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Measuring human capital in middle income countries

Asli Demirgüç-Kunt, Iván Torre

Office of the Chief Economist for Europe and Central Asia, World Bank, United States

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ABSTRACT

This paper develops an indicator that measures the level of human capital to address the specific education and health challenges faced by middle income countries. We apply this indicator to countries in Europe and Central Asia, where productive employment requires skills that are more prevalent among higher education graduates, and where good health is associated to low levels of adult health risk factors. The Europe and Central Asia Human Capital Index (ECA-HCI) extends the World Bank's Human Capital Index by adding a measure of quality-adjusted years of higher education to the original education component, and it includes the prevalence of three adult health risk factors—obesity, smoking, and heavy drinking—as an additional proxy for latent health status. The results show that children born today in the average country in Europe and Central Asia will be almost half as productive as they would have had they reached the benchmark of complete education and full health. Countries with good basic education outcomes do not necessarily have good higher education outcomes, and high prevalence of adult health risk factors can offset good education indicators. This extension of the Human Capital Index could also be useful for assessing the state of human capital in middle-income countries in general.

The development of human societies has proven to be a function of their stock of human capital, understood as the capacity of individuals to be productive (Becker, 1964). Measurement of human capital is, thus, an important exercise when assessing the potential productivity of a country. Typically, the average years of schooling of a country's population are used as the most common indicator of the stock of human capital. However, research has shown that school attendance is only partially correlated with skill acquisition, and that health is also an important determinant of individuals' productivity. In 2018, the World Bank launched the publication of the Human Capital Index (HCI) a measure of the human capital that a child born today can expect to attain by age 18, given the risks of poor health and poor education that prevail in the country where she lives (Kraay, 2019).

The HCI quantifies the trajectory from birth to adulthood in terms of the consequences for productivity by means of three components: (1) a measure of whether children survive from birth to school age (age 5); (2) a measure of expected years of basic education (primary and secondary), adjusted for quality; and (3) two broad measures of health: child stunting rates and adult survival from age 15 to age 60. The index is constructed so that a value of 1 represents the productivity in adulthood of a child born today if he or she enjoyed complete education and full health until age 18. Countries are measured with respect to this benchmark; the value of the index can thus be interpreted as a percentage of that productivity level.

This paper's findings, interpretations, and conclusions are entirely those of the authors and do not necessarily represent the views of the World Bank, its Executive Directors, or the countries they represent. We thank Aart Kraay for his guidance and advice, and Tania Dmytraczenko, Roberta Gatti, Harry Patrinos, Fadia Saadah, Gil Shapira, Christel Vermeersch and two anonymous referees for useful comments. Sharanya Venu Pillai provided excellent assistance.

E-mail address: itorre@worldbank.org (I. Torre).

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While useful in a global context, the original version of the HCI may not adequately reflect the productivity gaps that are relevant for specific regions of the world, particularly those of middle and high income. Productivity of human capital depends on its utilization (Pennings, 2020), and the technological and labor demand context matter for that purpose. Countries in Europe and Central Asia provide their citizens relatively good basic education and health services; the region's citizens begin their productive life in a much better position than their peers in other, less rich regions of the world. However, the environment they face when putting their human capital to work is different than that of poorer countries: the nature of labor demand is such that full basic education is not enough to ensure a productive employment. The jobs that are growing in the region demand workers with skills which are more prevalent among higher education graduates (Kelly et al., 2017). At the same time, longer productive lives -as a consequence of longer life expectancy and improved child health- imply that a focus on adult health is particularly important when assessing long-term productivity of workers.

This paper outlines an extension of the HCI which addresses the relevant education and health challenges of middle- and high-income countries like the ones in Europe and Central Asia, namely by including higher education in the education component of the index and by looking at three crucial adult health risk factors -obesity, heavy alcohol consumption and tobacco smoking- in the health component. This extension could also be useful for assessing the state of human capital in middle income countries in general, particularly for those where basic education attainment and child health are less of a concern but where significant challenges remain as young people transition into the labor market.

The results of this measurement exercise for countries in Europe and Central Asia point to some interesting findings: countries that exhibit relatively good basic education indicators lag considerably when looking at higher education. At the same time, some countries that exhibit relatively high levels of tertiary attainment show lags in basic education, suggesting insufficiencies in the overall skill acquisition process. In the realm of health, this extension of the HCI highlights the particularly dire productivity consequences that risk factors such as obesity, smoking and heavy drinking have in many countries in Eastern Europe – and show how part of the advantage some of these countries may have in the educational domain are offset by negative adult health indicators.

This paper is organized as follows. Section 2 presents the main analytical framework of the ECA-HCI, the proposed extension of the original HCI. Section 3 discusses the education component and section 4 discusses the health component. Section 5 presents the overall results and section 6 concludes.

1. Main framework

The basic structure of the Human Capital Index (HCI) is made up of three components:

$$HCI = \frac{p}{p^*} \times e^{\varphi(S_{NG}-S^*)} \times e^{\gamma(Z_{NG}-Z^*)} \tag{1}$$

The first term captures forgone productivity caused by child mortality. The second term captures forgone productivity as a result lack of full education, where S_{NG} refers to the schooling level of the generation of children born today and S^* refers to the full education benchmark. The productivity return to education is measured by parameter φ. The third terms captures forgone productivity as a result of lack of proper health, where Z_{NG} refers to the expected adult health status of the generation of children born today and Z^* refers to the full health benchmark. The productivity return to good health is measured by parameter γ.

The HCI's measure of child mortality is the probability of survival to age five. The education component of the HCI uses learning-adjusted years of schooling, a quality-adjusted measure of years of basic education. The benchmark is set at 14 years of schooling, equivalent to the whole cycle of primary and secondary education plus two years of preprimary education. The parameter φ is set at 0.08, based on estimations of the average return of one year of basic education.

The health component of the HCI uses child stunting (when available) and the adult survival rate (the probability that a child age 15 reaches age 60) as health status indicators. The benchmark is zero stunting and 100% adult survival rate. To establish a quantifiable productivity return to good health, both variables are transformed into implied adult height in centimeters, which has a productivity return of 0.034 per centimeter. Adult height is implied to be the most relevant proxy variable for latent health status (captured by Z in the equation above). The value of γ is 0.35 for child stunting and 0.65 for the adult survival rate.

