PISA SCORE AS A PREDICTOR OF AGE-STRUCTURED HUMAN CAPITAL

Eduard Nežinský[1,2]

Abstract

Sustainability of public finances associated with an aging population and the environmental challenges in the recent decades will be accompanied with significant changes in the labor market. Knowing the determinants of labor supply and demand can be of substantial help, informing institutional reforms in education which can be in aid of closing the gap between demand and supply through timely action. Due to the structure and interdependencies in the Slovak economy along with the high level of specialization in the automotive industry, labour market in Slovakia is in a constant need of technically educated labour. Theory links technical skills related human capital to performance in numeracy tests for students (PISA) and adults (PIAAC). The aim of this study is to exploit PISA numeracy scores in predicting PIAAC performance of the future labour market participants in Slovakia. PIAAC projections for 2030 are calculated by use of PISA results as a determinant of cognitive abilities in later life. The declining trend in PISA scores fuels the deterioration of PIAAC performance across age categories and shifts the "center of mass" of the population's cognitive skills towards older age groups. Along with that, PISA results can serve to gauge inequalities of opportunities across population. Forthcoming PIAAC 2023 survey provides the opportunity to augment time dimension of the results data, compare cohorts over time, and refine forecasts. Based on provided evidence, educational policy should counteract the downward trend in PISA performance and human capital depreciation.

Keywords

Technical Education, PISA, PIAAC, Numeracy Projection

I. Introduction and Literature Review

Rapid changes to technology brought forth by the Industry 4.0 along with population ageing determine the most important challenges in the labour market, affecting public finance sustainability in the short-run to long-run period. Assessment of the ongoing changes provides a basis for decision making.

Given the structure and interdependencies in the Slovak economy along with the high level of specialization in the automotive industry, labour market in Slovakia is in a constant need of technically educated labour. Empirically, higher skills generally pay off in higher wages, robust to different earnings and skill measures, additional controls, and various subgroups in developed countries (Hanushek et al., 2015). On the other hand, hard-to-fill and unfilled vacancies could reduce output per worker levels in high-tech firms (Bennett & McGuiness, 2009). Koedel & Thyhurst (2012) find positive effect of stronger *math* skills on labour market outcomes via resume-based field experiment in US. Focusing on specific skills, Joensen & Nielsen (2003) confirm causal effect between a high-school math and the later earnings of the students providing the evidence that more productive sectors are more demanding as to the mathematical content in knowledge and skills. Economic returns for an individual were found to be higher, along with medicine and education, in technical areas of engineering, architecture, computer science and IT (Kelly et al., 2008). Choice of technical track in vocational education makes students better off compared to science or business

[1] Center of Social and Psychological Sciences of the Slovak Academy of Science, Institute for Forecasting, Šancová 56, 811 05 Bratislava; E-mail: eduard.nezinsky@savba.sk
[2] University of Economics in Bratislava, Dolnozemská cesta 1, 85235 Bratislava

tracks (Meer, 2007). This predetermines a particular interest in technically educated labour force group.

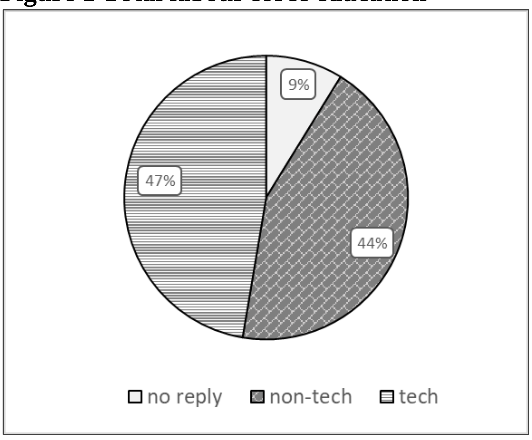
While most of the earlier studies employed grade point average (GPA) scores to assess students´ performance, specific cognitive skills have been successfully measured in OECD survey programmes – PISA and PIAAC. Policy-driven initiatives planned on a cyclic basis, both are intended to provide policy makers at the national and international levels with information that can inform policy-setting and planning of diverse types of social interventions and educational programs (Gall & Tout, 2014). While PISA (Program for International Student Assessment) focuses on competencies of 15-year-old students, PIAAC (Programme for International Assessment of Adult Competencies) assesses competencies of adult labour force aged 16–65.

