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An Education Gift -- Integrated Cognitive and Non-Cognitive Skills -- for Future Generations to Grow the Economy in the Digital Phase

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Abstract

This paper summarizes arguments driving education policy discussion about a relationship between the growth of the economy and early childhood cognitive and non-cognitive skills. The first finding is that rising Harmonized Test Scores, including PISA test scores, do not contribute to labor productivity per person in high income courtiers in Asia, Europe, and North America. On the other hand, the test scores can drive the economy in high income countries in Africa, Caribbean, Middle East, and South America; upper middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America; low middle-income countries; and low middle-income countries more than high-income countries. The second finding is that rising Harmonized Test Scores (HTS) are likely to connect to labor productivity per hour. By a simple regression by taking a logarithm, this study investigates the relationship between labor productivity per hour and the Program for International Student Assessment (PISA) test scores. The coefficient of determination is 0.60. It is not enough to get a sufficient result. Accordingly, the study discusses how labor productivity per hour in high income courtiers in Asia, Europe, and North America is associated with non-cognitive skills. In the digital economic phase, it seems that integrated cognitive skills and non-cognitive skills contribute to labor productivity per hour. We recommend that policymakers should invest in early childhood to not only maintain or improve PISA test scores but also to improve non-cognitive skills associated with psychology. Overall, this paper presents analysis and empirical results, aimed at building a more future-oriented education policy. The audience for this paper includes policymakers, educators, and economists.

Keywords: labor productivity, cognitive and non-cognitive skills, development of economics and education, education policy in digital economy.

JEL Classification: J01, I25, I28.

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1. Introduction

According to Hannushek and Woessmann (2020), cognitive skills are likely to be strongly associated with economic growth. Accordingly, education is one of the key drivers to determine economic growth and well-being. Indeed, rising human capital with added education[1] can increase aggregate economic inputs. Indeed, it could move to a higher level of output. A macroeconomic growth, therefore, can emphasize at least more human capital[2].

Due to COVID19, learning loss for human capital will have an impact on the growth of the world economy because this education loss impacts the balance amount of labor quantity and quality. Indeed, the next generation, where children lose education opportunities, is likely to lose economic benefits such as additional earnings. Ichino and Winter-Ebmer (2004) shows that World War II, an extraordinary systemic crisis, still negatively affected students' lives 40 years later, which resulted in the experience of an earnings loss (*i.e.*, the long-run cost of the war leads to the loss of human capital suffered by school-age children who receive less education).

UNESCO (2020) reported almost 1.6 billion children (more than 90 percent of world learners) were affected, and 192 countries had closed schools. According to the weekly Household Pulse Survey by the Census Bureau in November of 2020, 86% of U.S. students had transitioned toward online school. During school closings, many schools provided students with various forms of digital teaching and hybrid teaching formats, combining in-person instruction and remote teaching. There is still no evidence on whether the online class could effectively yield the learning environment like in-person classes. However, we strongly believe that it is hard to gauge the consequences of digital teaching. As a result, not only would there be the long-term impact of lost earnings on young generations, but the phenomenon will impact future global economy growth[3].

Hanushek and Woessmann (2008 and 2012) found a strong association between the economic growth and international cognitive test scores such as the PISA, TIMSS or PIRLS. This association is interpreted as evidence that cognitive skills to determine increasing productivity and economic growth. Notwithstanding, it seems that the test performance is not only the result of cognitive ability but also by non-cognitive skills associated with psychology. That is why the non-cognitive skills are also an important component for increasing productivity and other social outcomes in each individual level (Heckman and Rubinstein (2001)).

To grow the economy, changing economic structure due to a technological change such as automation and digital transformation needs not only cognitive skills but also the integration of cognitive skills with non-cognitive skills. The integration of cognitive skills with non-cognitive skills will support a basic long-term economic growth and future economic wellbeing. Given that education policymakers spend more investment to foster both cognitive skills with non-cognitive skills for early childhood, these investments will play an important role in fostering economic growth.

The remainder of the paper is organized as follows: Section 2 describes the data analysis and collection; Section 3 explains the methodology; Section 4 outlines the empirical results; Section 5 discusses a relationship between cognitive and non-cognitive skills and labor productivity. The last section contains concluding remarks.

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[1] Added education can facilitate an innovative capacity for a growth of an economy.

