

# Coping with Change: International Differences in the Returns to Skills\*

Eric A. Hanushek, Guido Schwerdt, Simon Wiederhold, Ludger Woessmann<sup>†</sup>

January 3, 2017

## Abstract

International data from the PIAAC survey allow estimation of comparable labor-market returns to skills for 32 countries. Returns to skills are larger in faster growing economies, consistent with the hypothesis that skills are particularly important for adaptation to economic change.

JEL: I2, J3, O15

Keywords: returns to skills; economic growth cognitive skills; international comparisons; disequilibria; knowledge capital

Corresponding author: Eric A. Hanushek, Hoover Institution, Stanford University, Stanford, CA 94305; [hanushek@stanford.edu](mailto:hanushek@stanford.edu); Tel: +1-650-736-0942

---

\* We gratefully acknowledge constructive comments from the editor and a referee. Wiederhold and Woessmann gratefully acknowledge financial support from the Leibniz Association through the project “Acquisition and Utilization of Adult Skills.”

<sup>†</sup> Hanushek: Hoover Institution, Stanford University, CESifo, and NBER, [hanushek@stanford.edu](mailto:hanushek@stanford.edu); Schwerdt: University of Konstanz, CESifo, and IZA, [guido.schwerdt@uni-konstanz.de](mailto:guido.schwerdt@uni-konstanz.de); Wiederhold: Catholic University Eichstaett-Ingolstadt, ifo Institute, and CESifo, [wiederhold@ifo.de](mailto:wiederhold@ifo.de); Woessmann: University of Munich, ifo Institute, CESifo, and IZA, [woessmann@ifo.de](mailto:woessmann@ifo.de).

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. The underlying idea is that a fundamental attribute of education and skill is providing the ability to adapt to emerging disequilibria and to prosper in changed environments. The relevant economic changes include not only technological change but also capital deepening and altered industrial structure. We rely on international comparisons to provide a test of this hypothesis based on the large aggregate differences in returns to skill observed across countries.

The most direct evidence on the relationship between returns to education and adaptation to changed economic environments is specialized on farmer decisions and not easily generalized to the entire labor market. Welch (1970) first considers the relationship between agricultural profitability and farmer education, and this is extended in models of adoption of new agricultural technologies by Foster and Rosenzweig (1996) and others. Less focused suggestive evidence comes, for example, from 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. Consideration of skill biased technological change generally focuses on the impact of technologies with different skill content (e.g., Katz and Murphy (1992), Goldin and Katz (2008), Acemoglu and Restrepo (2016)) but does not distinguish between adaptation to change and long-run embedded skill requirements. The relationship of schooling demand with vintages of capital in broad manufacturing industries is also consistent with expectations about adaptation to new technologies (Bartel and Lichtenberg (1987)) but might as well reflect other changes in demand 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 32 diverse

countries.<sup>1</sup> International variations in returns to these individual skills permits more direct linkage to the pace of economic change.

These new data on skills and earnings 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 adult skills (OECD (2016)). The first round of PIAAC data, administered to 23 countries between August 2011 and March 2012, and the second round, administered to an additional nine countries between April 2014 and March 2015, provide comparable skill data for 32 countries.

In each country, a representative sample of at least 5,000 adults between 16 and 65 years of age completed an internationally harmonized background questionnaire and was assessed on cognitive skills in three domains: numeracy, literacy, and problem solving in technology-rich environments. We focus on numeracy skills, standardized to have mean zero and standard deviation (SD) one. One SD in numeracy skills is roughly twice the learning difference between school-attending PIAAC respondents in lower secondary and upper secondary education.