For math skills evaluation, there are two respective similar constructs – “numeracy” and “mathematical literacy”. Related in terms of the core underlying ideas, both refer to the ability of individuals to cope with tasks that could likely to appear in the real world and could contain mathematical or quantitative information. While “numeracy” and “mathematical literacy” are not two labels for the same entity, the two are considered correlates. Individual´s school PISA math performance determines to an extent his/her adult lifelong math-related cognitive skills. Thus, for the purpose of this study we use “NUM” as a common label fusing “numeracy” and “mathematical literacy”.

As long as the goal of labour-market-related policy making is to ensure efficiency of the labour market, educational policy and the quality of human capital (HK) are involved to help overcome the mismatch between the supply and demand of the labour force. Given the demographic trends and human capital depreciation, future cognitive-skill-structure of the labour supply might raise concerns. In empirical studies, a volume of literature uses PISA / PIAAC scores as proxies for quality of HK and the core growth determinant (Hanushek & Woessmann, 2008). Newly a cohort-weighted average of past student test scores and mean years of schooling constitute a stock measure of HK that is strongly linked to productivity (Egert et al., 2022). A nuanced approach, accounting for the evolution of skills over the individual´s lifespan, makes use of PISA to predict PIAAC performance (Gustafson, 2016). PIAAC data can be used directly to assess a mismatch by means of analysing returns to numeracy skills (Allen, 2013; Hanushek et al., 2013).

In socially oriented efficiency-vs-equity studies exploiting Roemer´s (1998) conceptual framework PISA performance is used in equality of opportunity analyses (Gamboa & Waltenberg, 2012). The association of PISA scores and indices related to socio-economic inequality was demonstrated by Mazurek et al. (2021). Thorson & Gearhart (2018) brought forward causal claims regarding adverse effects of income inequality on educational outcomes, particularly in math.

Figure 1 Total labour force education



Source: LFS (2017)

In Slovak decision-making environment the need for increasing HK quality has been articulated in a number of multiple levels strategic statements. Labour market studies have exposed a persistent mismatch as to education (Štefánik, 2018). Massively specialized in automotive industry, Slovak labour market demands technically skilled labour to a greater extent. The overall share of technically educated (*tech*) labour[1] was 47% as displayed in Figure 1. A detailed breakdown across industries (NACE 2) is provided in Table 1.

Table 1 Composition of industries´ labour in Slovakia by education (2017)

Industry		*no reply*	*non-tech*	*tech*
A	Agriculture, forestry and fishing	0,07	0,49	0,44
B	Mining and quarrying	0,07	0,12	0,81
C	Manufacturing	0,09	0,25	0,67
D	Electricity, gas, steam supply	0,02	0,21	0,78
E	Water supply; waste management	0,12	0,18	0,70
F	Construction	0,06	0,15	0,79
G	Wholesale and retail trade	0,08	0,50	0,42
H	Transportation and storage	0,06	0,35	0,59
I	Accommodation and food service activities	0,08	0,65	0,27
J	Information and communication	0,04	0,39	0,57
K	Financial and insurance activities	0,11	0,70	0,18
L	Real estate activities	0,01	0,45	0,54
M	Professional, scientific and technical activities	0,04	0,67	0,29
N	Administrative and support service activities	0,25	0,32	0,42
O	Public administration and defence	0,18	0,51	0,31
P	Education	0,04	0,78	0,18
Q	Human health and social work activities	0,08	0,74	0,19
R	Arts, entertainment and recreation	0,13	0,60	0,26
S	Other service activities	0,08	0,67	0,24
TU	Activities of extraterritorial organisations and households as employers;	0,33	0,22	0,44

Source: LFS, Author´s calculation

One can notice from the Table 1 that the *tech* content is at quite a variance across the labour force in individual industries. A considerable *tech* content (above 70%) is demanded in mining and quarrying, energy and water supply, construction followed by manufacturing, transportation, ICT and real estate services. Abstracting from the allocating mechanism we are interested in how the overall *tech* content in HK is determined. Based on the aforementioned studies, we suggest PISA numeracy (NUM) performance as a determinant of the present level of *tech* related HK.

The aim of this study is thus to exploit PISA numeracy scores in predicting PIAAC performance of the future labour market participants in Slovakia. According to the demographic projections (Bleha et al., 2013), the year 2030 is a point when and significant changes in the assumptions used can be expected under the most optimistic scenario where the total population of Slovakia starts to decrease. Utilizing trends of determinants, projections for 2030 of PIAAC performance across age groups are calculated, conditioned on the available controls. We conclude that the centre of "cognitive skills mass" will shift as oncoming age groups will lose numeracy skills due to the down-trending PISA performance. In the following, the analysis unfolds providing methodological notes and data source description in Section II, presenting results in Section III thereafter. Section IV concludes and outlines the future path for the research.

