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CESIFO WORKING PAPER NO. 6114
CATEGORY 4: LABOUR MARKETS
SEPTEMBER 2016

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ISSN 2364-1428

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Abstract

Expanded international data from the PIAAC survey of adult skills allow us to analyze potential sources of the cross-country variation of comparably estimated labor-market returns to skills in a more diverse set of 32 countries. Returns to skills are systematically larger in countries that have grown faster in the recent past, consistent with models where skills are particularly important for adaptation to dynamic economic change.

JEL-Codes: J310, I200, O150.

Keywords: cognitive skills, returns to education, economic growth, international comparisons.

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September 12, 2016

Wiederhold and Woessmann gratefully acknowledge financial support from the Leibniz Association through the project “Acquisition and Utilization of Adult Skills.”

Introduction

The persuasive hypothesis that a prime value of education is the ability to adapt to a changed economic environment (Nelson and Phelps (1966), Welch (1970), Schultz (1975)) has actually received little testing. While developed in somewhat different ways, the underlying idea is that different economic conditions require worker adjustment and that a fundamental attribute of education and skill is providing the ability to adapt to emerging disequilibria and to prosper in new environments. The relevant economic changes can come from a variety of factors including capital deepening, technological change, and altered industrial structure. To test this, we suggest that international comparisons provide clearer evidence on this hypothesis than within-country analyses because of the better picture of broad differences in the economic environment.

The most direct evidence on the relationship between returns to education and adaption to changed economic environments is narrow and specialized, coming from analysis of farmer decisions. Welch (1970) first considers the relationship between agricultural profitability and farmer education, and this is extended in models of adoption of new technologies by Foster and Rosenzweig (1996) and others. The key to these types of analyses is the ability to observe distinct new technologies. Other investigations, while suggestive, offer less clear evidence on the specific role of education in coping with change. For example, the hypothesis is consistent with the finding that returns to schooling increased when former communist countries transitioned to a market economy (Münich, Svejnar, and Terrell (2005)), but this could also reflect nonmarket returns under the prior managed economy rather than returns to the ability to adjust to the changed economic setting. Consideration of skill biased technological change generally focuses on the impact of technologies with different skill contents (e.g., Katz and Murphy (1992), Goldin and Katz (2008), Acemoglu and Restrepo (2016)) but does not distinguish between adaptation to

change and any long-run embedded skill requirements. The relationship of schooling demand with vintages of capital in broad manufacturing industries is similarly consistent with expectations about adaptation to different technologies (Bartel and Lichtenberg (1987)) but also with alternative explanations of changing demand for skilled workers by age of plant and capital.

We turn to international evidence to investigate how changes in the economic environment relate to returns to skills. As is clear from work on variations in economic growth, there are wide differences in the pace of economic change across countries. This variation has been difficult to exploit in the past to test the education adjustment hypothesis as international skill comparisons have been limited. Specifically, school attainment is a very poor measure of productive skills in an international setting, because a year of schooling does not produce the same individual skills across diverse countries (Hanushek and Woessmann (2015)). Recently, however, new international data provide direct comparisons of adult cognitive skills across a significant number of countries. Exploiting international variations in returns to these skills has its own difficulties, but it permits more direct linkage to the pace of economic change.

We employ data on cognitive skills across 32 diverse economies to provide a preliminary exploration of the patterns of rewards to individual skills. These new data on skills and earnings across countries reveal that returns to skills vary more across countries than previously thought, offering sufficient variation to explore the cross-country association of skill returns with economic change. Results provide consistent support for the basic hypothesis, showing that the return to worker skills is systematically related to prior economic growth rates. While causal identification is clearly difficult, this relationship of returns to change holds up in the presence of plausible alternative explanations of the pattern of returns.

The PIAAC Survey of Adult Skills

Our analysis relies on the Programme for the International Assessment of Adult Competencies (PIAAC), developed by the OECD to provide internationally comparable data on the skills of the adult populations. The first round of PIAAC data, administered between August 2011 and March 2012, produced data on 23 (mostly OECD) countries (see OECD (2013), Hanushek et al. (2015)).¹ In a second round, PIAAC administered the same skill survey in an additional nine countries (including both non-OECD countries and new members to the OECD) between April 2014 and March 2015 (see OECD (2016)), extending the usable sample with comparable skill data to 32 countries. At least 5,000 adults participated in the PIAAC assessment in each country, providing considerably larger samples than in IALS, the predecessor of PIAAC. In each participating country, a representative sample of adults between 16 and 65 years of age was interviewed at home in the language of their country of residence. The standard survey mode was to answer questions on a computer, but respondents without sufficient computer knowledge could also do a pencil-and-paper survey.

PIAAC was designed to measure key cognitive and workplace skills needed for individuals to advance at work and participate in society. The survey assessed cognitive skills in three domains: numeracy, literacy, and problem solving in technology-rich environments. We focus on numeracy skills, which we deem most comparable across countries. We standardize skills to have mean zero and standard deviation (SD) one and employ the sample weights provided in PIAAC.² To provide perspective, one SD in numeracy skills corresponds to one out of five

¹ In this, we do not include the Russian Federation because its data are still subject to change and are not representative of the entire population because of the lack of the Moscow municipal area (OECD (2013)).