[2] Consider a standard Cobb-Douglas macroeconomic production function

$$Y = (hL)^{1-\alpha} K^{\alpha} A^{\lambda} \tag{1}$$

where Y is output, h is per-capital human capital, L is labor input, K is physical capital input, and A is total factor productivity. λ is the output elasticity.

Consider test scores and year of schooling to measure human capital

$$h = e^{\beta s + \gamma T} \tag{2}$$

where S is year of schooling, T is test scores, B and γ come from the micro literature. Caused by COVID19, learning loss will affect human capital by year of schooling and test scores.

[3] Lower lifetime educational attainment enables the global economy to reduce the productivity of the economy in the long run. The sources of change in aggregate economic output, or GDP, is known as "growth accounting." Long-run growth accounting breaks output changes into changes in labor and in productivity, meaning the efficiency of the economy in using labor inputs.

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2. Data

2.1 Data analysis

The first data analysis is that we analyzed a relationship between Harmonized Test Scores (HTS) and labor productivity per person by taking a logarithm. The data is classified by 6 categories: (1) 40 high income countries in Asia, Europe, and North America (2) 13 high income countries in Africa, Caribbean, Middle East, and South America, (3) 24 upper middle-income countries in Asia and Europe, (4) 24 upper middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America, (5) 20 low middle-income countries in Asia and Europe, (6) 19 low middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America, and (7) 18 low middle-income countries (Appendix A).

Harmonized Test Scores (HTS) show a major international student achievement. The scores are measured in Trends in International Mathematics and Science Study (TIMSS), Progress in International Reading Literacy Study (PIRLS), Programme for International Student Assessment (PISAA), Southern and Eastern Africa Consortium for Monitoring Educational Quality (SACMEQ), Latin American Laboratory for Assessment of the Quality of Education (LLECE), and Early Grade Reading Assessments (EGRA). Data are obtained from the World Bank, and data of 2019 is collected HTS.

Labor productivity per person is defined as an essential economic indicator that is closely linked to economic growth, competitiveness, and living standards[4]. Data is also obtained from the World Bank. The data of labor productivity per person is averaged from 2000 to 2019.

In the relationship between HTS and the labor productivity per person (Fig.1), there is like diminishing marginal utility. According to Gossen (1854), diminishing marginal utility[5] refers to a phenomenon that each additional unit of gain leads to an ever-smaller increase in subjective value.

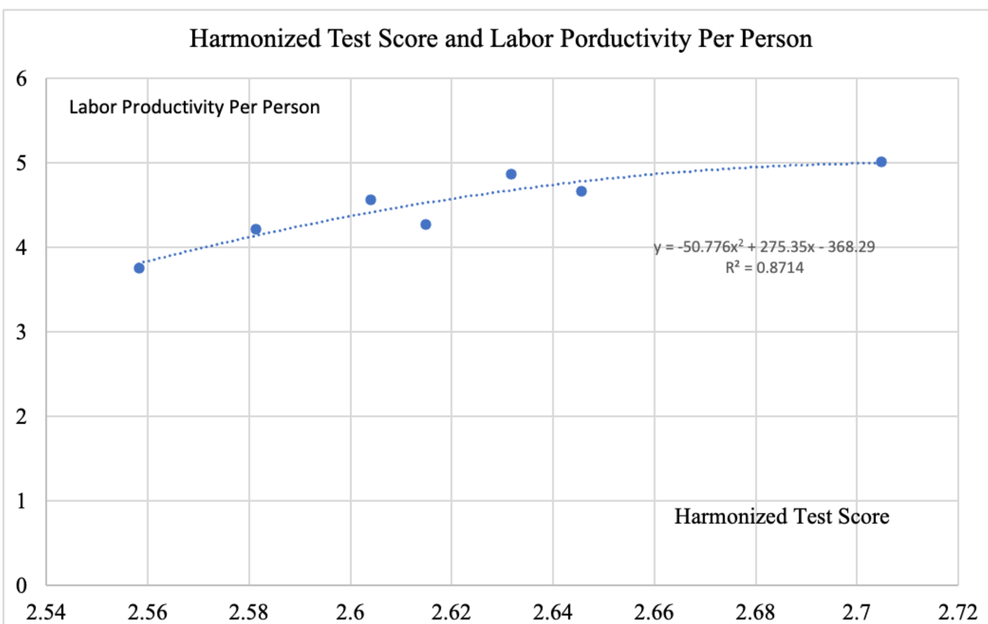

Figure 1. Harmonized test score and labor productivity per person

Source: World Bank.