[1] For the purpose of this study we use results from LFS survey (2017) with self-reported education categorized by ISCED classes.

II. Methodology and Data

PISA performance as a PIAAC score predictor

Cognitive skills evaluation is available from OECD surveys reports from *Data Explorer* feature of the respective survey. In Slovakia, six rounds of PISA were carried out as contrasted to a single PIAAC survey in 2012. As explained above, only the NUM dimension of the survey is considered for the further analysis. The NUM scores along with the standard errors[1] by age groups for Slovakia are displayed in Table 2.

Table 2 PIAAC numeracy scores by age group (2012)

Age group	NUM	
	score	*SE*
16-19	276	(2,9)
20-24	280	(2,2)
25-29	280	(2,3)
30-34	278	(2,4)
35-39	284	(2,1)
40-44	278	(2,6)
45-49	280	(2,1)
50-54	270	(2,5)
55-59	267	(2,4)
60-65	264	(2,1)
16-65	**276**	**(0,8)**

Source: OECD

In most cases, differences between age groups exceed the estimated standard errors. Predictions of cognitive abilities must account for this heterogeneity. There are three possible sources for the latter:

- Time effect;
- Cohort effect;
- Age effect.

With the PIAAC cross-sectional data at hand, i.e scores for individual age groups, the three effects cannot be reliably separated. We try to capture the time dimension by assuming that adult´s cognitive skills are determined by the latter of his/her school-age. Thus, PISA results of the individual can predict his/her later PIAAC performance. Formally, for the i^{th} individual (or the average representative of the group),

$$PIAAC_i = \alpha_i + \beta\, PISA_i + \boldsymbol{\gamma}^{\mathrm{T}}\mathbf{X} + \varepsilon_i, \qquad (1)$$

where $\boldsymbol{\gamma}$ denotes the vector of coefficients attached to the additional set of controls and determinants organized in data matrix $\mathbf{X}$ and ε_i stands for error term. Term α_i represents time-fixed cohort and age effects intermingled. Additional regressors could comprise factors capturing the general state of the economy as Human Development Index and the change in acquired qualifications (e.g. Gustafson, 2013). Due to data availability for Slovakia, we are restricted only having HDI for $\mathbf{X}$. As well, within the regression framework we cannot separate cohort and age effects and we include those in the error term. Given these constraints, regression-predicted values of PIAAC (2012) can be determined from the simplistic form of (1) as

$$\widehat{PIAAC}_i = \beta\, PISA_i + \gamma\, HDI_i \qquad (2)$$

[1] Employing matrix-sampling, each participating individual is only presented with a subset of the full set of items. Thus, for the final result, ten *plausible values* are estimated, together containing information about both the level and the uncertainty of a participant's score (OECD, 2013).

In (2), β and γ denote estimated coefficients for the two particular regressors. $PISA_i$ stands for the PISA performance of the individual whose score is $PIAAC_i$. Thus, PISA varies across age groups. Along with that, actual PISA values are only available for three PIAAC age categories, i.e. those having passed PISA in 2003 – 2009 as Table 3 documents.

Table 3 Data coverage PISA and PIAAC

PISA	year of birth	Age bracket in PIAAC (2012)	Age in (2030)
2003	1987	20-24	33
2006	1990	20-24	30
2009	1993	16-19	27
2012	1996		24
2015	1999		21
2018	2002		18

Source: OECD

Due to lack of the actual data, relevant PISA values for all PIAAC age categories, i.e. 16-19 through 60-65 are determined by means of extracted linear trend PISA values $\widehat{PISA} = d_0 + d_1 t,$ including those for which actual values exist. In the very same manner, $\widehat{HDI}$ trend values are obtained to control for the global environment in the period od PISA survey. Long HDI time series show instability of linear trend coefficient, a structural break in 2008 is depicted in Appendix Figure 3. Thus, just the relevant part of the time series is used for predicted values of HDI. The deterministic part of PIAAC is calculated by

$$\widehat{PIAAC}_i = \beta\,\widehat{PISA}_i + \gamma\,\widehat{HDI}_i \qquad (3)$$

Error term $PIAAC_i - \widehat{PIAAC}_i$ is used to obtain future values of PIAAC for 2030. In a simplistic way, we identify the error term with age effect only and assume that the differences attached to age groups shift in time intact. In this manner, future PIAAC performance in 2030 is computed from projected PISA, HDI, and fixed age-related component.