## **New Evidence on Returns to Skills**

We begin with how measured cognitive skills relate to labor market earnings in the different countries. As developed in Hanushek et al. (2015), our baseline empirical model focuses on the cognitive skill-earnings gradient, estimated in this Mincer-type equation:

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

where  $y_i$  is the gross hourly wage of individual  $i$ ,<sup>2</sup>  $C$  is measured numeracy skills,  $A$  is age,  $G$  is

---

<sup>1</sup> We previously analyzed returns to skills using the 23 countries that initially participated in this survey (Hanushek et al. (2015)). Although we did not analyze the adaptation hypothesis with the more limited data, we show below that they yield very similar results to those for the full sample.

<sup>2</sup> For countries with earnings data reported in deciles in the Public Use File (Singapore and Turkey in the second round), we assign the median wage of each decile of the country-specific wage distribution (obtained from

gender, and  $\varepsilon$  is a stochastic error. Our parameter of interest is  $\gamma$ , the earnings gradient associated with skills.<sup>3</sup> We estimate this for full-time workers aged 35-54, because prime-age earnings best approximate lifetime earnings (Hanushek et al. (2015)).

The results indicate that returns to skills are more diverse across countries than previously thought. Returns to numeracy skills in the original PIAAC sample of 23 countries, which ranged from 0.13 in Norway, Sweden, and the Czech Republic to 0.26 in the United States, expand on both ends with the nine new countries (dark bars in Figure 1).<sup>4</sup> The new estimates range from 0.11 in Greece to 0.47 in Singapore. The pooled estimate (with country fixed effects) indicates that a one standard deviation increase in numeracy skills is related to 20 percent higher earnings. (Full results including alternative specifications of the earnings process are presented in the working-paper version, Hanushek et al. (2016)). The cross-country pattern is quite similar for males and females as well as when using literacy or problem-solving skills, although we believe that numeracy skills are more reliably measured across countries.

## Economic Change and Differences in Returns to Skills across Countries

Our primary focus is how returns to skills are related to economic change. We gauge change across different economies by the average annual growth in real GDP per capita over 1990-2011 (from the Penn World Tables 9.0).<sup>5</sup> Figure 2 shows clearly that returns to skills are systematically larger in countries that experienced faster economic growth, consistent with the hypothesis that the economic value of skills relates to the ability to adapt to economic change.

To investigate this more rigorously, we pool the micro data for all countries, include country fixed effects ( $\eta_c$ ), and estimate interactions of numeracy scores with potentially influential country-level features as in:

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

where  $Z_c$  are different elements of the economic environment in country  $c$  and  $\gamma_1$  is the estimate

---

the OECD) to each person belonging to the respective decile. To limit the influence of outliers, we trim the bottom and top one percent of the wage distribution in each country.

<sup>3</sup> Prior estimates in Hanushek et al. (2015) estimated the skill gradient using actual labor market experience instead of age. Because of concerns about the endogeneity of experience, we rely on age, but all results with either actual experience or the Mincer-like potential experience are very similar.

<sup>4</sup> As noted, these estimates are not precisely comparable to those in Hanushek et al. (2015) because here we condition on age instead of actual experience. With actual experience, the skill gradient ranges between 0.10-0.45.

<sup>5</sup> Starting in 1990 allows inclusion of previously communist bloc countries.

of how the return to numeracy varies with  $Z$ .<sup>6</sup>

The simplest specification in the first column of Table 1 effectively replicates the bivariate scatterplot of Figure 2: There is a strong and statistically significant positive relationship between growth and returns to skills. But of course, it is necessary to consider possible confounding factors across countries. Our prior analysis of the original 23 PIAAC countries incorporated features of countries' labor markets and found returns to skills to be lower when union membership and public employment are higher (Hanushek et al. (2015)). Column 2 shows that this is also the case in the extended sample of countries.<sup>7</sup> Nonetheless, when these effects are netted out, 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.