² Throughout, we use the first plausible value of the PIAAC scores.

proficiency levels in PIAAC and roughly amounts to twice the learning difference between school-attending PIAAC respondents in lower secondary and upper secondary education.³

An internationally harmonized background questionnaire surveyed labor-market status, earnings, education, experience, and demographic characteristics. Our wage measure refers to gross hourly earnings of wage and salary workers.⁴ The measure of actual work experience refers to the number of years with at least six months spent in paid work. Appendix Table A-1 provides descriptive statistics for the second-round PIAAC participants (see Hanushek et al. (2015) for first-round participants).

To measure the amount of recent economic change, we use the annual growth rate in real GDP per capita at constant national prices between 1990 and 2011 from the Penn World Tables 9.0 (see Feenstra, Inklaar, and Timmer (2015)). For additional features of country labor markets, we follow Hanushek et al. (2015) in measuring union density as the share of employees who are

³ We calculate this “ISCED-level equivalent” by regressing numeracy skills of respondents aged 16-18 years in the 32-country sample on an indicator that takes the value 1 for respondents currently in upper secondary education (ISCED 3A-B, C long) and 0 in lower secondary education (ISCED 2, 3C short). Regressions control for gender, age, number of books at home, migrant background, and country fixed effects.

⁴ The earnings data in the Public Use File are reported only in deciles for Singapore and Turkey in the second round, as well as for Austria, Canada, Sweden, and the United States in the first round. For these countries, we assign the median wage of each decile of the country-specific wage distribution (obtained from the OECD) to each person belonging to the respective decile. Hanushek et al. (2015) show that using decile medians has no substantive impact on estimated returns to skills for those countries with continuous wage data. To limit the influence of outliers, we trim the bottom and top one percent of the wage distribution in each country.

trade union members (provided by the International Labour Organization) and in calculating public employment as the share of workers employed in the public sector in the PIAAC data.⁵

New Evidence on Returns to Skills

We consider how measured cognitive skills affect labor market earnings. As developed in Hanushek et al. (2015), our baseline empirical model is simply an analog to a Mincer equation except that it is built on measured cognitive skills (C) instead of years of schooling:

$$\ln y_i = \beta_0 + \gamma C_i + \beta_1 E_i + \beta_2 E_i^2 + \beta_3 G_i + \varepsilon_i, \quad (1)$$

where y_i is the hourly wage of individual i , E is experience, G is gender, and ε is a stochastic error. Our parameter of interest is γ , the earnings gradient associated with skills. Our analysis focuses on full-time workers aged 35-54, because prime-age earnings best approximate lifetime earnings (Hanushek et al. (2015)).⁶

The new results indicate that returns to skills are even more diverse than previously thought. Our estimates for the original PIAAC sample of 23 countries showed the returns to numeracy skills to range from 0.12 in Sweden to 0.25 in the United States.⁷ As shown in Figure 1, this range is expanded on both ends with the addition of the nine new countries (dark bars). The estimates now range from 0.10 in Greece to 0.45 in Singapore. (The full regression models for the newly added countries are shown in Table 1). The pooled estimate (with country fixed

⁵ Data refer to the beginning year of the respective PIAAC round or the most recent available year before that.

⁶ Full-time workers are defined as working at least 30 hours per week (see Hanushek et al. (2015) for detail).

⁷ This U.S. estimate is based on earnings data reported in deciles in the most recent Public Use File; with access to continuous earnings data at the national data center, our prior estimate was 0.28 (Hanushek et al. (2015)).

effects) across the 32 countries is 0.20; i.e., a one standard deviation increase in numeracy skills is related to 20 percent higher earnings.

Moreover, the general character of the estimates for the new countries follows closely what was seen in the smaller set of original PIAAC countries. In particular, we continue to find strong age-varying returns to skills. In the extended sample of employees aged 16-65, estimates of returns to skills increase steadily with age until age 35 and are reasonably flat from there on (Appendix Figure A-1).⁸ Just as earnings of prime-age workers tend to be good proxies for lifetime earnings (Haider and Solon (2006)), returns estimated in the prime-age category will more likely capture lifetime returns to skills.

Table 2 shows how the estimated returns vary across alternative specifications in each second-round country and in the pooled 32-country sample. While the baseline model standardizes scores within each country, results are quite similar when standardizing scores to have mean zero and SD one in the full international sample. The exception is Singapore, where the return drops from 0.45 to 0.35 with the international standardization, reflecting the large within-country score variation in Singapore; still, Singapore remains the largest estimate in the sample. The cross-country pattern is quite similar when using literacy skills or problem-solving skills instead of numeracy skills, as well as for males and females. Expectedly, estimates of skill returns are reduced when conditioning on years of schooling, which is one of the inputs into cognitive skills. In addition to their relationship with earnings, skills are also positively associated with employment. As in our previous analysis, in the pooled sample returns to skills are slightly larger for workers with high-educated parents, for those in the private as opposed to

⁸ The aggregate picture might suggest including older workers. But past age 50, variations in retirement and labor-force participation across countries come into play, leading us to focus just on prime-age workers.

public sector, and for full-time as opposed to part-time workers (not shown). But pooled returns do not differ statistically significantly between males and females and, surprisingly, between migrants and natives.