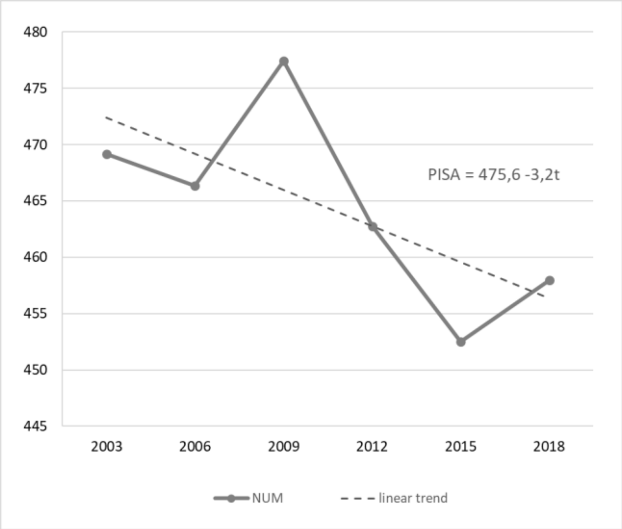
Data

PISA and PIACC survey data are available from OECD Data Observer. For the sake of simplicity and readability of the results, we use age groups with 3-year step instead of age brackets as in Table 2. Data on HDI were collected from Human Development Reports.

III. Results

We start with calculating linear trend values for PISA and HDI. Given the six surveys, PISA performance in Slovakia trends down as depicted in Figure 2.

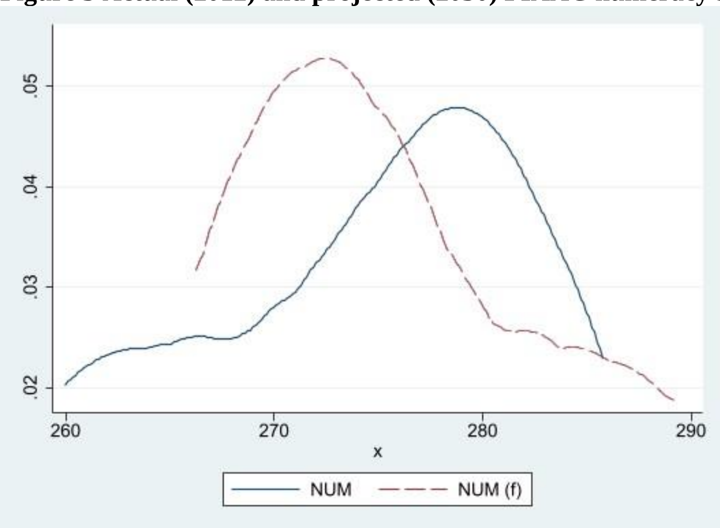
Figure 2 PISA numeracy scores and trend



Source: OECD, author´s elaboration

Given these results, the key determinant of later adult cognitive skills is decreasing leaving younger age groups with a less stock of skill-related human capital. This tendency is to an extent offset by ever rising human development index whose trend is upward sloping in both segments of the plot (Appendix Figure 5). Using equation (3), PIAAC deterministic trend values are obtained, representing the performance that would have been achieved had the PISA and HDI followed perfectly linear trend. To get the projections, age-related disturbances are added, by assumption, carrying the differences between the age groups from PIAAC 2012 over to 2030. The values of the variables involved in the calculation can be seen in Appendix Table 4.

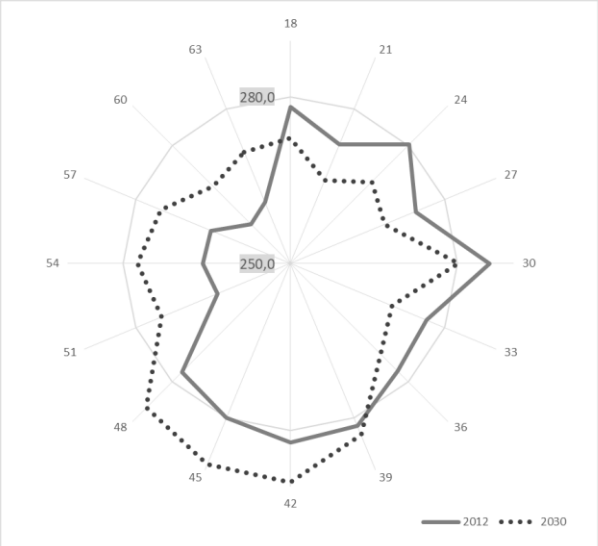
Figure 3 Actual (2012) and projected (2030) PIAAC numeracy scores



