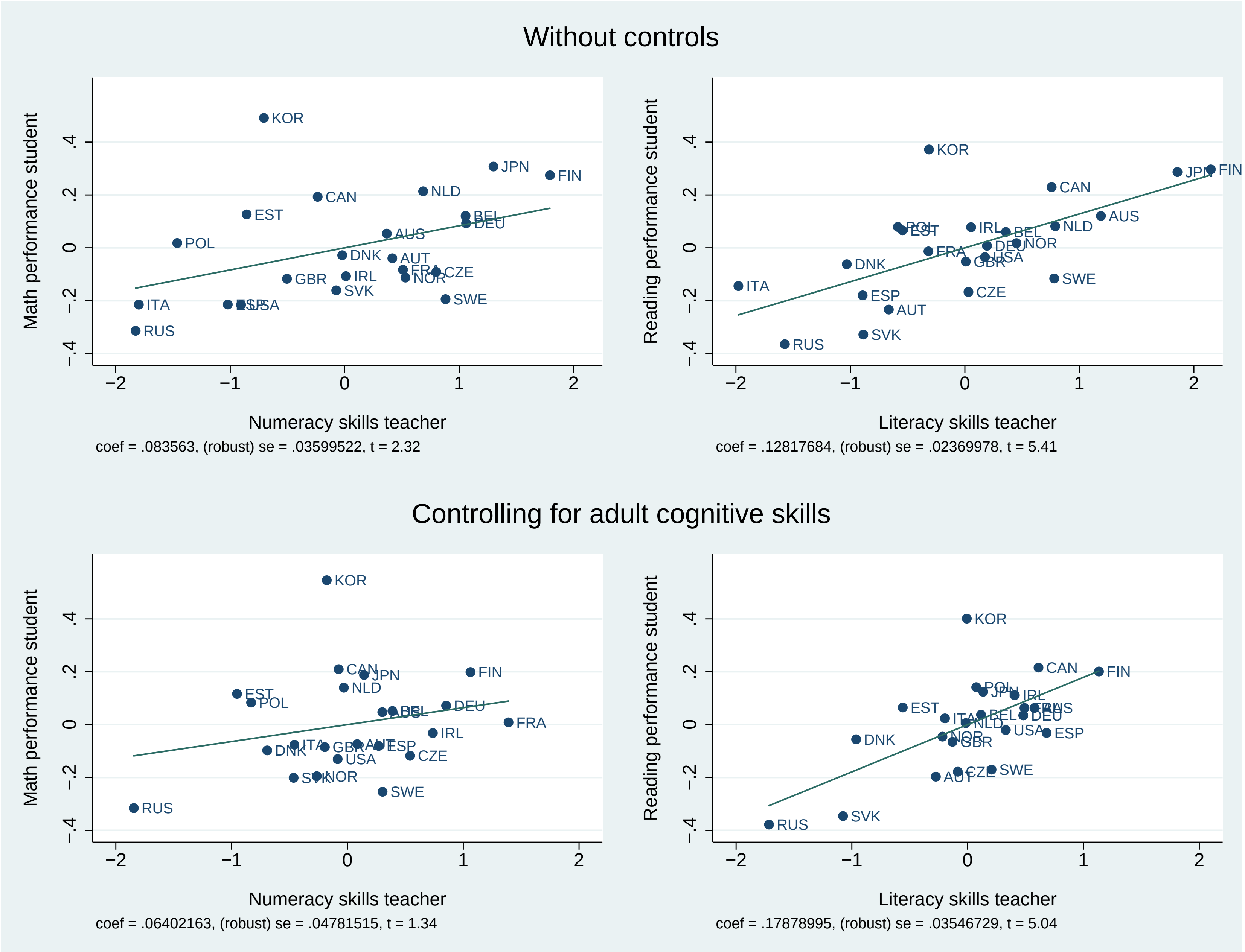
Note: The blue dots indicate country-specific teacher skills in numeracy and literacy (see text for construction of teacher cognitive skills). The orange circles indicate the median cognitive skills for three educational groups of employed adults aged 25-65 years in Canada (the largest national sample 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