[4] According to OECD, a growth in Gross Domestic Product (GDP) per capita can be broken down into growth in labor productivity, measured as growth in GDP per hour worked, and changes in the extent of labor utilization, measured as changes in hours worked per capita. High labor productivity growth can reflect greater use of capital, and/or a decrease in the employment of low-productivity workers, or general efficiency gains and innovation.

[5] A consequence of diminishing marginal utility is that subjective value changes most dynamically near the zero point, and quickly levels off as gains (or losses) accumulate.

If $y = f(x)$ is a continuous and bounded function, then a differential coefficient is given by

$$\frac{dy}{dx_i} = f'(x_i) \tag{3}$$

x_i stands for a log scale of HTS by each classified income level with x_1: high income countries in Asia, Europe, and North America, x_2: high income countries in Africa, Caribbean, Middle East, and South America, x_3: upper middle-income countries in Asia and Europe, x_4: upper middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America, x_5: low middle-income countries in Asia and Europe, x_6 : low middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America, and x_7: low middle-income countries , and y stands for a log scale of labor productivity per person.

The result of $\frac{dy}{dx} = f'(x)$, which I estimate Eq. (1) can be expressed as

$$\frac{dy}{dx_i} = f'(x_i) = -50.77x_i + 275.35 \tag{4}$$

Table 1 shows differential coefficients in 6 categories. In the relationship between HTS and labor productivity, adding labor productivity per person could not be likely to be yielded from high Harmonized Test Scores (HTS) in 40 high income countries in Asia, Europe, and North America. On the other hand, increasing labor productivity per person has a much more positive effect for high income countries in Africa, Caribbean, Middle East, and South America, upper middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America, low middle-income countries, and low middle-income countries than high-income countries -- a fact likely related to the diminishing returns of education spending on HTS outcomes. For example, low-income countries can add an unit of HTS on 15.58 labor productivity per hour compared to 0.70 labor productivity per hour in high income countries. These countries need to take into account international rankings of educational attainment. The results, therefore, reflect that these countries benefit by additional educational reform and innervation for the test scores.

Table 1. Differential coefficients in Classified Income Countries

Classified Income Countries	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Differential Coefficients	15.58	13.24	9.83	10.93	6.71	8.12	0.70

Source: compiled by authors.

The second data analysis is that we analyzed a relationship between HTS and labor productivity per hour by taking a logarithm. Labor productivity per hour is measured as Gross Domestic Product (GDP) per hour of work[6]. Data is also obtained from the Organization for Economic Cooperation and Development (OECD). Data are 2019 and include countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxemburg, Malaysia, Malta, Mexico, Netherland, New Zealand, Norway, Peru, Philippines, Poland, Portugal, Romania, Russia, Singapore, Slovak Republic, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, United States, and Uruguay.

In the relationship between HTS and the labor productivity per hour (Fig.2), there is not diminishing marginal utility. Rather than the relationship, there is a natural logarithm relationship[7]. Increasing HTS suggests rising labor productivity per hour.

[6] GDP is measured in constant 2011 US dollar, which means it is adjusted for price differences between countries (PPP adjustment) and for inflation to allow comparisons between countries and over time.
[7] $y = 0.0002\, e^{3.2438x}$ $R^2 = 0.6276$.