Economic Change and Differences in Returns to Skills across Countries

Our primary focus is how returns to skills are related to the amount of change in the economy. To capture varying amounts of change across different economies, we rely upon prior growth rates in GDP per capita.⁹ We use average annual growth in real GDP per capita over the period 1990-2011. Starting in 1990 ensures that we do not lose previously communist bloc countries. We consider growth up to the beginning of the PIAAC observations to capture longer-run changes in economic production.

Figure 2 shows clearly that returns to skills are systematically larger in countries that experienced faster economic growth in the recent past. This pattern is consistent with the hypothesis that part of the economic value of skills lies in the ability to adapt to economic change.

To investigate this association more rigorously and condition on the potentially confounding effects of other differences in environmental factors across countries, we pool the micro data for all countries, include country fixed effects (η_c), and estimate interactions of numeracy scores with the different country-level features as in:

$$\ln y_i^c = \beta_0 + \gamma_0 C_i + \gamma_1 (C_i \times Z_c) + \beta_1 E_i + \beta_2 E_i^2 + \beta_3 G_i + \eta_c + \varepsilon_i, \quad (2)$$

⁹ We refrain from restricting the measure of change to changes in total factor productivity (TFP) as this would leave out influences of adding new capital, foreign direct investment, and different industrial configurations that require labor-market adjustments.

where Z_c are different measures of the economic environment in country c and γ_1 is the estimate of how the return to numeracy varies with Z . In this interacted model, we de-mean all variables to facilitate interpretation.¹⁰

The first column of Table 3 has the simplest specification where numeracy skills enter directly and also vary by countries' prior growth rates in GDP per capita. This specification effectively replicates the bivariate scatterplot of Figure 2: There is a strong and statistically significant positive relationship between growth and returns to skills.

This investigation of course must also consider other possible confounding factors across countries. In our analysis of the original 23 PIAAC countries, we found that returns to skills are systematically related to features of countries' labor markets such as union density and public employment shares (Hanushek et al. (2015)). Column 2 shows that this is also the case in the extended sample of countries: Returns to skills are lower when union membership and public employment are higher. The growth estimates clearly are intertwined with these impacts, but when these effects of union density and public employment are netted out in column 2, the independent growth effect remains strong and highly significant.

The observed association of more rapid economic change with the value of skills is quite substantial. Average annual growth rates in our sample differ by 4 percentage points, ranging from 0.7 percent in Japan to 4.7 percent in Korea (see Figure 2). Evaluated at this range, the estimates in column 2 suggest a difference in the return to one standard deviation in numeracy skills of 0.13, which is sizeable compared to a mean return of 0.20. When similarly evaluated at the range of their respective distributions, differences in union density (0.04) and public employment (0.10) are also strongly related to returns but to a lesser extent than seen for growth.

¹⁰ The pooled analyses exclude Jakarta (Indonesia), for which we do not have the relevant country measures.

Robustness Checks

While the international comparisons offer substantial variation in the economic environment that makes it possible to describe the interplay with the labor-market returns to skill, it is simultaneously difficult to find clearly exogenous variation in economic change across countries to test the hypothesis. Concerns of direct reverse causation from the incentives created by larger skill returns feeding back into an economy's growth process are minimized in the basic model by our measurement of economic growth over a period that predates the estimation of skill returns. We also took a number of steps to address the most plausible threats that omitted country factors pose to identification of the relationship of skill returns with growth including estimating the models with just within-country variance (by including country fixed effects) and incorporating previously identified features of the labor market in each country. The analysis could nonetheless suffer from both reverse causation and omitted variables bias beyond that already considered. Although we cannot deal conclusively with all possible issues, we now extend this investigation to see how the results hold up under further potential threats to identification.

One concern with the cross-country analysis is that much of the country differences in returns to skills might reflect different occupational and industrial structures of the economies. As a check on this possibility, we introduce a full set of industry-by-occupation fixed effects (183 in total) so that the returns to skills are estimated just from variations within these cells (column 3). The main effect of numeracy drops, indicating that about half of the return to numeracy skills comes through the path of selection into specific occupations and industries. The within-industry and within-occupation impacts of growth and of the other environmental forces are, however, little changed from the overall effects in column 2.

A second issue about the basic estimates relates to the distribution of skills within each country. In reviewing prior research on how skill differences relate to the distribution of income,

Hanushek and Woessmann (2011) noted an apparent anomaly in that aggregate estimates of how skill and income distributions were related (Nickell (2004)) appeared to conflict with micro estimates that emphasized other aspects of the economy (e.g., Blau and Kahn (2005)). They resolved this conflict by noting that returns to skills appeared to be strongly related to the variation in skills across countries. This observation was, however, based on aggregate data from the limited country observations available in the IALS survey of the mid-1990s.