## **Robustness Checks**

While the international comparisons offer substantial variation in the economic environment that makes it possible to describe the interplay with returns to skill, it is simultaneously difficult to find clearly exogenous variation in economic change across countries. 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 model by our measurement of economic growth that predates the estimation of skill returns. We also took steps to address the most plausible threats that omitted country factors pose to identification, including estimating the models with just within-country variation (by including country fixed effects) and incorporating previously identified features of the labor market in each country. The analysis could nonetheless suffer

---

<sup>6</sup> In this interacted model, we standardize the numeracy skill measure to have mean zero and standard deviation one for the entire international sample, rather than within each country as in Figure 1. This ensures that our results are not affected by differences in within-country skill distributions. We also de-mean all variables to facilitate interpretation. Indonesia includes only Jakarta, which lacks aggregate data and is excluded.

<sup>7</sup> We take the share of employees who are trade union members from the International Labour Organization and calculate the share of workers employed in the public sector from the PIAAC data.

from 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.

To address the concern that differences in returns to skills might simply reflect different occupational and industrial structures of the economies, we introduce a full set of industry-by-occupation fixed effects (183 in total) so that the returns are estimated just from within-cell variation (column 3). The main effect of numeracy drops, indicating that about half of the return to numeracy skills comes through selection into specific occupations and industries. Yet, the within-industry within-occupation impacts of growth and of the other environmental forces are little changed.

Our prior analysis of the more limited sample of countries (Hanushek et al. (2015)) did not investigate the adaptation hypothesis. Nonetheless, the skill-growth relationship can be seen just in these countries. Columns 4 and 5 show the strong and statistically significant impact of economic growth, albeit with somewhat reduced coefficients.

An additional issue about the basic estimates relates to the distribution of skills within each country. Hanushek and Woessmann (2011) noted 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 6 relates the skill differences in each country (measured by the difference in numeracy scores between the 90<sup>th</sup> and 10<sup>th</sup> percentiles) to the returns to numeracy skills. Consistent with the prior aggregate observation, there is a significant positive 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 reverse causality. 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, higher opportunity cost of skill investment, and a shorter payback period. 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.

When the score difference between workers aged 20-34 and those aged 50-65 is added in column 7, overall skill inequality in fact loses significance. 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. Column 8 adds the country mean numeracy score, which shows a negative relationship with the return to skill (significant at the 5 percent level) while the age distribution of skills remains significant.

The prior estimates do not, however, include any of the institutional factors found significant in column 2, leading to the more complete specification in column 9. 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 10), where higher average skill levels in a country are also significantly related to lower returns to skills.

Results for the adaptation hypothesis are also robust to a number of further specifications not shown in the table. First, 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) included measures of employment protection, minimum wages, and product-market regulation; while available only for 29 of our 31 countries, employment protection also enters with a significant negative interaction with numeracy in our model, but leaves all other qualitative results unchanged (interactions with minimum wages and product-market regulations were insignificant).<sup>8</sup> Third, results are robust to using alternative periods over which to measure prior growth, such as 1990-2000, 1990-2005, or 1990-2007. Fourth, results are robust to dropping one country at a time or dropping both Singapore and Chile, indicating that the cross-country pattern is not driven by individual countries. 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. Sixth, because of concerns about differential selectivity into the labor force, we

---

<sup>8</sup> Similar results for this expanded specification are also obtained from the original 23 country sample.

allow returns to skill to vary with the aggregate male and female labor force participation rates. In models with industry-by-occupation fixed effects, higher female labor force participation significantly lowers a country's overall returns to skills – but this has no effect on the estimated adaptation to growth. 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**