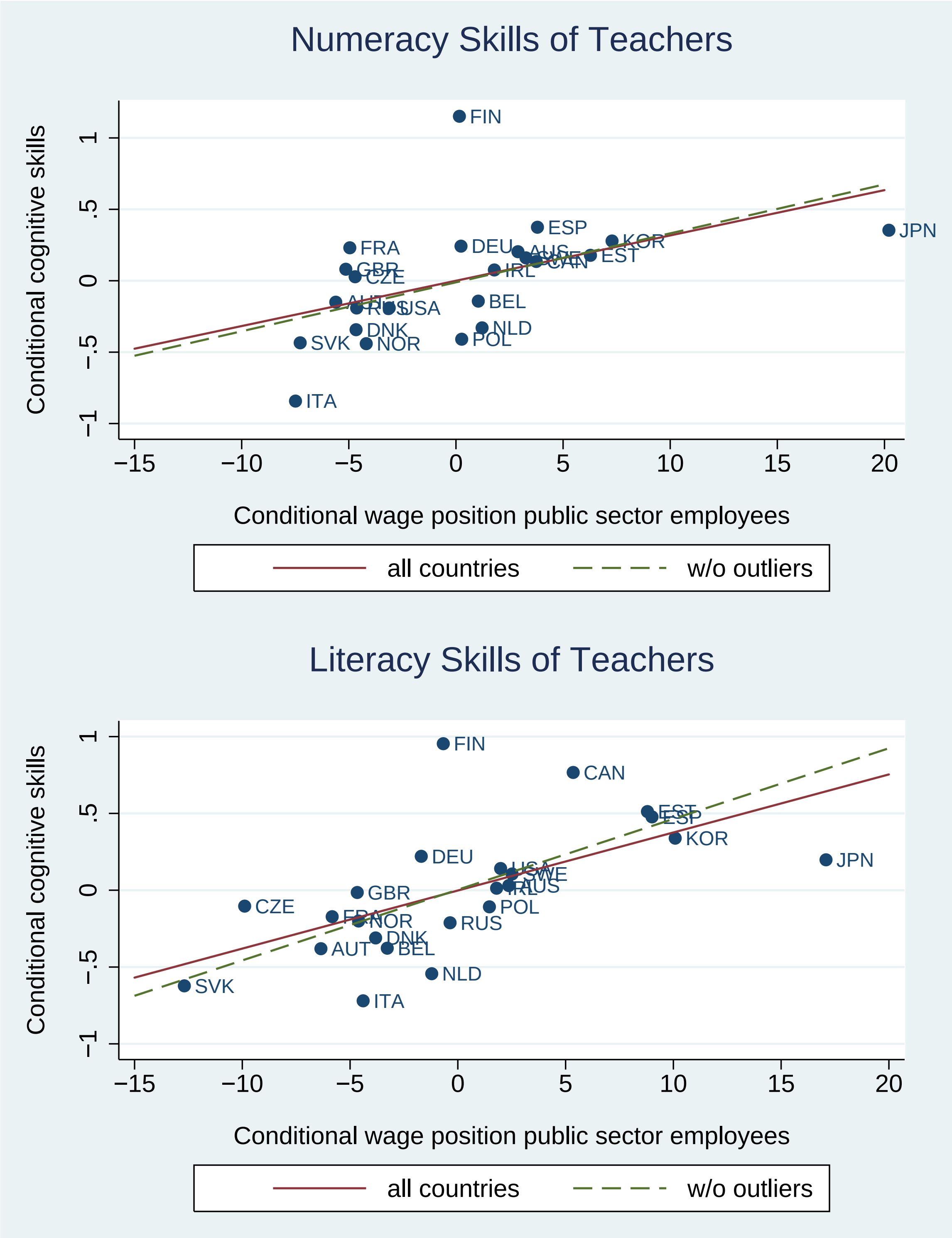
Note: Modified figure from Schleicher (2013). Vertical bars indicate median cognitive skills of teachers in a country. Horizontal bars show the interval of cognitive skill levels of all college graduates (including teachers) between the 25th and 75th percentile. Countries are ranked by the median teacher 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. Two graphs in bottom panel are added-variable plots that control for country-specific average literacy skills of all adults aged 25-65. Scales are deviations from country mean in standard deviations. *Data sources*: PISA 2009 and 2012, PIAAC.

Figure 4: Relative Wages of Public Sector Employees and Teacher Cognitive Skills



Note: Added-variable plot from first stage of instrumental-variable regression of teacher cognitive skills and wage position of public sector employees (w/o teachers) in the distribution of all employees and all the control variable included in Equation (2). Upper (lower) panel shows teacher numeracy (literacy) skills. Based on student-level regressions that are then aggregated to the country level. Solid line is fitted through all country-level observations; for fitting the dashed line, the outliers Finland, Italy, and Japan are excluded. *Data sources*: PISA 2009 and 2012, PIAAC, OECD.