The HCI is calculated using the following formula:

$$HCI = \frac{1 - Under\ 5\ mortality\ rate}{1} \times e^{0.08(LAYS-14^*)} \times e^{(0.35(Not\ \ Stunted\ \ Rate-1)+0.65(ASR-1))/2} \tag{2}$$

This paper outlines an alternative specification that may be particularly relevant for the education and health challenges faced in Europe and Central Asia. For the education component, we add higher education in addition to basic education. For the health component, we use a proxy of latent adult health status (based on the incidence of obesity, smoking, and alcoholism), along with the outcome proxy based on child stunting and adult survival rate used in the original HCI. The basic formulation of the Europe and Central Asia HCI (ECA-HCI) is as follows:

$$ECA - HCI = \frac{p}{p^*} \times e^{\eta(B-B^*)+\omega(C-C^*)} \times e^{\frac{\gamma_{RF}(RF-RF^*)+\gamma_O(O-O^*)}{2}} \tag{3}$$

where B refers to the quality-adjusted basic education schooling level of the generation of children born today, with an associated productivity return captured by parameter η and full basic education benchmark B^*; C refers to the quality-adjusted higher education schooling level, with an associated productivity return captured by parameter ω and full higher education benchmark C^*; RF refers to the prevalence of adult health risk factors (namely the share of non-obese individuals in the adult population, the share of adult nonsmokers, and the share of adults who report no heavy drinking), with an associated productivity return captured by parameter γ_{RF}. The benchmarks for these shares are set to 100% non-obese, nonsmokers, and non–heavy drinkers. O refers to the value of the relevant health outcomes (adult survival rate and child stunting); γ_o refers to their productivity effects, estimated via their relationship with adult height, as in the original HCI.

2. Education component

The 2019 *World Development Report* highlights the changing nature of work across the globe. In high- and middle-income countries, which include most of the countries in Europe and Central Asia, having a good basic education will not be enough for individuals to be productively included in the labor market in the next decades; higher education of good quality will be necessary for the next generations to be productive workers. Indeed, recent technological change has resulted in an increased demand for non-routine, cognitive skills in the region. This type of skills is more prevalent among tertiary degree graduates, especially when measured by the task intensity of the occupation they work on. Workers with a college degree are at least 60% more likely than workers with a primary education to carry out non-routine, cognitive tasks in their jobs, although the correlation is lower when controlling for actual skill measures (Kelly et al., 2017). This evidence suggests that tertiary education of good quality -that is, that trains students to be proficient in the skills in high demand- is necessary to be productive in the labor market. In the economies of Europe and Central Asia, then, high-school only graduates may increasingly find difficult to have a productive employment. A measure of productivity of human capital cannot ignore the way in which human capital is actually used (Pennings, 2020) and needs to take into account the technological and labor market environment in which individuals are immersed. Therefore, in the context of Europe and Central Asia -and of similar middle-income countries- a benchmark of full basic education may not be representative of the actual productivity maximum that could be achieved given the prevailing technology and labor demand. The education component of the ECA-HCI therefore extends the original education component by adding a measure of quality-adjusted years of higher education (QAYH) to the measure of learning-adjusted years of basic education (LAYS). Like LAYS, developed by Filmer et al. (2020), QAYH measures both quantity and quality.

The basic formulation of the education component of the ECA-HCI is the following:

$$ECA - HCI_{education} = e^{\eta(LAYS - LAYS^{*}) + \omega(QAYH - QAYH^{*})} \tag{4}$$

Where η and ω are the productivity returns of one additional year of quality basic and higher education respectively, and $LAYS^*$ and $QAYH^*$ are the benchmark number of years equivalent to full basic and higher education respectively.

As shown in Eq. (4), the education component of the ECA-HCI includes two subcomponents. The first measures the basic education schooling level expected for the generation of children born today. This component is the same as the overall education component in the standard version of the HCI. The main variable is learning-adjusted years of education, a quality-adjusted measure of schooling years in basic education. The benchmark (*LAYS)* is set at 14 years of basic education. The associated return in productivity terms (η) is set at 0.08.

The second component focuses on higher education. A quality-adjusted measure of years of higher education requires two inputs: a measure of expected years of higher education and a measure of the quality of higher education. This mirrors the structure of the LAYS indicator for basic schooling as developed by Filmer et al. (2020). The basic structure of the main outcome variable for higher education. —quality-adjusted years of higher education (QAYH)—is the following:

$$QAYH_c = EYH_C \times QA_c \tag{5}$$

where EYH_c represents the expected years of higher education of country c, and QA_c represents the average quality of higher education in country c, which has a maximum of 1 and a minimum of m. The minimum is greater than 0 on the assumption even very low-quality higher education has some intrinsic value, even if minimal. $QAYH$ is expressed in years of higher education of maximum quality.

2.1. *Expected years of higher education*

The standard approach for estimating expected years of basic education, as described by Kraay (2019), uses the age-specific enrollment rates over all ages in the 4–18 age range as the main input. The nature of higher education requires a different treatment, for several reasons.

First, there is no theoretical age at which higher education is expected to happen, although most individuals are enrolled at some point during their twenties. Second, higher education is not always carried out full time; many students combine their studies with part-time employment, which in many cases implies that it will take longer than expected to complete the degree. Third, the number of years required to obtain a higher education degree varies across disciplines and across countries (the norm in EU countries, after implementation of the Bologna Process, is for initial degrees to take three years; in the Russian Federation, a bachelor's degrees take four years). These reasons, then, push us to move from a definition of expected years of higher education based on *enrollment* to one based on *attainment*. The main limitation of this definition is that it does not account for the schooling of higher education dropouts[1]. In this sense, our definition of expected years of higher education should be understood as a lower bound estimate.

The approach adopted in this paper uses the percentage of individuals with a higher education degree (ISCED 6 or higher) at age 30–34 as the measure of educational attainment. By focusing on individuals with completed degrees at an age when most individuals are assumed to have finished their education, it abstracts from the pace and actual age at which the degrees were acquired. To express it in years of education, we assume that a university degree is equivalent to 3.5 years of higher education, to account for differences across disciplines and educational systems. This compares to the global estimate of 3.7 years of average duration of first degree programmes in tertiary education between 2000 and 2010 (UIS UNESCO 2013)[2]. Using a single value for the duration of a higher education degree across countries also ensures comparability when attributing wage returns to years of education. The calculation of expected years of higher education (*EYH*) is straightforward:

$$EYH_c = Tertiary\ attainment_c^{age\ 30-34} \times 3.5 \tag{6}$$

where *Tertiary attainment* corresponds to the share of individuals 30–34 in country *c* who hold a tertiary degree.