Note: Kernel densities
Source: Authors´ calculation

In Figure 3 one can observe how the distribution of the scores changed over time. Qualitatively, there is more of a probability mass around the higher value (280) in the former period. Over time, the “center of mass” shifts to the left to lower scores. Figure 4 depicts detailed comparative graphs of the PIAAC 2012 and projection for 2030 by age (groups). Age groups are represented by rays on which PIAAC scores starting from 250 pts are marked out.

Figure 4 PIAAC numeracy by age group (2012) and projections (2030)



Source: OECD, author´s elaboration

Better performance corresponds to a more distant point from the center. One can thus see overperformance attributed to age 30 – 48 in 2012, sticking to the 280 pts line. This cognitive skills stock shifted over time, eroded due to ageing and reinforced by rising HDI formed a strongly numeracy-skills-endowed 42 – 48 aged labour force group. The results should raise concerns about the future cognitive skills of the younger generation to enter labour market. The main suggested recommendation would be to adopt educational policies improving PISA results.

IV. Conclusions and Limitations

In the presented analysis, a simplistic approach to determining future cognitive skills was applied. Although regression-based calculations of PIAAC determinants have been carried out, existing analyses utilized cross-sectional data from a number of countries. Due to the lack of longitudinal data on PIAAC for Slovakia, the cohort and age effects stay indistinguishable. Along with that, no direct information on the evolution of the skills over time could be extracted. The age structure of the numeracy performance is now assumed to be determined solely by age-related factors. Cohort-related time-fixed effects should be neglected. In this regard, the upcoming PIAAC 2023 survey presents a great opportunity for educational policy analysts. Future results from the models augmented in time dimension can bring evidence that would inform educated policy setting.

Minor issues comprise robustness check w.r.t. technical and non-tech categorization of the labour force and determining importance of numeracy and literacy dimensions for future labour market demand. PISA trend regressions suffer from few observations. From a broader social perspective, inequality in individual PISA results can serve to gauge inequality of opportunity across population.

In-depth examination of the future labour demand involves large-scale macroeconomic modelling. Complemented by the presented study of expected human capital quality, enriched by the data from the upcoming PIAAC survey in Slovakia, the results will contribute even more to a detailed and precise picture.

Acknowledgements

This research is part of the project VEGA 1/0716/19 "Policies evaluation beyond GDP" and VEGA 2/0001/22 "Slovakia 2030".

References

Allen, J. P., Levels, M., & van der Velden, R. K. W. (2013). Skill mismatch and use in developed countries: Evidence from the PIAAC study. Maastricht university.

Bennett, J., & McGuinness, S. (2009). Assessing the impact of skill shortages on the productivity performance of high-tech firms in Northern Ireland. *Applied Economics*, 41(6), 727–737.

Bleha, B., Šprocha, B., & Vaňo, B. (2013). *Prognóza vývoja populačného Slovenskej republiky do roku 2060*. INFOSTAT, Bratislava.

Égert, B., de la Maisonneuve, C., & Turner, D. (2022). A new macroeconomic measure of human capital exploiting PISA and PIAAC: Linking education policies to productivity. *CESifo Working Paper* No. 9728.

Gal, I., & Tout, D. (2014). Comparison of PIAAC and PISA frameworks for numeracy and mathematical literacy. *OECD Education Working Papers*, No. 102, OECD Publishing, Paris.

Gamboa, L. F., & Waltenberg, F. D. (2012). Inequality of opportunity for educational achievement in Latin America: Evidence from PISA 2006–2009. *Economics of Education Review*, 31(5), 694–708. https://doi.org/https://doi.org/10.1016/j.econedurev.2012.05.002

Gustafsson, J.-E. (2016). Lasting effects of quality of schooling: Evidence from PISA and PIAAC. *Intelligence*, 57, 66–72. https://doi.org/https://doi.org/10.1016/j.intell.2016.05.004

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, 73, 103–130.

Hanushek, E. A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature*, 46(3), 607–668.