Column 4 relates the skill differences in each country to the simple model of returns to numeracy skills.¹¹ Consistent with the prior aggregate observation, there is a positive and statistically significant association of the skill distribution with returns to numeracy. There are nevertheless three immediate concerns with this. First, it is unclear how to interpret the relationship between returns and the skill differences. In particular, if there are high returns to skills, individuals would have an incentive to invest more in skills, leading to questions about the direction of causality that is implied. Second, if there is an incentive to invest more, the young are surely more able to respond to this incentive, as the old will be constrained by a lower malleability of skills and a higher opportunity cost of skill investment. Indeed, looking across countries, there are very strong age-achievement patterns for some of the fast-growing countries such as Singapore and Korea (OECD (2016)). Third, standard economic theory would suggest that higher overall skill levels would tend to dampen the returns to skill as skills are less scarce.

To investigate these additional issues, column 5 adds the score difference between workers aged 20-34 and those aged 50-65, and column 6 adds the country mean numeracy score. Column

¹¹ Consistent with Nickell (2004) and Blau and Kahn (2005), these estimates use the difference in numeracy scores between the 90th and 10th percentiles; using the percentile ratio rather than the percentile difference yields the same qualitative results.

5 shows that overall skill inequality in fact loses significance when the age pattern of skills is included. This suggests that it is not skill inequality in general but the age differences in skills that are related to skill returns, consistent with the incentive effects of high returns and reverse causation driving the estimated association of the skill distribution with returns. In column 6, the addition of the mean skill shows a negative relationship with the return to skill (significant at the 10 percent level), and the age distribution of skills remains significant.

The prior estimates do not, however, include any of the factors found significant in column 2, leading to the more complete specification in column 7. Once we account for the impact of growth, unionization, and public employment on skill returns, the measure of skill distribution in fact becomes small and statistically insignificant. This also holds when we look at the relationships within industry-occupation cells (column 8), where higher average skill levels in a country are significantly related to lower returns to skills. These results are consistent with an interpretation where the association between skill inequality and skill returns is fully driven by the fact that skill returns are larger in changing environments.

Results are also robust to a number of alternative specifications not shown in the table. First, when added to the baseline model, an interaction of numeracy with the initial level of GDP per capita does not enter significantly and does not alter the interaction of numeracy with the GDP growth rate. Second, Hanushek et al. (2015) also included a measure of employment protection; while available only for 29 of our 31 countries, this measure also enters with a significant negative interaction with numeracy in our model, but leaves all other qualitative results unchanged.¹² Third, results are robust to using alternative periods over which to measure prior

¹² Hanushek et al. (2015) also showed that returns to skills are not systematically related to product-market regulations and minimum wages.

growth, such as 1990-2000, 1990-2005, or 1990-2007, indicating that results are not affected by the 2008 recession. Fourth, results are robust to dropping one country at a time, indicating that the cross-country pattern is not driven by individual country observations.¹³ Fifth, results are also robust to restricting the analysis to variation within continents by adding a set of interactions of numeracy with continental fixed effects and to restricting the sample to European countries only. In sum, direct analysis of plausible confounding factors and elimination of potentially suspect variations across countries and continents leave the strong relationship between the returns to skills and the amount of change in the economic environment intact.