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	0.084**	0.117***	0.096***	0.128***	0.086***	0.082***
	(0.035)	(0.021)	(0.021)	(0.023)	(0.020)	(0.022)
Parent cognitive skills			0.039***			0.007
			(0.011)			(0.010)
Student characteristics	No	Yes	Yes	No	Yes	Yes
Parent characteristics	No	Yes	Yes	No	Yes	Yes
School characteristics	No	Yes	Yes	No	Yes	Yes
Country characteristics	No	Yes	Yes	No	Yes	Yes
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 within each PISA cycle. 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:* PIAAC, PISA 2009 and 2012, OECD.

Table 3: Student Performance and Teacher Cognitive Skills (Student FE)

	Student performance difference: math – reading		
	(1)	(2)	(3)
Teacher skills: numeracy – literacy	0.075***	0.090***	0.053*
	(0.024)	(0.021)	(0.027)
Parent skills: numeracy – literacy			0.053
			(0.031)
Instruction time: math – reading		0.066***	0.073***
		(0.017)	(0.015)
Shortage teachers: math – reading		–0.004	–0.003
		(0.007)	(0.007)
Students	406,564	406,564	406,564
Countries	23	23	23
Adj. R2	0.01	0.02	0.02

Notes: Dependent variable: difference in standardized student test scores between math and reading. All regressions include controls for respective imputation dummies and for the PISA wave. Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* PIAAC, PISA 2009 and 2012.

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

Second stage						
	Student Math Performance			Student Reading Performance		
	(1)	(2)	(3)	(4)	(5)	(6)
Teacher cognitive skills	0.319***	0.217***	0.202***	0.326***	0.103**	0.099**
	(0.106)	(0.070)	(0.072)	(0.084)	(0.047)	(0.050)
Parent cognitive skills			0.029**			0.008
			(0.014)			(0.011)
Student characteristics	No	Yes	Yes	No	Yes	Yes
Parent characteristics	No	Yes	Yes	No	Yes	Yes
School characteristics	No	Yes	Yes	No	Yes	Yes
Country characteristics	No	Yes	Yes	No	Yes	Yes
First stage						
	Teacher Numeracy Skills			Teacher Literacy Skills		
Wage position public sector employees	0.034***	0.031***	0.031***	0.029***	0.034***	0.034***
	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Parent cognitive skills			0.038			0.006
			(0.055)			(0.049)
Instrument F statistic	18.0	19.0	17.9	22.6	30.3	29.4
Students	406,564	406,564	406,564	406,564	406,564	406,564
Countries	23	23	23	23	23	23

Notes: Dependent variable: standardized student PISA test score in math (Columns 1–3) and reading (Columns 4–6), respectively. *Wage position public sector employees* is the country-specific percentile rank of the mean wage of nonteacher public sector employees in the wage distribution of nonteacher private sector college graduates; the cross-country standard deviation is 12.7. All skill measures in Columns (1)–(3) (4–6) refer to numeracy (literacy). Student, parent, school, and country characteristics are the same as in the OLS models (see Table 2). All regressions additionally control for median cognitive skills of university graduates in a country. All regressions include controls for respective imputation dummies and for the PISA wave. Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* PIAAC, PISA 2009 and 2012, OECD.

Table 5: Student Performance and Teacher Cognitive Skills (Robustness)

Second stage	Student Math Performance				Student Reading Performance			
	Parent skills	Adult skills	Excluding outliers	Mean teacher skills	Parent skills	Adult skills	Excluding outliers	Mean teacher skills
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Teacher cognitive skills	0.224***	0.215**	0.394***	0.188**	0.136**	0.143*	0.131*	0.103**
	(0.075)	(0.083)	(0.138)	(0.091)	(0.065)	(0.074)	(0.077)	(0.052)
Parent cognitive skills (country level)	–0.007				–0.051			
	(0.039)				(0.040)			
Adult cognitive skills (country level)		0.002				–0.063		
		(0.048)				(0.053)		
Parent cognitive skills			0.038**	0.029**			0.007	0.011
			(0.017)	(0.012)			(0.009)	(0.010)
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage								
	Teacher Numeracy Skills				Teacher Literacy Skills			
Wage position public sector employees	0.031***	0.029***	0.028***	0.033***	0.032***	0.030***	0.033***	0.033***
	(0.006)	(0.007)	(0.005)	(0.007)	(0.006)	(0.007)	(0.005)	(0.010)
Instrument F statistic	23.7	19.6	25.9	22.4	28.9	20.8	45.4	10.4
Students	406,564	406,564	317,508	406,564	406,564	406,564	317,508	406,564
Countries	23	23	20	23	23	23	20	23