An alternative measure of tertiary attainment corresponds to the gross graduation ratio calculated by UIS UNESCO, defined as the ratio between the annual number of graduates from first degree tertiary programmes (ISCED 6 and 7, bachelors and master degrees respectively) and the population in the theoretical age of the most common first degree programme. The main limitation of this publicly available measure is that it adds up graduates from two different levels of tertiary programmes. In particular, it may overestimate attainment in those countries where a typical higher education graduate earns two short degrees (for instance, a three-year bachelor degree followed immediately by a one-year master degree) and underestimate attainment in those countries where a typical higher education graduate earns a single degree after a longer period (for instance, a four or five year bachelor degree). Appendix Fig. A.1 compares the estimation of *EYH* using the share of individuals age 30-34 with a higher education degree and using the gross graduation ratio. The correlation between both estimates is 0.625[3] and the gross graduation ratio is significantly higher than the actual share of individuals age 30-34 with a tertiary degree in more than half of the countries. This confirms that the gross graduation ration may indeed overestimate attainment for the reasons detailed before and, therefore, we prefer to use the share of individuals age 30-34 with a tertiary degree as the attainment measure.

2.2. Quality adjustment of higher education attainment

Quality adjustment of higher education should be done primarily by measuring the quality of outputs, such as the skill proficiency of university graduates. This mirrors the way in which harmonized test score results are used to measure the quality of learning among primary and high school students (Angrist and Patrinos, 2018) and is consistent with the spirit of the HCI and the academic consensus on the importance of skills -and not just diplomas (Sondergaard et al., 2012)- as the relevant factor that makes human capital productive (Angrist et al, 2021; Hanushek and Woessman, 2012; Pritchett, 2013). The ECA-HCI presents therefore an estimate of the quality of higher education using measures of adult skill proficiency from the Programme for the International Assessment of Adult Competencies [PIAAC] and the Skills Towards Employability and Productivity [STEP] surveys.[4] However, these measures are available only for a limited set of countries. In order to provide a wider country coverage, the ECA-HCI presents also an alternative estimate of the quality of higher education which relies on the quality of inputs—such as the quality of universities. While this measure deviates from the approach of the original HCI, it is more widely available and, for countries where the comparison is possible, it correlates strongly with a skill-based quality adjustment. This suggests that the average quality of universities in a given country is a strong predictor of the average quality of skills acquired by tertiary graduates.

2.2.1. Skill-based measure of higher education quality

Adult skill proficiency is multidimensional. This analysis focuses on two dimensions that are measured by the Program for the International Assessment of Adult Competencies (PIAAC) survey: literacy proficiency and numeracy proficiency. The PIAAC survey, run by the Organisation for Economic Co-operation and Development, has been carried out in 40 countries, of which 24 are in Europe and Central Asia. The Skills Towards Employment survey, which is run by the World Bank, measures literacy proficiency on a scale equivalent to the PIAAC in three additional countries in Europe and Central Asia. The literacy and numeracy proficiencies are

[1] There is limited evidence on the effect of incomplete higher education on skill acquisition. Evidence from labor market outcomes -which are only a partial reflection of individuals' skills- shows that higher education dropouts in Europe may have a slight advantage over individuals with only secondary education (Schnepf, 2015). Evidence from community college graduates and dropouts in the United States presents a similar pattern (Kane and Rouse, 1999).

[2] Based on the same statistic, the estimates of mean years of schooling by UIS Unesco nevertheless use 4 years as the benchmark for complete tertiary education. We prefer to err on the conservative side and not attribute additional years of education to individuals who may have not achieved them.

[3] Excluding two significant outliers (Luxembourg and Cyprus), for which the gross graduation rate is unusually low.

[4] For a comparison of output quality in tertiary education, see Loyalka and others (2019), who compare the computer science skills of computer science undergraduates in their last year in China, India, the Russian Federation, and the United States.

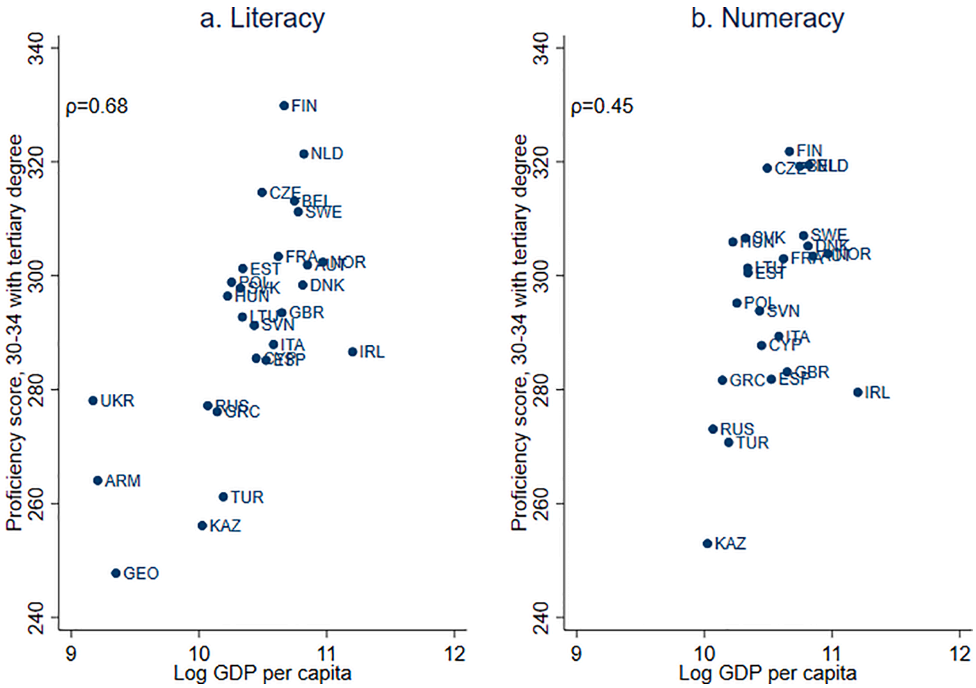

Figure 1. Correlation between skill proficiency and country income level
Note: This graph plots, for every country with available data, the log GDP per capita at PPP in 2019 (vertical axis) and the literacy score (horizontal axis, panel a) and numeracy score (horizontal axis, panel b). Literacy and numeracy scores are from PIAAC and STEP surveys, and the country average for individuals age 30 to 34 with a tertiary degree is plotted.

measured on a 0–500 scale; any value greater than 376 is considered highly proficient. The benchmark for full proficiency is set at 400, which exceeds the value reported at the 90th percentile of the score distribution of the average adult population in all countries. Each skill type is weighted equally.