Conclusions

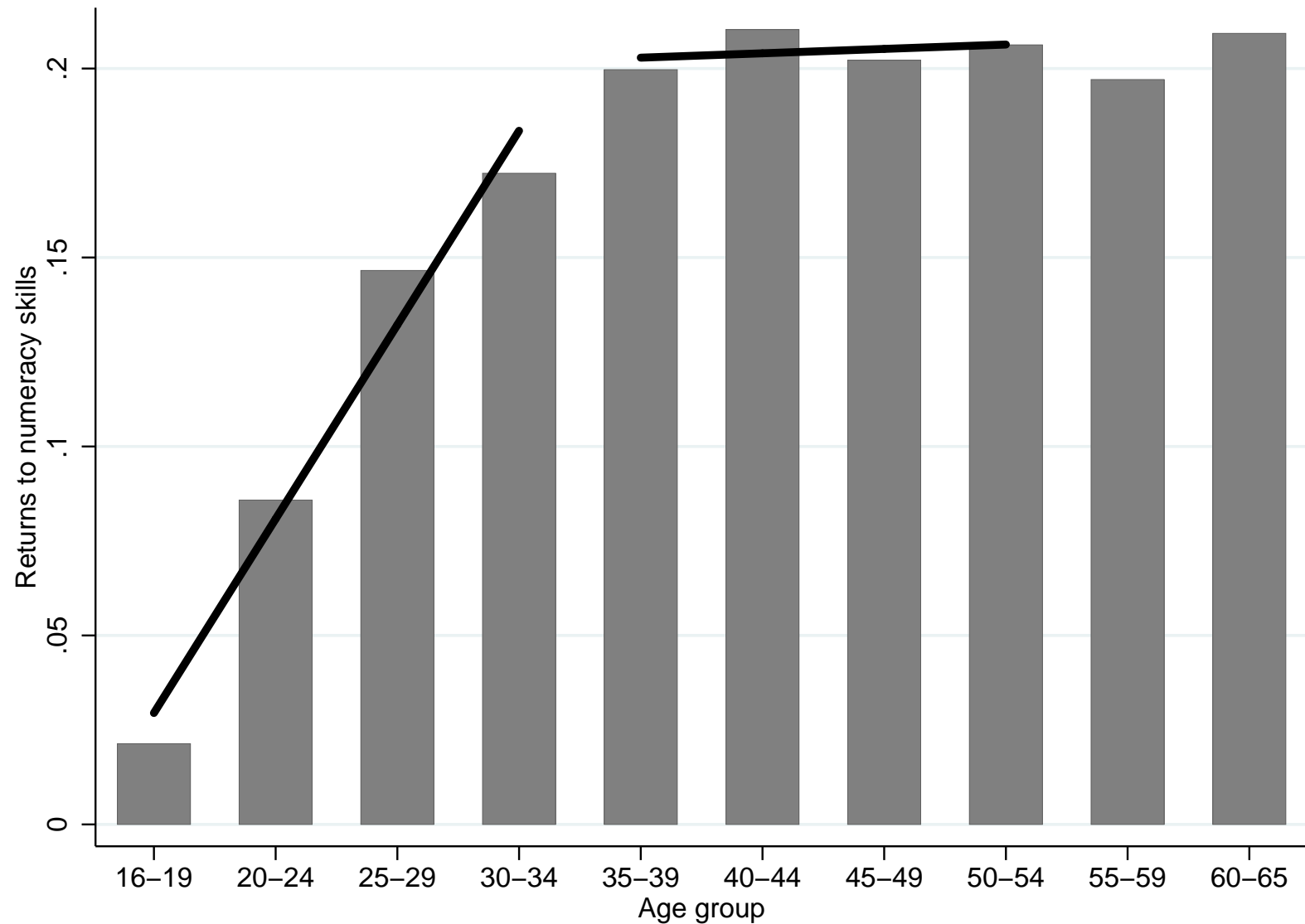
The availability of new information about earnings and skills in a broader set of 32 countries permits closer investigation than previously possible of the hypothesis that education has a stronger payoff when there is faster economic change. It turns out that the range of differences in labor-market returns to skills across countries is even larger than previously thought, with two of the nine newly added countries – Singapore and Chile – having by far the highest returns to skills in the sample and newly added Greece having the lowest. The main observed cross-country pattern is simply that returns to skills are larger in countries with faster prior economic growth, consistent with skilled workers being able to adjust more readily to economic change. These descriptive estimates of course are subject to questions about causality, but considering a range of alternative influences does not change this overall pattern.

¹³ Results are also robust to dropping both Chile and Singapore, the two countries with the highest returns.

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Figure A-1: Returns to Skills by Age Group



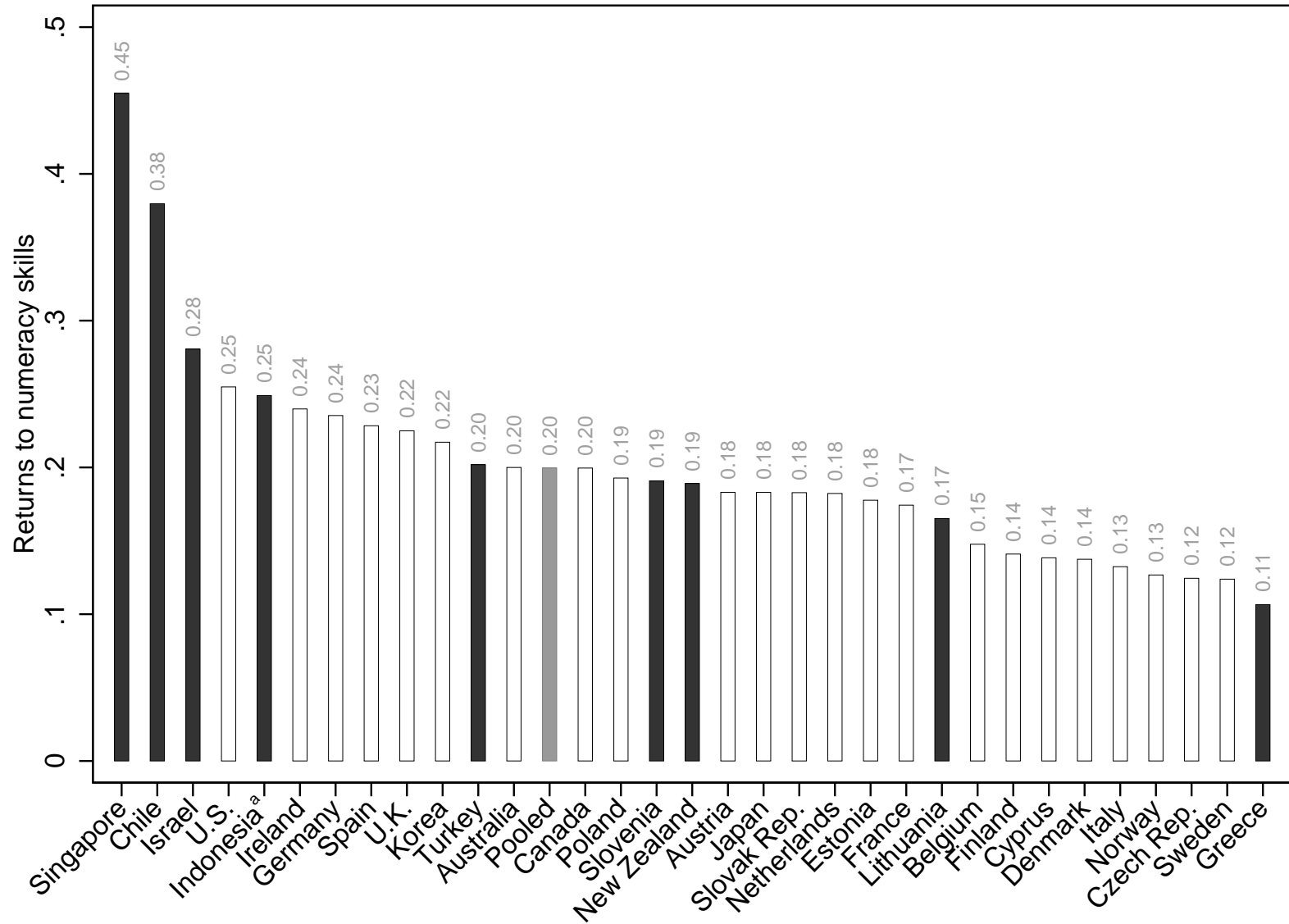
Notes: Coefficient estimates on numeracy score (standardized to std. dev. 1 within each country) for indicated 5-year age groups in a regression of log gross hourly wage on numeracy, gender, a quadratic polynomial in actual work experience, and country fixed effects, sample of full-time employees pooling all countries. Sample includes 32 PIAAC countries. Regressions weighted by sampling weights, giving same weight to each country. Slopes of solid lines reflect average change in returns by age groups (separately estimated for ages 16-34 and 35-54). *Data source:* PIAAC 2016.