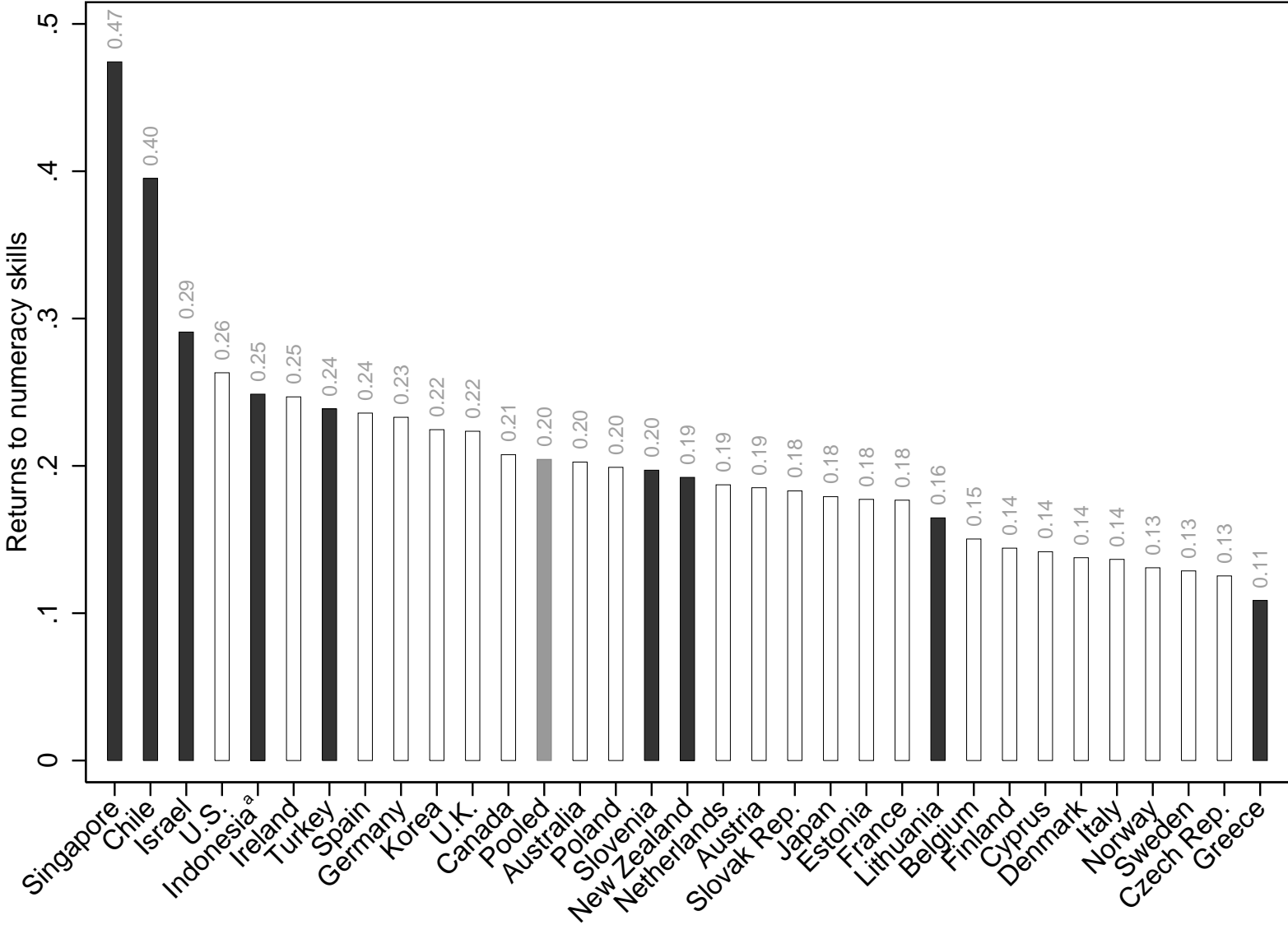
The availability of new information about earnings and skills in a broader set of 32 countries permits closer investigation than previously possible of the hypothesis that education has a stronger payoff when there is faster economic change. It turns out that the range of differences in labor-market 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.