The quality-adjustment measure uses as main input the proficiency in both types of skills of individuals 30–34 who completed a tertiary degree in each country. This demographic group was chosen to match the group for which attainment rates of tertiary degrees are used. Just as the quality adjustment of basic education schooling years proposed by Filmer et al. (2020), in this case the actual levels of skills proficiency are expressed as a ratio with respect to the “full proficiency” benchmark. The skill-based quality adjustment is then derived using the following formula:

$$QA_c^S = \left(\frac{Literacy_c^{age\ 30-34}}{400} + \frac{Numeracy_c^{age\ 30-34}}{400} \right) \frac{1}{2} \quad (7)$$

Among tertiary graduates age 30 to 34, the average skill proficiency in literacy is consistently higher for countries with higher income levels, while in the case of proficiency in numeracy there is more dispersion across countries despite a positive gradient (Fig. 1).

2.2.2. *Input-based measure of higher education quality*

The quality-adjustment factor in our study is calculated in the following way:

$$QA_c^U = m \times e^{\beta \times Q_c} \quad (8)$$

where m corresponds to the productivity of a tertiary degree coming from a “zero-quality” institution; Q corresponds to the average quality score of universities in country c, ranging from 0 to 100; β is a productivity-adjustment factor that transforms the quality score into productivity units; and m is scaled in a way that quality adjustment (QA_c) equals 1 if Q_c equals 100.

The measure of quality corresponds to the information collected by global university rankings. These rankings, published by private, for-profit companies, have grown in number over the years. They are usually based on an underlying score that is usually a weighted average of scores on different aspects of higher education (the volume and quality of research, research influence, the quality of teaching, international outlook, links to industry). These rankings do not include all higher education institutions (universities need to send their information, usually at a cost, to the publishers), and they use different methodologies. Our analysis relies on a combination of several of these ranking, including the scores from the Times Higher Education (THE) ranking; the Quacquarelly Symonds (QS) ranking; the Academic Ranking of World Universities (ARWU, also known as the “Shanghai” ranking); the Center for World University Rankings (CWUR); the U.S. News Global Universities Ranking; and the U-Multirank ranking (a nonnumeric, user-defined ranking). These rankings contain information on 400–1,000 universities in 43 countries in Europe and Central Asia. We use the

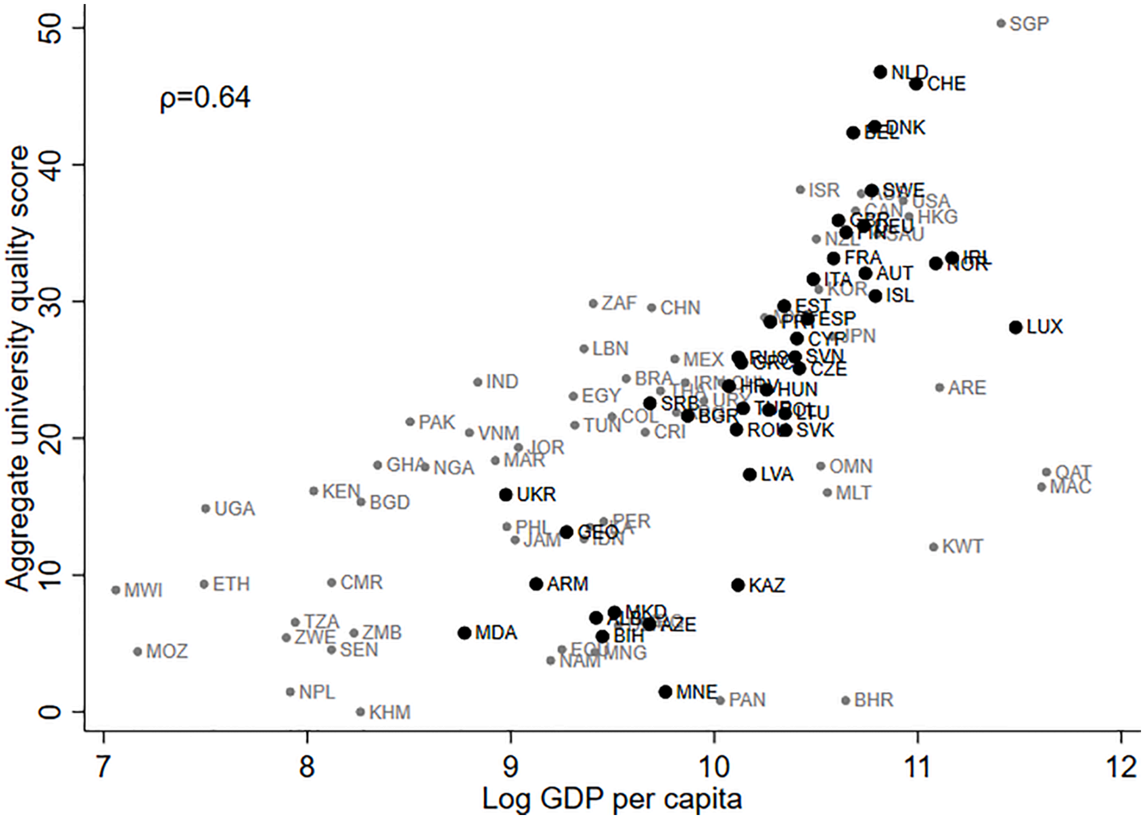

Figure 2. Correlation between aggregate quality score of universities and country income level
Note: This graph plots, for every country with available data, the aggregate university quality score (vertical axis) and the log GDP per capita at PPP in 2019 (horizontal axis) Only countries present in at least one of the six rankings are included. Black points indicate countries in Europe and Central Asia.