Notes: Robustness checks of the instrumental-variable estimation. Dependent variable: standardized student PISA test score in math (Columns 1–4) and reading (Columns 5–8), respectively. *Wage position public sector employees* is the country-specific percentile rank of the mean wage of nonteacher public sector employees in the wage distribution of nonteacher private sector college graduates. All skill measures in Columns (1)–(4) (5–8) refer to numeracy (literacy). In Columns (1) and (5), 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 (2) and (6), we use median cognitive skill level of all PIAAC respondents aged 25–65 instead of individual parent cognitive skills. In Columns (3) and (7), we drop Finland, Italy, and Japan, which appear as outliers in the first-stage regression (see Figure 3). In Columns (4) and (8), we use teacher mean cognitive skills instead of median cognitive skills. Student, parent, school, and country characteristics are the same as in the baseline IV models (see Table 4). All regressions also control for median cognitive skills of university graduates in a country and include controls for imputation dummies and the PISA wave. Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* PIAAC, PISA 2009 and 2012, OECD.

Table 6: Student Performance and Teacher Cognitive Skills with Instructional Practices (IV Results)

Second stage	Student Math Performance		Student Reading Performance	
	(1)	(2)	(3)	(4)
Teacher cognitive skills	0.202***	0.218***	0.099**	0.104**
	(0.072)	(0.070)	(0.050)	(0.048)
Parent cognitive skills	0.029**	0.027*	0.008	0.004
	(0.014)	(0.015)	(0.011)	(0.012)
Instructional practices		0.120		0.350**
		(0.129)		(0.157)
Student characteristics	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes
School characteristics	Yes	Yes	Yes	Yes
Country characteristics	Yes	Yes	Yes	Yes
First stage				
	Teacher Numeracy Skills		Teacher Literacy Skills	
Wage position public sector employees	0.031***	0.033***	0.034***	0.034***
	(0.007)	(0.008)	(0.006)	(0.006)
Instrument F statistic	17.9	17.8	29.4	29.7
Students	406,564	406,564	406,564	406,564
Countries	23	23	23	23

Notes: Dependent variable: standardized student PISA test score in math (Columns 1–2) and reading (Columns 3–4), respectively. *Wage position public sector employees* is the country-specific percentile rank of the mean wage of nonteacher public sector employees in the wage distribution of nonteacher private sector college graduates. All skill measures in Columns (1)–(2) ((3–4)) refer to numeracy (literacy). We derive the indicator for teacher instructional practices using the PISA survey data. See text for details on the construction of the instructional practices indicator. All control variables are the same as in the baseline IV models (see Table 4). Specifications give equal weight to each country. Robust standard errors, adjusted for clustering at country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* PIAAC, PISA 2009 and 2012, OECD.

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

Panel A: Student Math Performance	Gender		Parental background		Natives vs. Migrants	
	Boys	Girls	High SES	Low SES	Natives	Migrants
	(1)	(2)	(3)	(4)	(5)	(6)
Teacher cognitive skills	0.162**	0.244***	0.158**	0.283***	0.188***	0.246*
	(0.073)	(0.072)	(0.078)	(0.078)	(0.071)	(0.140)
Parent cognitive skills	0.034**	0.023	0.045**	0.024*	0.037**	–0.005
	(0.014)	(0.015)	(0.018)	(0.014)	(0.015)	(0.018)
Instrument F statistic	17.9	18.0	20.7	16.7	17.8	14.9
Panel B: Student Reading Performance						
Teacher cognitive skills	0.099**	0.100*	0.026	0.199***	0.087*	0.059
	(0.048)	(0.053)	(0.053)	(0.053)	(0.051)	(0.110)
Parent cognitive skills	0.009	0.005	0.026*	0.000	0.014	–0.018
	(0.011)	(0.012)	(0.013)	(0.010)	(0.012)	(0.013)
Instrument F statistic	28.4	30.6	29.3	31.1	29.0	22.6
Additional controls in Panels A + B						
Student characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Parent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
School characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Country characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Students	204,424	202,140	207,914	198,650	350,912	20,433
Countries	23	23	23	23	23	22

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 first-generation or 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. Migrants are second-generation migrants. 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 OLS models (see Table 2). All regressions additionally control for median cognitive skills of university graduates in a country. 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 country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* PIAAC, PISA 2009 and 2012, OECD.