## References

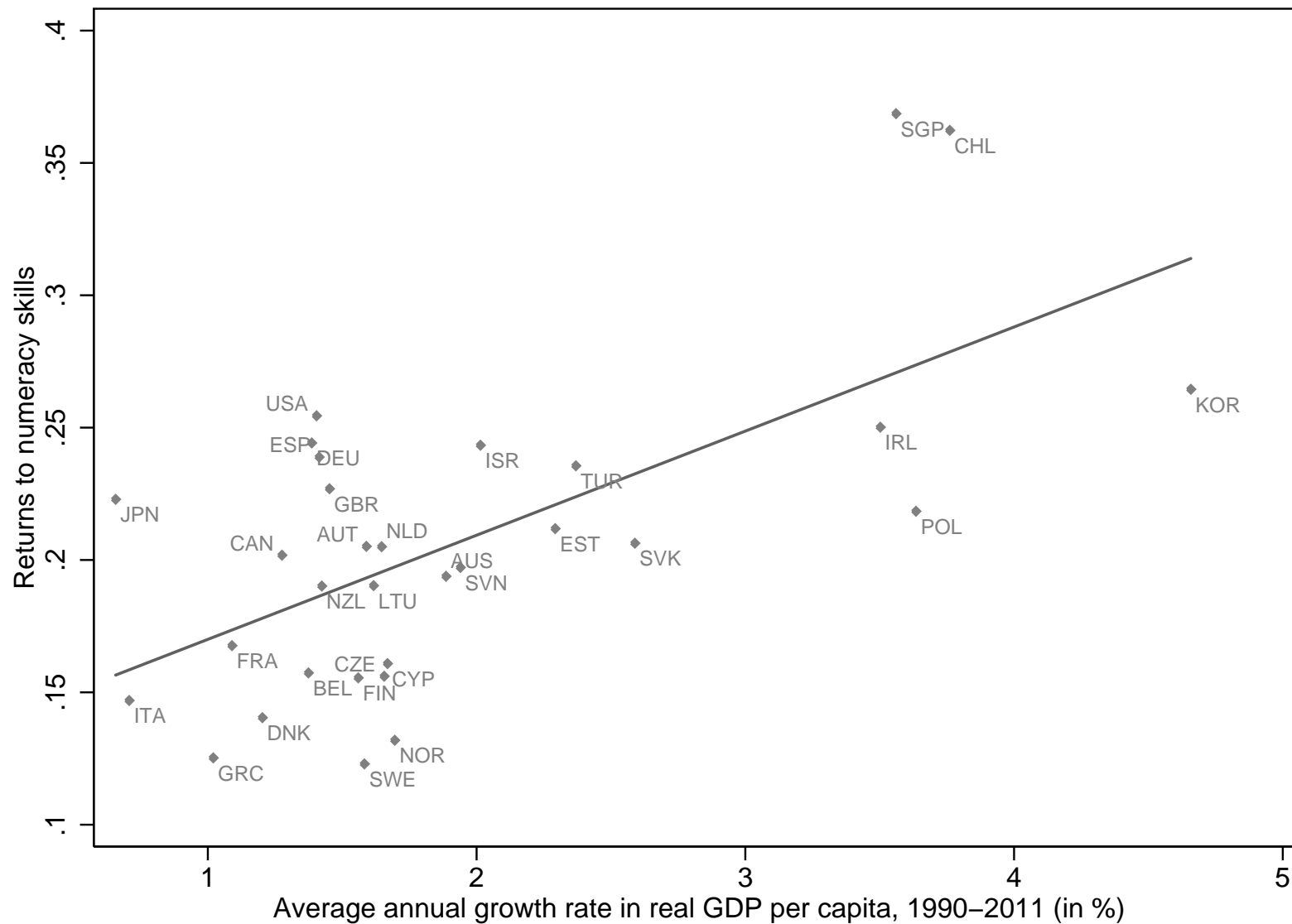
- Acemoglu, Daron, and Pascual Restrepo. 2016. "The race between machine and man: Implications of technology for growth, factor shares and employment." NBER Working Paper 22252. Cambridge, MA: National Bureau of Economic Research.
- Bartel, Ann P., and Frank R. Lichtenberg. 1987. "The comparative advantage of educated workers in implementing new technology." *Review of Economics and Statistics* 69, no. 1: 1-11.
- Blau, Francine D., and Lawrence M. Kahn. 2005. "Do cognitive test scores explain higher US wage inequality?" *Review of Economics and Statistics* 87, no. 1: 184-193.
- Foster, Andrew D., and Mark R. Rosenzweig. 1996. "Technical change and human-capital returns and investments: Evidence from the green revolution." *American Economic Review* 86, no. 4: 931-953.
- Goldin, Claudia, and Lawrence F. Katz. 2008. *The race between education and technology*. Cambridge, MA: Harvard University Press.
- Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann. 2015. "Returns to skills around the world: Evidence from PIAAC." *European Economic Review* 73: 103-130.
- Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann. 2016. "Coping with change: International differences in the returns to skills." NBER Working Paper 22657. Cambridge, MA: National Bureau of Economic Research.
- Hanushek, Eric A., and Ludger Woessmann. 2011. "The economics of international differences in educational achievement." In *Handbook of the Economics of Education, Vol. 3*, edited by Eric A. Hanushek, Stephen Machin, and Ludger Woessmann. Amsterdam: North Holland: 89-200.
- Hanushek, Eric A., and Ludger Woessmann. 2015. *The knowledge capital of nations: Education and the economics of growth*. Cambridge, MA: MIT Press.
- Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in relative wages, 1963-1987: Supply and demand factors." *Quarterly Journal of Economics* 107, no. 1: 35-78.
- Münich, Daniel, Jan Svejnar, and Katherine Terrell. 2005. "Returns to human capital under the communist wage grid and during the transition to a market economy." *Review of Economics and Statistics* 87, no. 1: 100-123.
- Nelson, Richard R., and Edmund Phelps. 1966. "Investment in humans, technology diffusion and economic growth." *American Economic Review* 56, no. 2 (May): 69-75.
- Nickell, Stephen. 2004. "Poverty and worklessness in Britain." *Economic Journal* 114, no. 494: C1-C25.
- OECD. 2016. *Skills matter: Further results from the survey of adult skills*. Paris: Organisation for Economic Co-operation and Development.
- Schultz, Theodore W. 1975. "The value of the ability to deal with disequilibria." *Journal of Economic Literature* 13, no. 3: 827-846.
- Welch, Finis. 1970. "Education in production." *Journal of Political Economy* 78, no. 1: 35-59.