Joensen, J. S., & Nielsen, H. S. (2009). Is there a causal effect of high school math on labor market outcomes? *Journal of Human Resources*, 44(1), 171–198.

Kelly, E., O'Connell, P. J., & Smyth, E. (2010). The economic returns to field of study and competencies among higher education graduates in Ireland. *Economics of Education Review*, 29(4), 650–657.

Koedel, C., & Tyhurst, E. (2012). Math skills and labor-market outcomes: Evidence from a resume-based field experiment. *Economics of Education Review*, 31(1), 131–140.

Mazurek, J., García, C. F., & Rico, C. P. (2021). Inequality and Students' PISA 2018 Performance: a Cross-Country Study. Comparative Economic Research. *Central and Eastern Europe*, 24(3), 163–183.

Meer, J. (2007). Evidence on the returns to secondary vocational education. *Economics of Education Review*, 26(5), 559–573.

OECD. (2013). Technical report of the survey of adult skills (PIAAC). OECD Publishing Paris, France. https://www.oecd.org/skills/piaac/_Technical Report_17OCT13.pdf

OECD (2022). PIAAC Data Explorer. Retrieved June 15, 2022, from https://piaacdataexplorer.oecd.org/ide/idepiaac/.

OECD (2022). *PISA Data Explorer*. Retrieved June 15, 2022, from https://pisadataexplorer.oecd.org/ide/idepisa/.

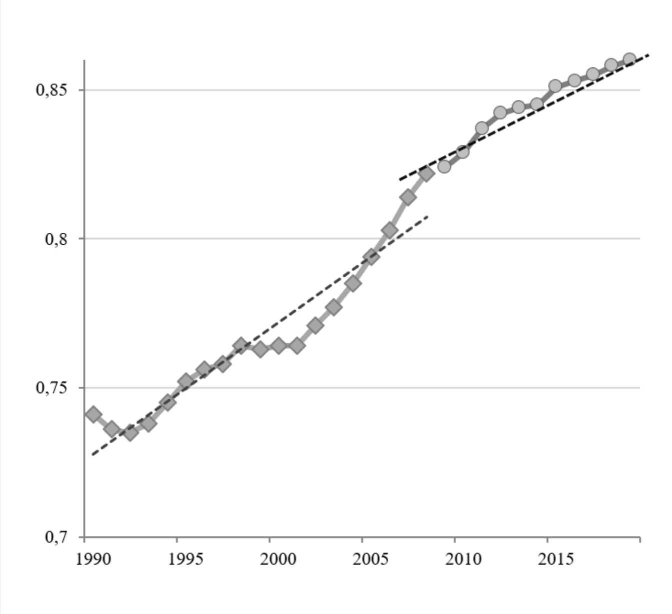
Roemer, J. E. (1998). *Equality of Opportunity*. Harvard University Press.

Štefánik, M., Džambazovic, R., Gerbery, D., Karasová, K., Lichner, I., Miklošovic, T., Polacková, Z., Radvanský, M., Rublíková, E., & Studená, I. (2018). *Labour Market in Slovakia 2019*. Ekonomický Ústav SAV.

Thorson, G. R., & Gearhart, S. M. (2018). The adverse effects of economic inequality on educational outcomes: An examination of PISA scores, 2000–2015. *World Affairs*, 181(3), 286–306.

Appendix

Figure 5 HDI evolution trends



Note: Structural break in 2007, rolling Chow test, F(2, 18) = 14,65 with p-value 0,0002
Source: Our World in Data, author´s elaboration

Table 4 PIAAC 2030 numeracy projections calculation details

Age	NUM_t	NUM _hat	NUM_res	NUM_f
18	468,57	269,76	2,74	272,50
21	472,17	270,96	-4,71	266,25
24	475,76	272,17	-1,44	270,73
27	479,35	275,97	-7,58	268,39
30	482,95	274,58	5,55	280,13
33	486,54	273,74	-4,04	269,70
36	490,13	275,37	-2,45	272,92
39	493,73	277,82	5,42	283,24
42	497,32	281,65	7,60	289,25
45	500,91	281,91	7,10	289,01
48	504,50	280,24	6,34	286,58
51	508,10	280,50	-5,43	275,07
54	511,69	279,66	-2,25	277,41
57	515,28	276,10	-0,92	275,18
60	518,88	274,48	-4,80	269,67
63	522,47	272,86	-1,15	271,71

Note: NUM trend, predicted value, error term and projection by age in columns
Source: OECD, author´s calculation