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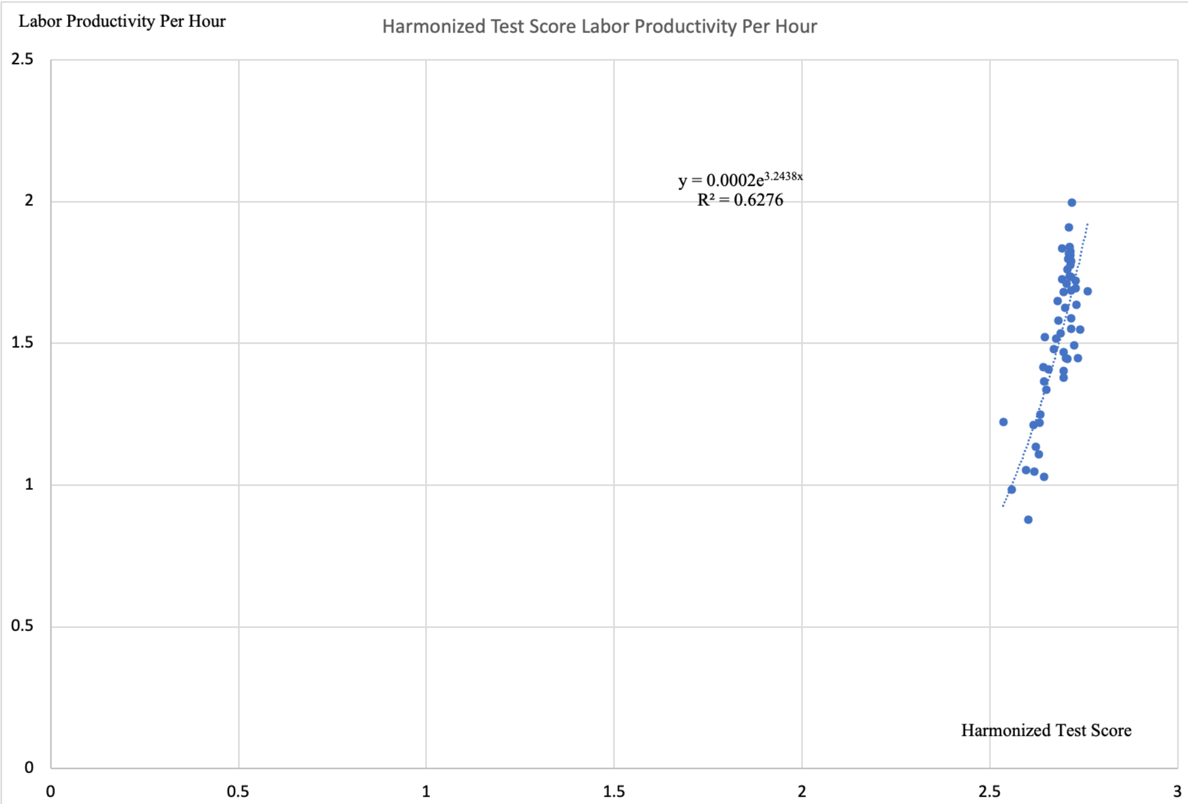

Figure 2. Harmonized test score and labor productivity per hour

Source: World Bank and OECD.

2.2. Additional DATA Collection for Methodology

This empirical study analyzes a relationship between labor productivity per hour and the Program for International Student Assessment (PISA).

The labor productivity per hour is a measure of a country's productivity, excluding unemployment or hours worked per week. The labor productivity can measure how efficiently labor input -- the total hours worked by all the persons engaged in production -- is combined with other factors of production and used in a production process. Data are obtained from the World Bank.

The Program for International Student Assessment (PISA) is an international assessment that measures 15-year-old students' reading, mathematics, and science literacy every 3 years. The major domain of study rotates between reading, mathematics, and science in each cycle. PISA also includes measures of general or cross-curricular competencies, such as collaborative problem solving. By design, PISA emphasizes functional skills that students have acquired as they near the end of compulsory schooling. Data in 2019 are obtained from the Organization for Economic Cooperation and Development (OECD)[8].

Before the empirical study, we look for the correlation between HTS and PISA. A result of the correlation is 0.99. As a comparison with HTS data, PISA data is very effective.

[8] Data are 2019 and include countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxemburg, Malaysia, Malta, Mexico, Netherland, New Zealand, Norway, Peru, Philippines, Poland, Portugal, Romania, Russia, Singapore, Slovak Republic, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, United States, and Uruguay.

3. Methodology

A simple regression is a widely used econometric to describe the relationship between a variable by fitting a line to the observed data. A statistical technique can be used to analyze a relationship between a single dependent variable and an independent (explanatory) variable.

The simple regression model assumes a linear relationship,

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{5}$$

between a dependent variable y and an independent variable x, with the noise (measurement error) term ε encompassing omitted factors. β_0 is the intercept, the predicted value of y when the x is 0. β_1 is the regression coefficient. A coefficient of determination R^2 compares the model's sum of the squared prediction errors to the sum of the squared deviations of y about its mean. The coefficient of determination can be interpreted as the fraction of the variation in the dependent variable that is explained by a regression model. A correlation coefficient is equal to the square of the square root of R^2. Moreover, the model allows the observation of the effect magnitude and to test the coefficients' statistical significance (p-value and confidence intervals).