Table 1
Parameters of the quality-adjustment factor used to assess universities

	THE Overall (1)	RTC (2)	QS Overall (3)	RTC (4)	ARWU RTC (5)	CWUR Overall (6)	U.S. News Overall (7)	U-Multirank Overall (8)	RTC (9)	Aggregate quality score (overall) All sample (10)	Common (11)
β	0.0032	0.0031	0.0027	0.0024	0.0045	0.0073	0.0019	0.0040	0.0032	**0.0024**	0.0044
m	0.726	0.733	0.763	0.787	0.638	0.747	0.826	0.668	0.728	**0.787**	0.647

Note: ARWU = Academic Ranking of World Universities; CWUR = Center for World University Rankings; QS = Quacquarelly Symonds; RTC = research, teaching, and citations; THE = Times Higher Education.

underlying scores used to derive the position of each university in the ranking – we do not use the rank value. We generate a country-level average by averaging the scores for all the universities in a given country included in each ranking, yielding six values for each country (one for each ranking source). As detailed in Annex A, we normalize each of them, and then take the average of them as the aggregate quality score. Fig. 2 plots the values of the aggregate quality score by country and income level. Only countries that are present in at least one of the six rankings are included.[5] The correlation between income level and the aggregate quality score is particularly steep for Europe and Central Asia.

To estimate the productivity effect of university quality (parameters β and m in Eq. (8)), we rely on a cohort-college-level data set for 294 U.S. colleges. Focusing on the U.S. data allows us to control for parental income, one of the key drivers of individual income. The data set comes from the *Mobility Report Cards* constructed by Chetty et al. (2017), which combines college and administrative data that link the parental and post-college earnings of about 28.1 million students born between 1980 and 1991 for 2463 colleges. We match this data set with the six university rankings. Among U.S. higher education institutions, 294 are present in at least one of the

[5] In that countries have a value of zero in the quality score Q_c, the quality adjustment factor QA_c has a value of m: having a tertiary degree from these countries has an intrinsic value of m but no *additional* quality premium.

Table 2
Education component of the Europe and Central Asia extension of the Human Capital Index (ECA-HCI)

Subregion/country	Learning-adjusted years of basic education	Share of population 30–34 with tertiary degree (%)	Aggregate higher education quality score	Skill proficiency, 30-34 with tertiary degree		Quality-adjusted years of higher education		Education component, ECA-HCI	
				Literacy score	Numeracy score	Input based	Skills based	Input based	Skills based
Central Asia	**8.8**	**21.3**	**2.5**			**0.59**		**0.424**	
Kazakhstan	9.1	34.4	9.3	256	253	0.97	0.77	0.461	0.447
Kyrgyz Republic	8.7	29.5	–	–	–	0.81	–	0.433	–
Tajikistan	6.8	22.4	–	–	–	0.62	–	0.362	–
Uzbekistan	9.1	12.1	–	–	–	0.33	–	0.419	–
Central Europe and Baltic countries	**10.4**	**39.2**	**22.3**	**300**	**301**	**1.14**	**1.13**	**0.526**	**0.552**
Bulgaria	8.7	32.4	21.6	–	–	0.94	–	0.443	–
Croatia	10.4	28.1	23.8	–	–	0.82	–	0.501	–
Czech Republic	11.1	35.7	25.1	315	319	1.04	0.99	0.547	0.542
Estonia	11.7	48.0	29.7	301	300	1.42	1.26	0.607	0.593
Hungary	10.3	29.6	23.5	296	306	0.86	0.78	0.497	0.491
Latvia	11.0	44.0	17.3	–	–	1.26	–	0.559	
Lithuania	11.0	56.7	21.8	293	301	1.65	1.47	0.592	0.577
Poland	11.4	48.5	22.1	299	295	1.41	1.26	0.590	0.577
Romania	8.4	29.8	20.6	–	–	0.86	–	0.427	
Slovak Republic	9.8	36.6	20.6	298	307	1.06	0.97	0.493	0.486
Slovenia	11.4	41.1	25.9	291	294	1.20	1.05	0.572	0.558
Eastern Europe	**9.9**	**52.5**	**16.3**	–	–	**1.50**	**1.36**	**0.534**	**0.520**
Belarus	10.8	42.1	22.1	–	–	1.22	–	0.547	–
Moldova	8.3	35.1	5.8	–	–	0.98	–	0.432	–
Ukraine	9.9	56.0	15.9	278	–	1.60	1.36	0.539	0.520
Northern Europe	**11.4**	**51.2**	**37.3**	**311**	**309**	**1.54**	**1.38**	**0.605**	**0.591**
Denmark	11.1	57.9	42.8	298	305	1.77	1.53	0.609	0.588
Finland	11.7	42.8	35.1	330	322	1.28	1.22	0.596	0.590
Iceland	10.7	53.7	30.4	–	–	1.59	–	0.575	–
Norway	11.2	50.2	32.8	302	304	1.50	1.33	0.591	0.577
Sweden	11.6	52.4	38.1	311	307	1.58	1.42	0.616	0.600
Russian Federation	**10.9**	**61.0**	**25.9**	**277**	**273**	**1.79**	**1.47**	**0.601**	**0.573**
South Caucasus	**8.2**	**29.9**	**8.5**	**255**	–	**0.84**	**0.81**	**0.421**	**0.416**
Armenia	8.0	30.3	9.4	264	–	0.85	0.70	0.414	0.404
Azerbaijan	8.3	25.4	6.4	–	–	0.71	–	0.414	–
Georgia	8.3	41.7	13.1	248	–	1.19	0.90	0.445	0.426
Southern Europe	**10.5**	**34.1**	**29.7**	**286**	**286**	**1.01**	**0.85**	**0.518**	**0.503**
Cyprus	10.9	55.8	27.3	285	288	1.64	1.40	0.589	0.568
Greece	10.0	44.6	25.5	276	282	1.31	1.09	0.519	0.502
Italy	10.5	27.1	31.6	288	289	0.80	0.68	0.500	0.491
Malta	10.2	34.1	16.0	–	–	0.97	–	0.502	–
Portugal	11.3	32.7	28.5	–	–	0.96	–	0.548	–
Spain	10.5	40.6	28.7	285	282	1.20	1.01	0.533	0.518
Turkey	**9.2**	**27.5**	**22.2**	**261**	**271**	**0.80**	**0.64**	**0.453**	**0.442**
Western Balkans	**8.8**	**28.5**	**13.3**	–	–	**0.81**	–	**0.442**	–
Albania	9.0	23.5	6.9	–	–	0.66	–	0.434	–
Bosnia and Herzegovina	7.8	21.0	5.5	–	–	0.59	–	0.391	–
Kosovo	7.9	–	–	–	–	–	–	–	–
Montenegro	8.9	34.0	1.5	–	–	0.94	–	0.451	–
North Macedonia	7.3	29.9	7.3	–	–	0.84	–	0.390	–
Serbia	9.8	33.3	22.6	–	–	0.97	–	0.485	–
Western Europe	**11.3**	**45.9**	**36.2**	**303**	**301**	**1.38**	**1.20**	**0.583**	**0.568**
Austria	10.9	47.2	32.1	302	303	1.40	1.25	0.568	0.555
Belgium	11.2	48.9	42.3	313	319	1.49	1.35	0.588	0.576
France	11.3	47.0	33.1	303	303	1.40	1.25	0.584	0.571
Germany	11.0	34.0	35.5	305	308	1.02	0.91	0.541	0.532
Ireland	11.6	59.7	33.2	287	280	1.78	1.48	0.635	0.607
Luxembourg	9.8	49.7	28.1	–	–	1.46	–	0.524	–
Netherlands	11.5	55.0	46.8	321	319	1.70	1.54	0.624	0.610
Switzerland	10.9	51.2	45.9	–	–	1.57	–	0.584	–
United Kingdom	11.5	55.0	35.9	293	283	1.65	1.39	0.620	0.596
ECA (country average)	**10.1**	**40.2**	**22.8**	**292**	**297**	**1.18**	**1.16**	**0.520**	**0.540**
ECA (population-weighted average)	**10.4**	**42.4**	**26.2**	**288**	**289**	**1.25**	**1.13**	**0.539**	**0.538**