Table 8: 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)
Australia	17	28.7	10	9.5
Austria	17	27.8	30	27.9
Belgium	9	14.9	19	17.7
Canada	25	40.9	15	13.8
Czech R.	12	20.0	22	21.0
Denmark	22	36.6	33	31.5
Estonia	32	53.4	28	26.7
France	16	25.9	26	24.5
Germany	9	14.8	21	19.4
Ireland	22	35.9	22	20.8
Italy	44	72.4	43	40.9
Japan	6	9.9	3	2.9
Korea	31	50.4	26	24.4
Netherl.	14	22.3	14	13.5
Norway	15	25.4	18	16.8
Poland	40	65.6	29	27.1
Russia	44	73.0	39	36.9
Slovak R.	23	37.6	32	30.1
Spain	34	56.7	32	30.2
Sweden	11	18.4	14	13.6
U.K.	28	46.3	22	21.2
U.S.	33	54.4	21	19.6

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 4. Columns (1) and (3) show difference in teacher skills to Finland. *Data sources:* PIAAC, PISA 2009 and 2012, OECD.

Table 9: Relative Teacher Pay and Teacher Cognitive Skills

	Teacher Numeracy Skills			Teacher Literacy Skills		
	(1)	(2)	(3)	(4)	(5)	(6)
Teacher position in college graduates wage distribution /10	0.28***	0.26***	0.27***	0.20***	0.19***	0.20***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Numeracy skills college graduates (w/o teachers)	1.05***	0.98***	1.00***			
	(0.10)	(0.12)	(0.12)			
Literacy skills college graduates (w/o teachers)				1.03***	0.94***	1.00***
				(0.13)	(0.16)	(0.15)
GDP per capita		0.03*			0.02	
		(0.01)			(0.01)	
Wage college graduates (w/o teachers)			0.02			0.01
			(0.02)			(0.02)
Constant	–1.67***	–2.48***	–1.96***	–1.01***	–1.65***	–1.17***
	(0.29)	(0.55)	(0.45)	(0.28)	(0.50)	(0.40)
Countries	23	23	23	23	23	23
Adj. R2	0.76	0.80	0.76	0.72	0.73	0.71

Notes: Dependent variable: teacher skills in numeracy (Columns 1–3) and literacy (Columns 4–6). *Teacher position in college grads wage distribution / 10* is the percentile rank of the country-specific mean teacher wage in the wage distribution of all nonteacher college graduates (divided by 10). Country-level regressions. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* PIAAC, OECD.

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. *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 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	0.140***	0.140***
	(0.019)	(0.014)
Female	–0.154***	0.349***
	(0.012)	(0.016)
First-generation migrant	–0.144***	–0.124**
	(0.050)	(0.049)
Second-generation migrant	–0.092*	–0.030
	(0.050)	(0.043)
Other language at home	–0.090**	–0.177***
	(0.033)	(0.037)
Family background		
11-25 books	0.204***	0.253***
	(0.024)	(0.022)
26-100 books	0.431***	0.507***
	(0.037)	(0.036)
101-200 books	0.607***	0.699***
	(0.048)	(0.045)
201-500 books	0.805***	0.883***
	(0.053)	(0.053)
More than 500 books	0.830***	0.883***
	(0.057)	(0.056)
ISCED 1	0.100*	0.166**
	(0.053)	(0.077)
ISCED 2	0.091	0.221***
	(0.065)	(0.062)
ISCED 3B,C	0.188**	0.313***
	(0.075)	(0.071)
ISCED 3A, 4	0.234***	0.353***
	(0.072)	(0.069)
ISCED 5B	0.188**	0.352***
	(0.078)	(0.066)
ISCED 5A, 6	0.260***	0.417***
	(0.078)	(0.063)
Blue collar-high skilled	0.112***	0.094***
	(0.013)	(0.016)
White collar-low skilled	0.180***	0.177***
	(0.017)	(0.017)
White collar-high skilled	0.399***	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	0.003	0.051*
	(0.028)	(0.029)
City	–0.001	0.062*
	(0.031)	(0.032)
Large City	0.019	0.089*
	(0.040)	(0.044)
Private school	0.188***	0.164***
	(0.028)	(0.032)
No. students per school (in 1000)	0.294***	0.247***
	(0.062)	(0.055)
Content autonomy	0.056	0.018
	(0.038)	(0.030)
Personnel autonomy	–0.164***	–0.159***
	(0.042)	(0.034)
Budget autonomy	0.031	0.029
	(0.040)	(0.041)
Shortage math teacher	–0.034**	
	(0.013)	
Shortage language teacher		–0.046***
		(0.016)
Weekly hours math classes	0.060**	
	(0.028)	
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	0.076*	0.030
	(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:* PIAAC, PISA 2009 and 2012, OECD.