This model can be easily transformed into a simple regression model by taking a logarithm:

$$\log(y) = \beta_0 + \beta_1 \log(x) + \varepsilon \tag{6}$$

Notice that the right-hand side of the equation above looks like the linear regression equation.

4. Empirical result

The result of y: labor productivity per hour about $\beta_0,\ \beta_i,\ and\ \varepsilon$ with x: PISA test score which I estimate Eq. (6) can be expressed as

$$\log(y) = -9.67 + 4.19\log(x) + 0.15 \tag{7}$$

$$R^2 = 0.60$$

Table 2 and Table 3 show that the p-value of PISA (X variable 1) is significant because more than 0.01. On Eq. (6), labor productivity per hour can be explained by the PISA test score with R^2= 0.60.

Table 2. Testing the Overall Significance of the Regression Model

?	Degree of Freedom	Regression Sum of Squares	Mean Square	F Statistic	Significance F (P-Value)
Regression	1	1.74	1.74	73.47	3.61E-11
Residual	47	1.11	0.02	?	?
Total	48	2.86	?	?	?

Source: compiled by authors.

Table 3. Testing the Overall Significance of the Regression Model

Source: compiled by authors.

	Coefficients	Standard Error	T-Statics	P-Value	Lower 95%	Upper 95%	Lower 95%	Upper 95%
Intercept	-9.67	1.30	-7.39	2.09E-09	-12.309	-7.04	-12.30	-7.04
X Variable 1	4.19	0.48	8.57	3.61E-11	3.21	5.18	3.21	5.18

We use a simple regression model by taking a logarithm to infer effects or predict future outcomes, but an inference is uncertain. Given the model assumptions, we need to quantify this uncertainty with standard errors, and from these standard errors we can compute confidence intervals and *p*-values.

The quantile-quantile plot (Q-Q plot) by Wilk and Gnanadesikan (1968), which provides visualization techniques for assessing the quality of the fit of the data, plausibly came from some theoretical distribution such as a normal or exponential, to a model. For example, if we run a statistical analysis that assumes our dependent variable is

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normally distributed, we can use a normal Q-Q plot to check that assumption. Fig. 3 is a set of diagnostic plots for this model linear that indicate problems with the fit. Normal Q-Q plots indicate a good fit.

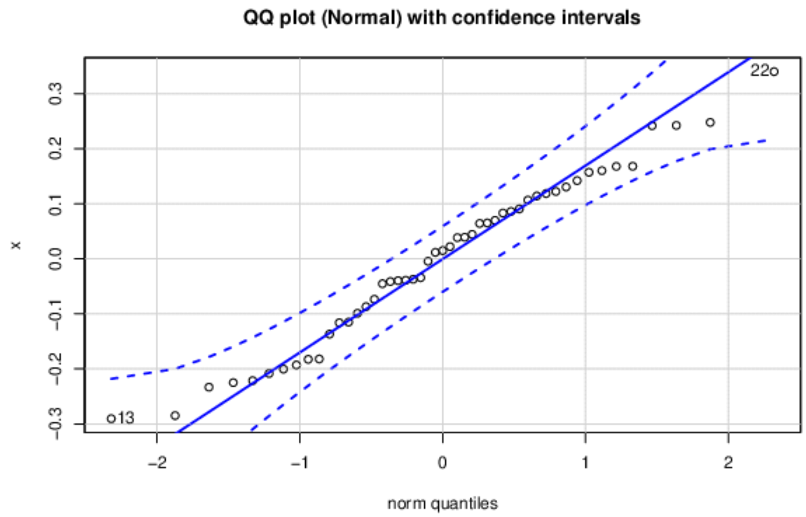

Figure 3. Normal Q-Q Plots

Source: compiled by authors.

5. Discussion: Return to Investment in Rate of Human Capital - Cognitive Skills and Non-Cognitive Skills for Early Children

According to the OECD, human capital is defined as the knowledge, skills, competencies, and other attributes embodied in individuals or groups of individuals acquired during their life and used to produce goods, services, or ideas in market circumstances. The concept of human capital[9] is the economic value of the abilities and qualities of labor that influence productivity. To improve economic output and productivity, human capital -- education, technical or on-the-job training, health, mental and emotional well-being, punctuality, problem-solving, management, and communication skills --- is a key driver.

