Brief Methodological Overview of Skills Clock

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Overview

The Skills Clock projects current learning trends of both secondary literacy/numeracy and digital skills for the global population of ages 15 to 24, disaggregated by country.

1. Population projection

The population projections[1] used for these analyses come from the International Institute for Applied Systems Analysis (IIASA) Shared Socioeconomic Pathways Database using SSP 1[2]. Missing data was interpolated using the standard exponential growth function based on the growth rate between data points, which are provided in five-year intervals.

The annual growth rate for a given interval is calculated as $r = \ln\left(\frac{Population_{y+5}}{Population_{y}}\right) * \frac{1}{5}$, and the corresponding interpolations are calculated as $Population_{y+1} = Population_{y} * e^{rt}$, where t=1.

2. Secondary literacy and numeracy skills

Secondary literacy and numeracy skills represent traditional reading and math skills typically associated with in-school learning. To assess the proportion of youth with secondary literacy and numeracy skills, data were primarily taken from the UNESCO Institute for Statistics (UIS) database, which reports data for the monitoring of Sustainable Development Goal 4.4.1 on the proportion of children and young people (a) in grades 2/3; (b) at the end of primary; and (c) at the end of lower secondary achieving at least a minimum proficiency level in reading.

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[1] https://tntcat.iiasa.ac.at/SspDb; The file used is SspDb_country_data_2013-06-12.csv.

[2] Detlef P. van Vuuren, Elke Stehfest, David E.H.J. Gernaat, Jonathan C. Doelman, Maarten van den Berg, Mathijs Harmsen, Harmen Sytze de Boer, Lex F. Bouwman, Vassilis Daioglou, Oreane Y. Edelenbosch, Bastien Girod, Tom Kram, Luis Lassaletta, Paul L. Lucas, Hans van Meijl, Christoph Müller, Bas J. van Ruijven, Sietske van der Sluis, Andrzej Tabeau, **Energy, land-use and greenhouse gas emissions trajectories under a green growth paradigm**, Global Environmental Change, Volume 42, 2017, Pages 237-250,
ISSN 0959-3780, DOI:10.1016/j.gloenvcha.2016.05.008

For the secondary school learning benchmarks, the equivalents are set at PISA or TIMSS (grade 8) level 1 or higher. For countries that had both literacy and numeracy data in a given year, the average value of these two measures was used. For countries that had either literacy or numeracy data in a given year, this value was used. Because there were many countries that had not participated in either of these two secondary assessments, we estimated learning for countries without data with a statistical predictive model that builds on earlier models for identifying the determinants of learning outcomes[3].

We tested a range of variables suggested by this earlier research to be correlated with learning outcomes, and the primary level learning dataset. These were compiled into a hierarchical set of predictive learning production models using multivariate regression.[4] These regressions use the most recent available year of data for each country with at least one data point. The two models used are shown below.

Table 1. Regression results for the learning production functions.

	(1)	**(2)**
Ln GNI per capita	2.84*	13.51***
Extraction rent as a percent of GDP	-0.38	-0.44
Percent reaching primary learning benchmark	0.67***	
Socialist/communist state dummy		27.41
Vietnam dummy		24.70
Constant	-6.61	-69.22***
N	59	93
R-squared	0.78	0.49

*significant at p<.05, **at p<.01, ***at p<.001

Model (1) represents the best fit using economic variables and primary learning assessments. When primary learning data was available, this model was used to predict secondary numeracy and literacy learning. Model (2) represents the second-best fit using economic and political variables. When primary learning data was unavailable in any year for a given country, this model was used to predict secondary numeracy and literacy learning. The resulting data were used to calculate growth rates for each country where two or more historical or imputed data points are available. The average growth rate was then calculated for each income group, and the remaining countries without growth rates were assigned their income group average. The floor of the growth rates is set to 0.

After filling in missing data from years 2010 to 2019, linear trend forecasting was used to predict country values for the year 2020. The predictions for the year 2020 are multiplied by a

[3] Some of this literature was summarized in the UNESCO 2008 Global Monitoring Report on learning. In 2011, the Education Policy and Data Center (EPDC) proposed a production function to predict learning outcomes using a multi-stage regression analysis (Education Policy and Data Center. 2011. "Estimating Education output in Developing Countries". EPDC Working paper 2011-1. FHI-360, Washington, DC.). Hanushek and Krueger also analyzed school-level inputs as determinants of learning outcomes in various publications (Hanushek, Eric A. 1995, "Interpreting Recent Research on Schooling in Developing Countries." World Bank Research Observer, 10(2):227-246; Hanushek, Eric A. 1997, "Assessing the Effects of School Resources on Student Performance: An Update", Educational Evaluation and Policy Analysis 19(2), Summer 1997, pp. 141-164.; Hanushek, Eric A. and J.A. Luque, 2003. "Efficiency and equity in schools around the world." Economics of Education Review 22 (2003) 481–502; Krueger 2003.)
[4] The predicted learning outcome for each country is: $L = c + \sum_f \beta_f * F_f$. In the equation, F denotes the factors of learning, β_f the regression coefficient, and c the constant.

factor representing the effect of learning loss due to COVID-19. The calculation of this multiplier is detailed in Section 4 of this document. An additional adjustment is made for out-of-school youth that assumes roughly half of the OOS population acquire secondary literacy and numeracy at the rate of in-school youth, based on the projected 2020 value of Total Net Enrolment Rate (TNER)[5].