Sources: Attainment data were calculated from the *European* Union Statistics on Income and Living Conditions and household surveys. Learning-adjusted years of basic education (LAYS) were obtained from the HCI database. Skill proficiency calculated from PIAAC and STEP surveys.
Note: For the average standardized quality score for higher education, the quality scores from each of the six university rankings (the Times Higher Education, the Quacquarelly Symonds, Academic Ranking of World Universities, the Center for World University Rankings, the U.S. News Global Universities Ranking, and U-Multirank) are first standardized to a global mean of 0 and a standard deviation of 1 and then averaged for every country. For presentational purposes, this value is then rescaled to range from 0 to 100. A value of 0 for the quality measure implies that no university in that country appears in any of the six university rankings. Skill proficiency in literacy and numeracy was calculated as the average score in each domain for individuals age 30-34 with a tertiary degree. ECA-HCI = Europe and Central Asia extension of the HCI.
- Not available.
a. Based on population age 25 and older.
b. Based on population 25–34.

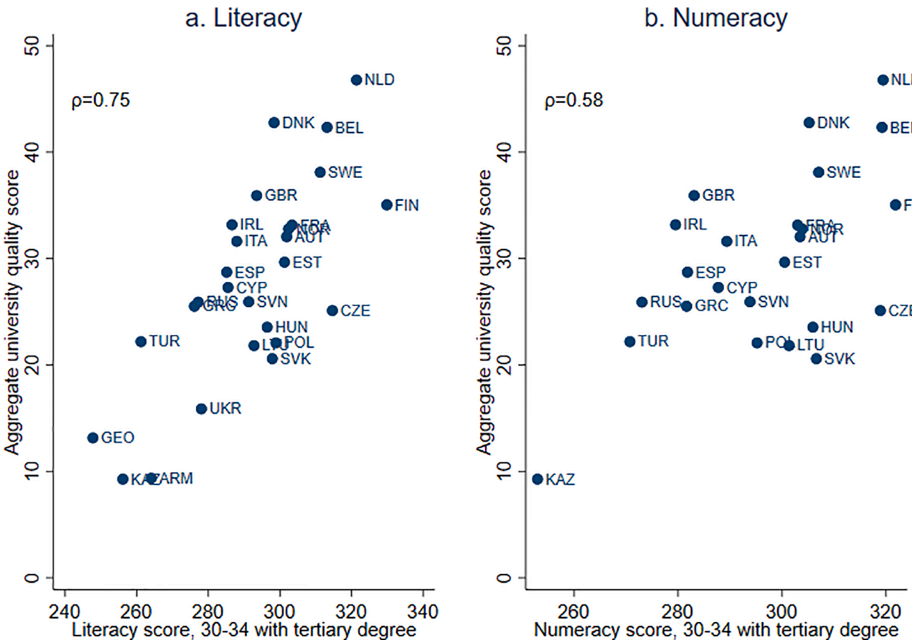

Figure 3. – Correlation between aggregate university quality score and skill proficiency
Note: This graph plots, for every country with available data, the aggregate university quality score (vertical axis) and the literacy score (horizontal axis, panel a) and numeracy score (horizontal axis, panel b). See Appendix A for a detailed methodology of the aggregate university quality score. Literacy and numeracy scores are from PIAAC and STEP surveys, and the country average for individuals age 30 to 34 with a tertiary degree is plotted.

rankings, and 108 are present in all four. Table 1 summarizes the values of β and m (the implied productivity of a "zero-quality" institution) that arise from the econometric analysis detailed in Appendix A.

To estimate the ECA-HCI, we use the values estimated from the use of the aggregate quality score in the extended sample (Table 5, column 10). These values can be understood as a conservative estimate of the productivity effects of quality, as the estimates from the sample of universities present in the six rankings (Table 5, column 11) imply a larger effect. The parameters are derived from the implied differences in the wages of graduates of a low-quality university compared with those of a high-quality university in the United States. This implied wage differential may be even higher when comparing a low-quality university in a given country with a high-quality university in another country. Interpretation of the results emerging from the use of this quality-adjustment factor needs to take these limitations into account.