Pascharopoulos and Patrious describes that the concept of the rate of return on investment in education is very similar to savings accounts or government bonds because it is expressed in an annual (percentage) yield. Return on investment in education is based on human capital theory. The theory puts forward the concept that investments in education increase future productivity. Carneiro and Heckman (2003) shows that the rate of human capital return to invest at different stages of the life cycle (Fig.4). There is a higher rate of return at younger ages for a constant level of investment. Karoly et al. (2005) finds that a development of cognitive skills -- human capital qualities -- associated with intervening early in a child's life clearly outweigh the costs. Early childhood investment can lead to the optimal time to intervene to yield a high economic and social return in the future. It also suggests that a rational economic investment in early childhood could bring reducing not only future educational inequalities but future income inequalities[10].

[9] Human capital is a concept used by economists and social scientists to designate personal attributes considered useful in the production process.

[10] According to Brooks-Gunn et al. (1999), children from poorer households have lower verbal and cognitive skills.

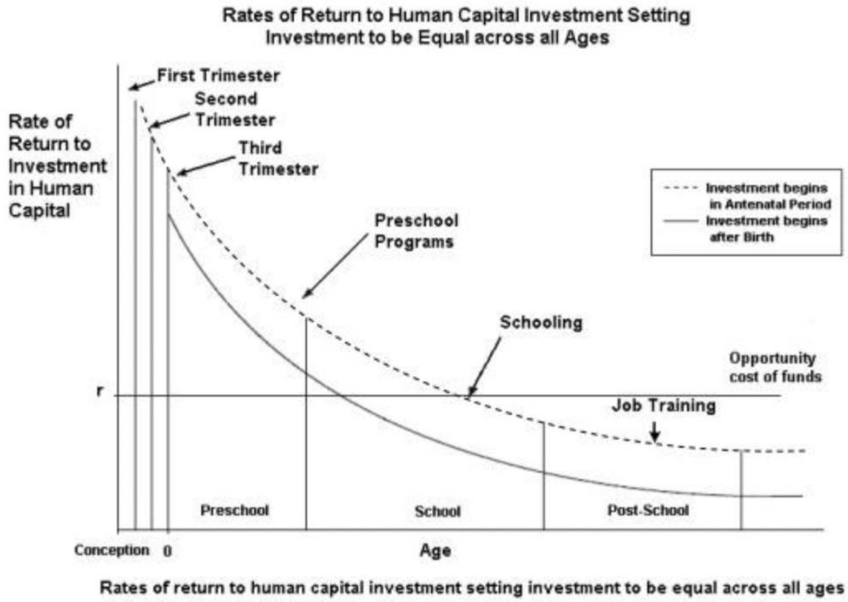

Figure 4. Rates of return human capital investment setting (investment to be equal across all ages)

Source: Carneiro and Heckman (2003).

According to Hanushek and Kimko (2000), an assessment of cognitive skills which is based on students' performance of the PISA test score links to economic development. In other words, students' success on tests of cognitive skills substantially contributes to more economic growth. Hanushek and Woessmann (2010a, 2010b, and 2020) concludes that there is strong evidence that the cognitive skills are powerfully related to labor productivity such as individual earnings, to the distribution of income, and to economic growth. Also, the International Bureau of Education (IBE)[11] insists that the PISA test scores on cognitive skills have a significant effect on the growth in real GDP per capita in the period from1960 to 2000. If every OECD country were to raise PISA test scores to that of Finland, the best performing country, the increase in GDP will be more than double under the modest scenario[12].

From our result in Section 4, the PISA test scores can drive to economic growth because increasing labor productivity per person has a much more positive effect for high income countries in Africa, Caribbean, Middle East, and South America, upper middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America, low middle-income countries, and low middle-income countries than high-income countries. On the other hand, there is not enough results about a relationship between the PISA test scores and the labor productivity per person in high income countries in Asia, Europe, and North America.

For example, the U.S. National Assessment of Education Progress (NAEP) shows that the reading skills of 13-year-olds have not changed appreciably since 1971. Reading scores for 9-year-olds have barely changed since 2004 when the assessment was revised. More importantly for both 9- and 13-year-olds, the gap between the highest scoring and lowest scoring students has increased as the scores for children in the lowest 10% declined. U.S. children fare no better from an international perspective: scores from the PISA show that among 15-year-olds between 2000-2018 there has been no change in math scores and that students in the U.S. score below the OECD average. There has also been no change in reading scores or in comparison with the OECD average. These unchanged scores could be associated with small improvements in cognitive skills among economically

[11] The IBE is a global center of excellence in curriculum and related matters. As a leading UNESCO Institute we are recognized and valued for the specialist knowledge and expertise that we bring to member states promoting new shared global understanding of curriculum issue.
[12] The IBE says, "a recent growth scenario for OECD countries based on quite modest increase in each countries PISA score by 25 points over the next 20 years would increase the combined GDP of OECD countries by USD 115 trillion in present value terms," based on OECD (2010).