Table A-1: Descriptive Statistics

	Chile	Greece	Indonesia ^a	Israel	Lithuania	New Zealand	Singapore	Slovenia	Turkey
Gross hourly wage (national currency)	3.3 [†] (2.9)	7.1 (3.6)	16.8 [†] (17.0)	57.8 (37.3)	11.6 (6.8)	29.1 (13.9)	23.8 (16.4)	7.7 (3.5)	11.8 (10.5)
Numeracy	213.5 (59.9)	263.5 (47.9)	208.3 (55.5)	263.1 (59.0)	270.0 (48.0)	278.9 (54.8)	259.0 (67.5)	263.1 (51.6)	233.7 (54.9)
Schooling (years)	11.8 (3.4)	13.0 (3.2)	11.8 (3.8)	13.8 (2.6)	13.7 (2.3)	14.2 (2.6)	12.3 (3.2)	10.7 (1.9)	9.2 (3.6)
Experience (years)	18.5 (8.8)	19.1 (7.1)	16.5 (8.2)	22.4 (7.4)	21.8 (7.1)	23.5 (8.0)	19.9 (7.9)	22.7 (7.8)	16.0 (8.4)
Female (share)	0.38	0.40	0.20	0.48	0.55	0.42	0.43	0.49	0.22
Observations	903	623	806	908	1260	1204	1507	1306	674