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 age, 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. <sup>a</sup>Jakarta 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: Economic Change and Differential Returns to Skills across Countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Numeracy (international standardization)	.203*** (.009)	.200*** (.006)	.097*** (.006)	.189*** (.007)	.091*** (.007)	.204*** (.010)	.202*** (.009)	.201*** (.008)	.199*** (.006)	.096*** (.006)
× GDP per capita growth 1990-2011	.052*** (.014)	.035*** (.008)	.031*** (.007)	.017*** (.006)	.017*** (.006)				.026** (.010)	.024** (.009)
× Union density		-.069** (.028)	-.083*** (.026)	-.113*** (.036)	-.106*** (.033)				-.066** (.028)	-.067** (.028)
× Public employment		-.390*** (.090)	-.321*** (.071)	-.170* (.082)	-.166** (.079)				-.328*** (.077)	-.284*** (.074)
× Skill inequality						.020*** (.007)	.008 (.006)	.005 (.006)		
× Skill ratio young vs. old							.025** (.009)	.022** (.008)	.008 (.007)	.005 (.006)
× Skill mean								-.011** (.005)	-.004 (.003)	-.007** (.003)
Country fixed effects	X	X	X	X	X	X	X	X	X	X
Occupation × industry fixed effects [183]			X		X					X
R <sup>2</sup>	.227	.232	.421	.206	.400	.223	.227	.228	.233	.421
Countries	31	31	31	23	23	31	31	31	31	31
Observations	44309	44309	43263	35919	35009	44309	44309	44309	44309	43263

\* 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. Columns 4 and 5 include only countries that participated in Round 1 of 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 age, 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.