2.2.3. Comparison between skill-based and input-based quality scores

The correlation between the skill-based quality scores and the input-based quality scores is heterogeneous – it is particularly higher for literacy scores than for numeracy scores (see Fig. 3). This suggests that, at a country level, an input-based quality adjustment is a better proxy for the proficiency in literacy of university graduates than for the proficiency in numeracy. Given that, at the individual level, the correlation of literacy and numeracy skills is very high (above 0.87 as reported by Hanushek et al., 2015), the difference at the country level is suggestive of a compositional effect in the field of study – namely that an input-based quality adjustment does not account for differences in field of study choices between countries. This is partly expected, as the field of study choice is an output rather than an input in the educational process. Also, out of the six university rankings used to estimate the input-based quality score, only one includes the focus on science, technology, engineering in mathematics (STEM) -probably an indicator of the quality of

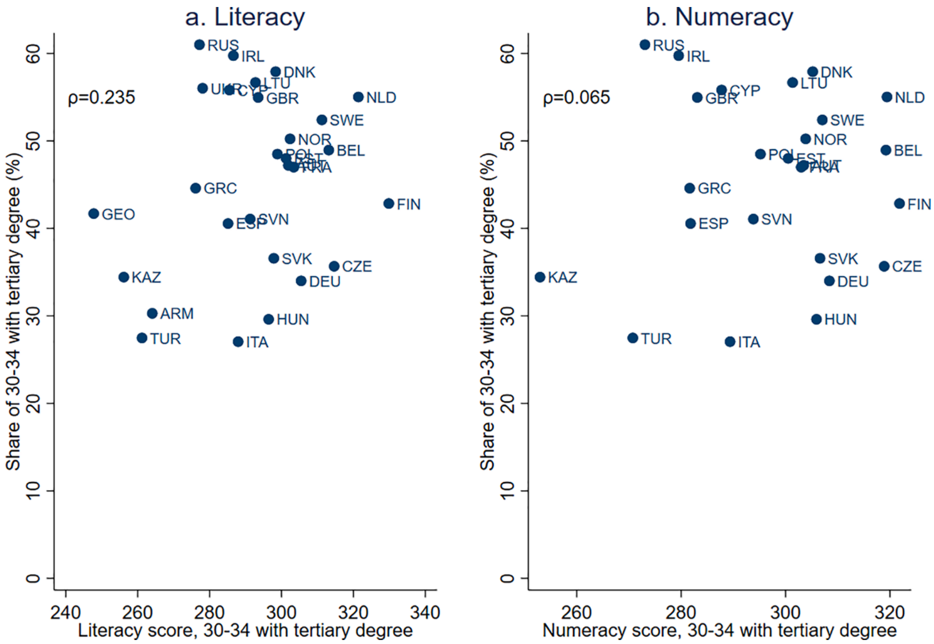

Figure 4. Tertiary attainment and skill proficiency

Note: This graph plots, for every country with available data, the share of adults age 30-34 with a tertiary degree (vertical axis) and the literacy score (horizontal axis, panel a) and numeracy score (horizontal axis, panel b). Literacy and numeracy scores are from PIAAC and STEP surveys, and the country average for individuals age 30 to 34 with a tertiary degree is plotted.

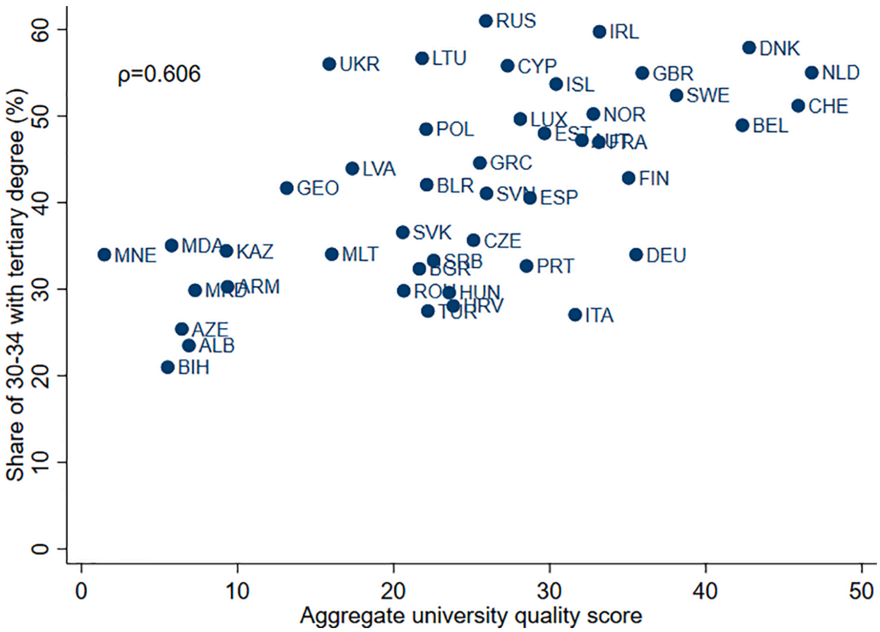

Figure 5. tertiary attainment and university quality score

Note: This graph plots, for every country, the share of adults age 30-34 with a tertiary degree (vertical axis) and the aggregate university quality score (horizontal axis). See Appendix A for a detailed methodology of the aggregate university quality score.

training in numeracy skills- as a component. However, as shown later, the difference in country-level productivity terms between a skill-based adjustment and an input-based adjustment is very small, implying that differences in the field of study choices, while meaningful at the individual level, may not necessarily translate into significant productivity differences across countries, where overall educational attainment is a more relevant factor.

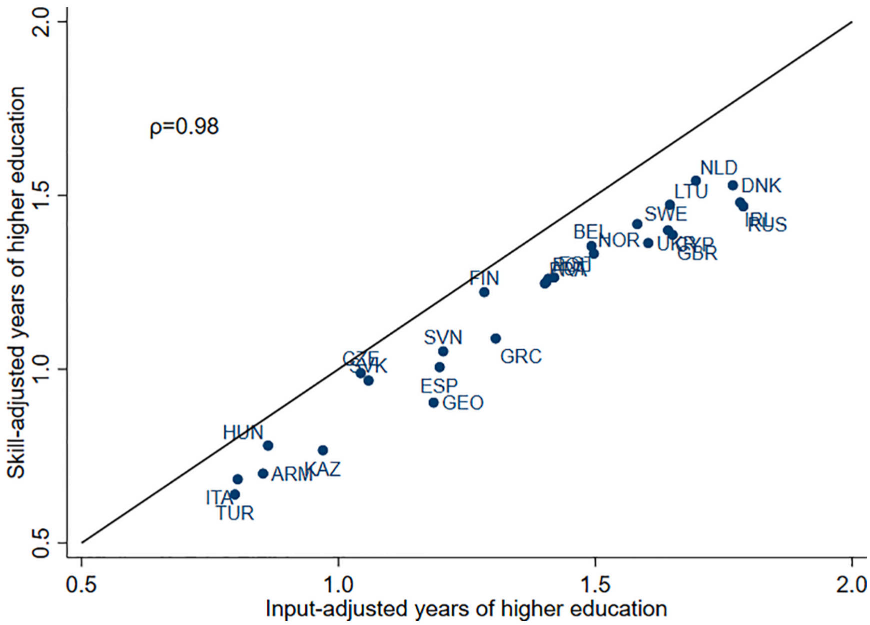

Figure 6. Correlation between skill-based quality-adjusted and input-based quality-adjusted years of higher education
Note: This graph plots, for every country with available data, the skill-based quality adjusted years of higher education (vertical axis) and the input-based quality adjusted years of higher education (horizontal axis).