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disadvantaged children. On the other hand, the U.S. labor productivity per person increased 44.52 percent from 2000 to 2019[13].

According to Heckman et al. (2013), non-cognitive skills have also been found to be important for labor productivity. The non-cognitive skills are likely to have a variable parameter the relationship between cognitive skills and the labor productivity per hour. In section 4, our results suggest a relationship between PISA test scores and labor productivity per hour. However, it would not be enough to show the result because of R^2= 0.60.

Our assumption of an econometric model suggests that there is a correlation between cognitive skills[14] and non-cognitive skills and labor productivity per hour.

A multiple regression model by taking a logarithm assumes a linear relationship;

$$\log(y) = \beta_0 + \beta_1 \log(x_1\!: Cognative\ Skills) + \beta_2 \log(x_2\!: Non - Cognative\ Skills) + \varepsilon \qquad (7)$$

β_0 is the intercept, the predicted value of y when the x is 0. $\beta_1,\ \beta_2$ are the regression coefficients. The equation includes y: labor productivity per hour about $\beta_0,\ \beta_i,\ and\ \varepsilon$ with x_1: PISA test scores as cognitive skills and x_2: non-cognative skills.

Morandini et al. (2020) states non-cognitive skill items -- interaction and communications, managing and supervisions, readiness to learn and creativity, trust in persons, and conscientiousness -- can increase labor productivity. Also, Deming (2017) discusses that higher-paying jobs increasingly require non-cognitive (social) skills because a wage premium on non-cognitive skills is likely to reflect productivity differentials. Why are non-cognitive skills likely to connect labor productivity? The skills might be more emerged by technological changes such as automation and digital transformation compared to pre-technological changes. Digital technologies such as computers, robots, machine learning, and artificial intelligence (AI) require skills from simple cognitive skills to enhance productivity like a process capability to the integration of cognitive skills with non-cognitive skills[15].

From this discussion, we suggest reforming education policy. First, policymakers should invest in early childhood to maintain or improve PISA test score because they yield a high labor productivity in the future. Secondly, the policymakers should pay attention to improving non-cognitive skills, which is associated with psychology, as well as cognitive skills for early childhood to increase labor productivity per hour in a digital phase. The integration of cognitive skills with non-cognitive skills will support basic long-term economic growth and future economic wellbeing. Given that educational policymakers spend well-focused investments in early childhood development to foster both cognitive skills with non-cognitive skills for early childhood, the investment will yield high returns for the growth of the economy. In particular, investing in high-quality early care and education, which targets children from disadvantaged environments like a low income family[16], could achieve a high return for economic growth. However, policymakers discuss that investing in high-quality program elements often cost a great deal. Nevertheless, investing in educational quality has the potential to produce higher returns.

5. Conclusion

In summary, the first finding is that rising the Harmonized Test Scores (HTS), including the Program for International Student Assessment (PISA) test scores, does not contribute to labor productivity per person in high income countries in Asia, Europe, and North America, while the test scores can drive to economic growth in high income countries in Africa, Caribbean, Middle East, and South America; upper middle-income countries in Africa, Caribbean, Middle East, Ocean, and South America; low middle-income countries, and low middle-

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[13] Authors calculated it. Source: https://fred.stlouisfed.org/series/OPHNFB.

[14] A non-cognitive skill items; self-organization, interaction and communications, managing and supervisions, readiness to learn and creativity, trust in persons, and conscientiousness from the Program for the International Assessment of Adult Competencies (PIAAC), which is a program of assessment and analysis of adult skills. https://www.oecd.org/skills/piaac/.

[15] In our view, integrated cognitive skills with non-cognitive skills could facilitate adaption to change of the labor productivity per hour.

[16] For example, if a low-income parent is able to secure a place for her child in a high quality daycare program, that child is likely to benefit from exposure to a wider array of learning opportunities than he or she might have at home. Enrolling her child in daycare may also open the door for the parent to take on employment or further her education in order to improve her career prospects. Those individual benefits can be substantial, and life-changing. https://live-penn-impact.pantheon.io/wp-content/uploads/2016/2015/06/Why-Invest-High-Return-on-Investment.pdf.

income countries than high-income countries. The second finding is that rising HTS test scores are likely to connect to labor productivity per hour.