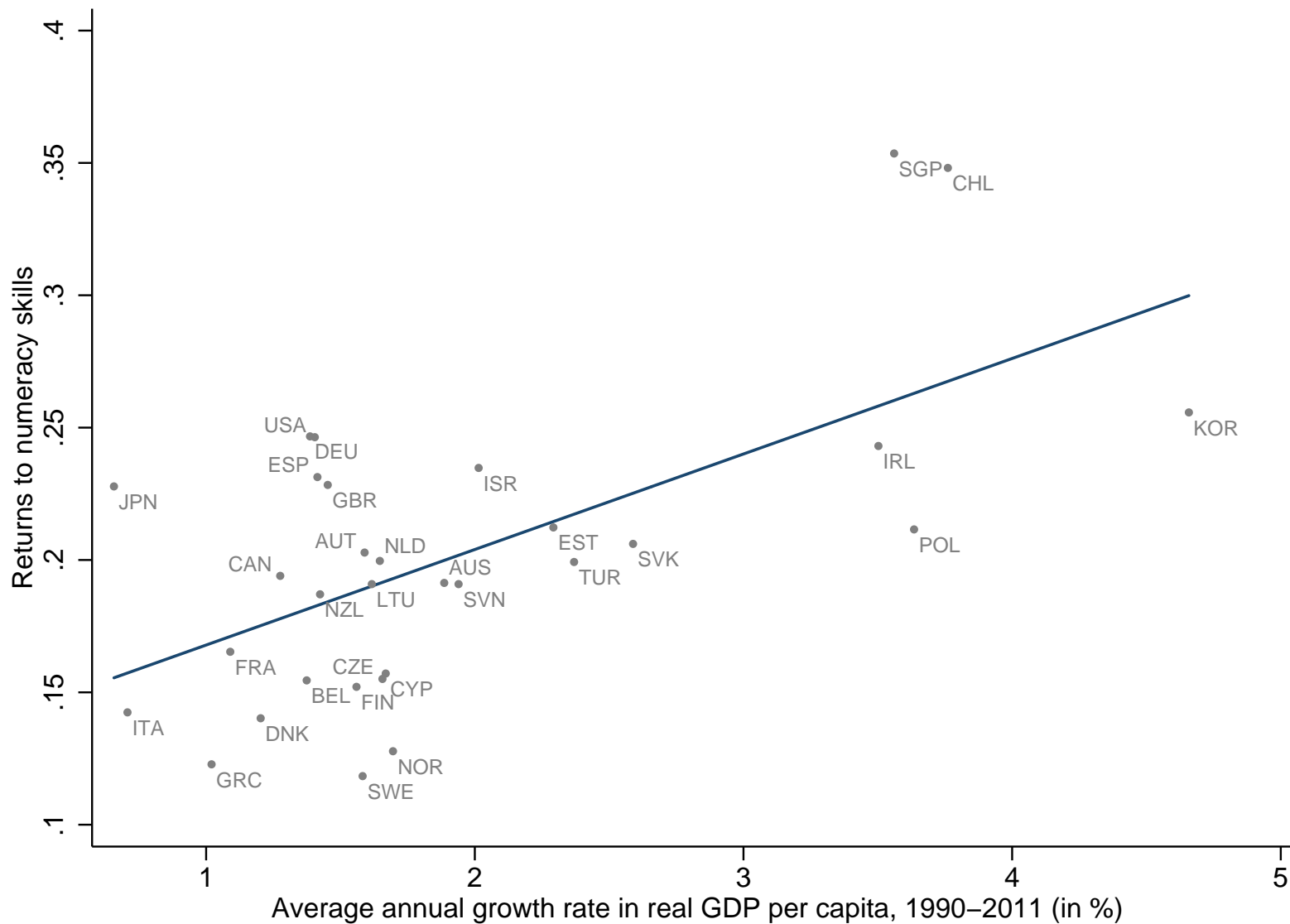
Notes: Means, standard deviations (in parentheses), and numbers of observations for selected variables by country. Sample: full-time employees aged 35-54. [†]wages divided by 1000. ^aJakarta only. *Data source:* PIAAC 2016.

Figure 1: Returns to Skills across PIAAC Countries



Notes: Coefficient estimates on numeracy score (standardized to std. dev. 1 within each country) in a regression of log gross hourly wage on numeracy, gender, and a quadratic polynomial in actual work experience, sample of full-time employees aged 35-54. Regressions weighted by sampling weights. Pooled specification includes country fixed effects and gives same weight to each country. Hollow bars indicate first-round countries, black bars indicate second-round countries. ^aJakarta only. Data source: PIAAC 2016.

Figure 2: GDP Growth and Returns to Skills



Notes: Scatter plot of returns to numeracy skills (international standardization) against average annual growth rate in real GDP per capita, 1990-2011. Data sources: Penn World Tables, PIAAC 2016.

Table 1: Returns to Skills in Second-Round PIAAC Countries

	Pooled	Chile	Greece	Indonesia ^a	Israel	Lithuania	New Zealand	Singapore	Slovenia	Turkey
Numeracy	.200*** (.003)	.380*** (.026)	.107*** (.021)	.249*** (.028)	.281*** (.016)	.165*** (.016)	.189*** (.011)	.455*** (.013)	.191*** (.011)	.202*** (.027)
Experience	.028*** (.001)	.019 (.012)	.026** (.010)	.045*** (.011)	.034*** (.007)	.015 (.012)	.023*** (.007)	.049*** (.007)	.009 (.007)	.075*** (.010)
Experience ²	-.052*** (.003)	-.027 (.032)	-.046* (.025)	-.089*** (.029)	-.055*** (.017)	-.033 (.027)	-.042*** (.014)	-.110*** (.017)	-.024 (.016)	-.173*** (.028)
Female	-.145*** (.005)	-.116** (.051)	-.055 (.039)	-.261*** (.063)	-.082** (.032)	-.217*** (.035)	-.116*** (.023)	-.158*** (.028)	-.071*** (.021)	-.009 (.068)
R ²	.218	.365	.099	.171	.277	.158	.265	.480	.215	.208
Observations	45064	903	623	806	908	1260	1204	1507	1306	674

* p<0.10, ** p<0.05, *** p<0.01

Notes: Least squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time employees aged 35-54. Pooled specification includes all 32 PIAAC countries; includes country fixed effects and gives same weight to each country. Numeracy score standardized to std. dev. 1 within each country. Experience² divided by 1000. R² refers to within-country R². Robust standard errors in parentheses. ^aJakarta only. *Data source:* PIAAC 2016.