We assume the growth rates calculated for the time period before 2020 are unchanged for the years 2021-2050. Thus, once the adjusted value for 2020 is set for each country, linear trend forecasting was used to predict country values for the years 2021-2050.

3. Digital skills

Digital skills support the development of skills to use and understand technology, search for and manage information, communicate, build knowledge and solve problems. To assess the proportion of youth with digital skills, data were primarily taken from the UNESCO Institute for Statistics (UIS) database, which reports data for the monitoring of Sustainable Development Goal 4.4.1 on the proportion of youth and adults with information and communications technology (ICT) skills, by type of skill. This indicator refers to individuals that have undertaken certain computer-related activities in the last three months, as collected by the International Telecommunication Union (ITU) and Eurostat.

The latest SDG 4.4.1 figures from the UIS were extracted for the following skills: copying or moving a file or folder, using copy and paste tools to duplicate or move information within a document, sending e-mails with attached files, and transferring files between a computer and other devices[6]. For each country, the average among these figures is taken as the proportion of youth and adults with basic digital skills for each country. Data for China[7] and India[8] were extracted from national reports on the proportion of adults with basic ICT skills. Data for the United States were extracted from the Programme for International Assessment of Adult Competencies (PIAAC) on the proportion of youth with digital literacy (i.e., proportion of 16- to 24-year-olds who participated in the 'problem solving in a technology rich environment' assessment).

Based on PIAAC[9] results suggesting youth aged 16-24 years are 24 per cent more likely to have basic ICT skills than the total 16- to 65-year-old population, data on youth and adults (i.e., data from UIS and national reports on proportion of youth and adults with basic ICT skills) were narrowed to youth by multiplying each value by 1.24, capping the final country values at 100 per cent.

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[5] Source: UIS.

[6] These four computer-related activities are used by ITU for the reporting of basic ICTskills (e.g., see: International Telecommunication Union, *Measuring the Information Society Report 2018, Volume 1*, ITU, Geneva, 2018).

[7] *Blue Book of New Media 2021: Annual Report on Development of New Media in China No. 12 (2021)*, Social Sciences Academic Press (China), 2021.

[8] Government of India Ministry of Statistics & Programme Implementation, *Household Social Consumption on Education in India: NSS 75th Round*, July 2017-June 2018.

[9] Organisation for Economic Co-operation and Development, *Skills Matter: Additional Results from the Survey of Adult Skills*, OECD Skills Studies, OECD Publishing, Paris, 2019.

For countries with missing data, regression-based imputation was conducted using the natural log of gross national income per capita, calculated using the World Bank Atlas method, and the percentage of population using the Internet (Model (2) in the table below). Data for these variables were extracted from the World Bank Open Data.

Table 2. Regression results for the digital learning production functions.

	(1)	(2)	(3)
Ln GNI per capita	16.10***	11.03***	10.62***
Internet usage (% of population)		0.33**	0.50**
Access to electricity (% of population)			-0.22
Constant	-97.33***	-74.72***	-62.48***
N	97	97	97
R-squared	0.71	0.73	0.74

*significant at p<.05, **at p<.01, ***at p<.001

After filling in missing data from years 2010 to 2020, linear trend forecasting was used to predict country values for years 2021 to 2050. For countries resulting with imputed values of '0%' for 2020, the highest figure from the last 10 years is imputed, or, if no data is available for previous years, a value of '1% is imputed. For these countries, and for countries with declining or flat trends, the average growth rates of their respective country income groups were applied. These adjustments are based on the assumption that digital skills have been accelerated by the COVID-19 pandemic starting in 2020.

4. Modeling for the COVID-19 Shock

We apply the equation below to estimate the COVID dampening effect on skill attainment for youth and in and out of education.

pre-COVID youth skill rate X (1 – in-person school time lost / pre-COVID length of country school life X (1 – pre-COVID Internet access rate))

In this equation, the *in-person school time lost / pre-COVID length of country school life* is used to proxy learning loss if no mitigation. We use data from the UNESCO Global Monitoring of School Closures[10] to estimate the loss of in-person schooling year as of 31st October 2021, which covers 624 days or about 1.7 years with traceable records of school closures. Each partially open day is counted as a 0.5 full-closure day. For each country, we multiply the 1.7 year with "(full-closure days + partial closure days/2) divided by total non-academic-break days" to estimate in-person schooling lost in year unit. We then divide lost year by the school life expectancy of primary and secondary education, which is available on the UIS.

The *pre-COVID internet access rate* from ITU is used to proxy a country's capacity to mitigate the learning loss. It is true that online learning is just one mitigation measure. We therefore run a correlation test between the pre-COVID internet access rate and the UNICEF remote learning readiness index[11] (RLRI) covering 67 countries. The result shows 0.63 correlation, implying a

[10] https://en.unesco.org/covid19/educationresponse
[11] https://data.unicef.org/resources/remote-learning-readiness-index/

moderate-to-strong correlation. RLRI is composed of three domains: households, a government's policy response capacity, and the emergency preparedness of the national education sector calculated from multiple data sources of household surveys, government surveys and UNICEF's Strategic Monitoring Questions.

Together, *1 – in-person school time lost / pre-COVID length of country school life X (1 – pre-COVID Internet access rate)* signals what percentage of pre-COVID skill achievement can be preserved given the school-closure situation as of 31st October 2021. Note that in this modelling pre-COVID means data for 2019 or the latest available pre-2020. For simplification, we also assume a same dampening effect to both youth in and out of education, and that the additional COVID-related dropout is offset by the pre-COVID decline trend in out-of-school.