In the digital economic phase, it seems that integrated cognitive skills and non-cognitive skills contribute to labor productivity per hour. We recommend that policymakers should invest in early childhood to not only maintain or improve PISA test scores but also to improve non-cognitive skills associated with psychology. These investments lead to high social return in the future to grow the economy.

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Australia	Asia
Austria	Europe
Bahrain	Middle East
Belgium	Europe
Brunei Darussalam	Asia
Canada	North America
Chile	South America
Croatia	Europe
Cyprus	Europe
Czech Republic	Europe
Denmark	Europe
Estonia	Europe
Finland	Europe
France	Europe
Germany	Europe
Greece	Europe
Hong Kong SAR, China	Europe
Hungary	Europe
Iceland	Europe
Ireland	Europe
Israel	Middle East
Italy	Europe
Japan	Asia
Korea, Rep.	Asia
Kuwait	Middle East

Appendix A

High Income Countries

Latvia	Europe
Lithuania	Europe
Luxembourg	Europe
Macao SAR, China	Asia
Malta	Europe
Mauritius	Africa
Netherlands	Europe
New Zealand	Asia
Norway	Europe
Oman	Middle East
Panama	South America
Poland	Europe
Portugal	Europe
Qatar	Middle East
Romania	Europe
Saudi Arabia	Middle East
Singapore	Asia
Slovak Republic	Europe
Slovenia	Europe
Spain	Europe
Sweden	Europe
Switzerland	Europe
Trinidad and Tobago	Caribbean
United Kingdom	Europe
United States	North America
Uruguay	South America

Upper Middle-Income Countries

Belarus	Europe
Bosnia and Herzegovina	Europe
Botswana	Africa
Brazil	South America
Bulgaria	Europe
China	Asia
Colombia	South America
Costa Rica	South America
Dominican Republic	Caribbean
Ecuador	South America
Fiji	Oceana
Gabon	Africa
Georgia	Middle East
Guatemala	South America
Guyana	South America
Indonesia	Asia
Iran, Islamic Rep.	Middle East
Iraq	Middle East
Jamaica	Caribbean
Jordan	Middle East
Kazakhstan	Asia
Lebanon	Middle East
Malaysia	Asia
Mexico	South America
Montenegro	Europe
Namibia	Africa
North Macedonia	Europe

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Upper Middle-Income Countries (cont.)

Belarus	Europe
Paraguay	South America
Peru	South America
Russian Federation	Europe
Samoa	Oceana
Serbia	Europe
South Africa	Africa
Thailand	Asia
Tonga	Oceana
Turkey	Europe

Lower Middle-Income Countries

Morocco	Africa
Myanmar	Asia
Nepal	Asia
Nicaragua	South America
Nigeria	Africa
Pakistan	Asia
Papua New Guinea	Oceana
Philippines	Asia
Senegal	Africa
Solomon Islands	Oceana
Sri Lanka	Asia
Tanzania	Africa
Timor-Leste	Asia
Tunisia	Africa
Ukraine	Europe
Uzbekistan	Asia
Vanuatu	Oceana
Vietnam	Asia
West Bank and Gaza	Middle East
Zambia	Africa
Zimbabwe	Africa
Bangladesh	Asia
Benin	Africa
Bhutan	Asia
Cambodia	Asia
Cameroon	Africa
Comoros	Africa
Côte d'Ivoire	Africa
Egypt, Arab Rep.	Middle East
El Salvador	South America
Eswatini	Africa
Ghana	Africa
Honduras	South America
India	Asia
Kenya	Africa
Kyrgyz Republic	Asia
Lao PDR	Asia
Lesotho	Africa
Mauritania	Africa
Moldova	Europe
Mongolia	Asia

Low Income Countries

Burkina Faso	Africa
Burundi	Africa
Central African Republic	Africa
Chad	Africa
Ethiopia	Africa
Guinea	Africa
Haiti	Caribbean
Liberia	Africa
Madagascar	Africa
Malawi	Africa
Mali	Africa
Mozambique	Africa
Niger	Africa
Rwanda	Africa
Sierra Leone	Africa
Sudan	Africa
Tajikistan	Asia
Togo	Africa
Uganda	Africa