Table 2: Returns to Skills in Alternative Specifications

	Pooled	Chile	Greece	Indonesia ^a	Israel	Lithuania	New Zealand	Singapore	Slovenia	Turkey
(1) Baseline model	.200*** (.003)	.380*** (.026)	.107*** (.021)	.249*** (.028)	.281*** (.016)	.165*** (.016)	.189*** (.011)	.455*** (.013)	.191*** (.011)	.202*** (.027)
(2) International standardization	.210*** (.003)	.348*** (.024)	.123*** (.024)	.256*** (.029)	.235*** (.014)	.191*** (.019)	.187*** (.011)	.354*** (.010)	.191*** (.011)	.199*** (.027)
(3) Literacy	.187*** (.003)	.318*** (.027)	.083*** (.019)	.237*** (.034)	.259*** (.017)	.144*** (.016)	.176*** (.011)	.430*** (.015)	.184*** (.010)	.210*** (.026)
(4) Problem solving	.159*** (.003)	.309*** (.035)	.083*** (.022)		.223*** (.019)	.206*** (.017)	.154*** (.012)	.297*** (.017)	.180*** (.011)	.101*** (.034)
(5) Numeracy conditional on years of schooling	.109*** (.003)	.148*** (.031)	.041* (.021)	.062** (.028)	.198*** (.019)	.087*** (.018)	.127*** (.012)	.227*** (.017)	.075*** (.012)	.077*** (.025)
(6) Males	.199*** (.004)	.380*** (.034)	.094*** (.030)	.201*** (.034)	.299*** (.023)	.160*** (.026)	.194*** (.014)	.458*** (.017)	.185*** (.015)	.221*** (.032)
(7) Females	.199*** (.004)	.384*** (.038)	.126*** (.028)	.377*** (.041)	.259*** (.023)	.174*** (.018)	.184*** (.017)	.445*** (.022)	.200*** (.015)	.130*** (.043)
(8) Employment regression	.079*** (.002)	.103*** (.014)	.036*** (.011)	.013 (.008)	.107*** (.010)	.083*** (.012)	.074*** (.009)	.035*** (.008)	.093*** (.009)	.058*** (.011)

* p<0.10, ** p<0.05, *** p<0.01

Notes: Least squares regressions weighted by sampling weights. Dependent variables: log gross hourly wage in rows (1) to (7); employment indicator, taking the value of one if a person is employed (self-reported), in row (8). Samples: full-time employees aged 35-54 in wage regressions; all individuals aged 35-54 with self-reported employment status in employment regressions. Pooled specification includes all 32 PIAAC countries; includes country fixed effects and gives same weight to each country. Estimations control for gender and a quadratic polynomial in work experience in wage regressions and for gender and a quadratic polynomial in age in employment regressions. Robust standard errors in parentheses. ^aJakarta only. *Data source:* PIAAC 2016.

Table 3: Economic Change and Differential Returns to Skills across Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Numeracy	.199*** (.009)	.195*** (.006)	.094*** (.006)	.199*** (.009)	.198*** (.009)	.197*** (.008)	.195*** (.006)	.094*** (.006)
× GDP per capita growth 1990-2011	.050*** (.014)	.033*** (.008)	.030*** (.007)				.025** (.010)	.022** (.009)
× Union density		-.069** (.027)	-.081*** (.024)				-.071** (.027)	-.069** (.027)
× Public employment		-.377*** (.085)	-.314*** (.066)				-.316*** (.073)	-.277*** (.068)
× Skill inequality				.019*** (.007)	.007 (.006)	.005 (.005)		
× Skill difference young vs. old					.024** (.009)	.022** (.008)	.008 (.007)	.005 (.006)
× Skill mean						-.010* (.005)	-.003 (.003)	-.006** (.003)
Country fixed effects	X	X	X	X	X	X	X	X
Occupation × industry fixed effects [183]			X					X
R ²	.237	.242	.428	.234	.237	.238	.242	.428
Countries	31	31	31	31	31	31	31	31
Observations	44258	44258	43213	44258	44258	44258	44258	43213

* p<0.10, ** p<0.05, *** p<0.01

Notes: Least squares regressions pooling all countries with country fixed effects, weighted by sampling weights (giving same weight to each country). Indonesia is excluded because only Jakarta was sampled in PIAAC. Dependent variable: log gross hourly wage. Sample: full-time employees aged 35-54. Numeracy score standardized to std. dev. 1 in international sample. All regressions control for gender, a quadratic polynomial in actual work experience, and country fixed effects. All variables are de-measured. *GDP per capita growth 1990-2011*: annual growth rate in real GDP per capita at constant national prices between 1990 and 2011. *Union density*: share of wage and salary earners who are trade union members. *Public employment*: share of workers employed in the public sector. *Skill inequality*: numeracy score differential between 90th and 10th percentile of numeracy skill distribution; divided by 10. *Skill difference young vs. old*: numeracy score differential between those aged 20-34 and those aged 50-65; divided by 10. *Skill mean*: mean numeracy score of the country; divided by 10. Number in square brackets reports the number of occupation × industry fixed effects. Robust standard errors (adjusted for clustering at country level) in parentheses. *Data sources*: ILO, Penn World Tables, PIAAC 2016.