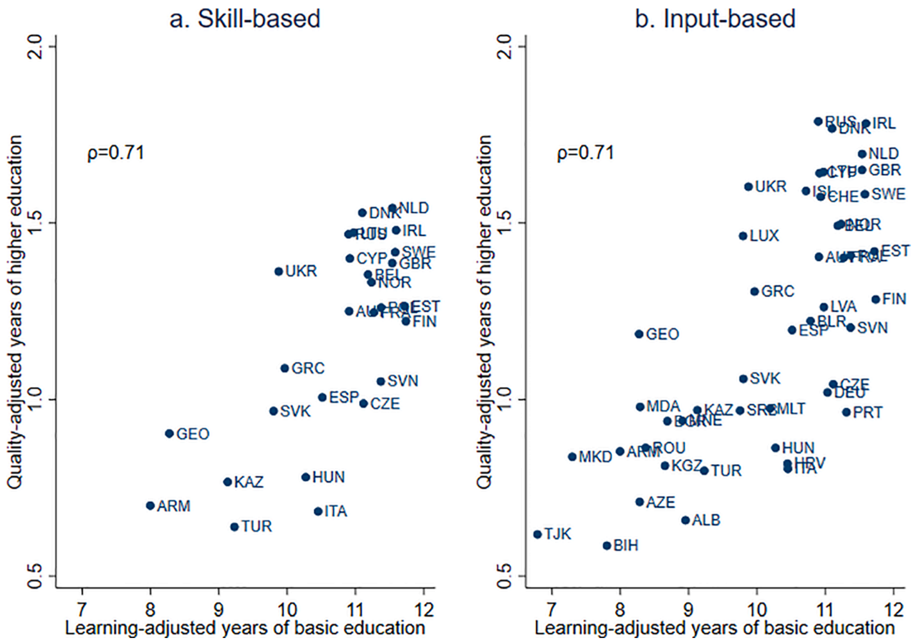

Figure 7. Quality adjusted years of higher education and learning adjusted years of basic education
Note: This graph plots, for every country with available data, the learning-adjusted years of basic education (vertical axis) and the skill-based quality-adjusted years of higher education (horizontal axis, panel a) and the input-based quality-adjusted years of higher education (horizontal axis, panel b).

2.3. Quality-adjusted years of higher education

The measure of quality-adjusted years of higher education brings together an indicator of quantity and an indicator of quality. Fig. 4 presents the correlation between our preferred measure of quantity -tertiary degree attainment at age 30-34- and the first measure of quality -skill proficiency in literacy and numeracy among tertiary degree graduates at age 30-34. This correlation is only

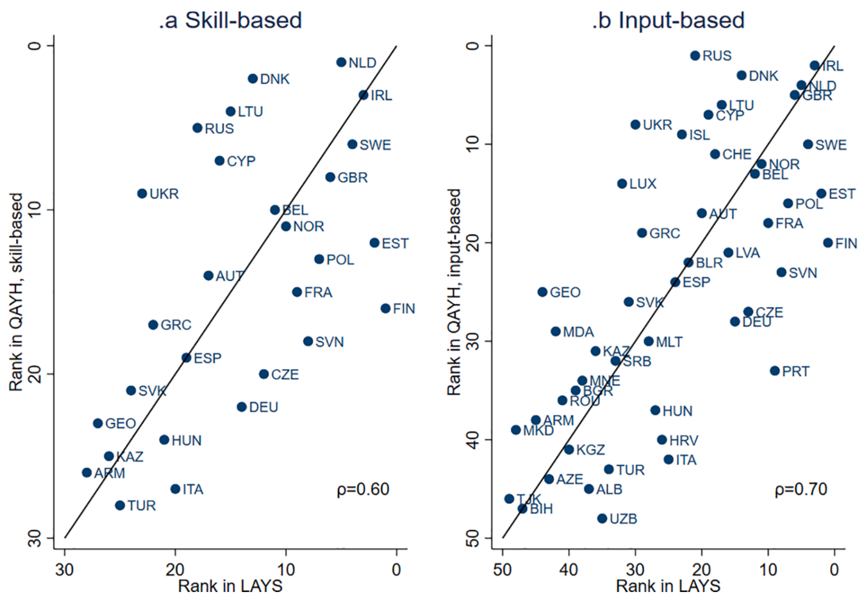

Figure 8. Correlation between the ranks quality-adjusted years of higher education and learning-adjusted years of basic education

Note: This graph plots each country's rank based on their value of quality-adjusted years of higher education (skill-based, vertical axis in panel a; input-based, vertical axis in panel b) and on their value of learning-adjusted years of basic education (horizontal axis, both panels).

possible for a subset of 27 countries in Europe and Central Asia for which both measures are available. The correlation between quantity and quality is particularly low. Some countries like Ireland, Russia and Ukraine, appear to have very high levels of attainment but below average levels of skill proficiency. Other countries, like Finland and the Czech Republic appear to have high levels of skill proficiency among tertiary degree graduates but below average levels of attainment. Fig. 5 presents the correlation between tertiary attainment and the second measure of quality – input-based, university quality-, which is available for 45 countries in Europe and Central Asia. The correlation between quantity and quality in this analysis is higher but there is still considerable heterogeneity. Just as in the case of skill proficiency, countries like Russia or Ukraine combine very high levels of attainment with below average quality levels. Evidence from labor market outcomes of university graduates in Ukraine suggests that, indeed, the higher education system in that country is producing a very large number of graduates with poor skills, indicating overall poor quality of universities (Kupets, 2016). Overall, these correlations show that tertiary education may be suffering from the same kind of pattern that basic education is going through at the global level – namely, that attending an educational institution does not imply learning valuable knowledge. To put it in the terms of Pritchett (2013), "schooling (at the tertiary level) is not learning".

The detailed calculation formula for the skill-based quality-adjusted years of higher education (*QAYH*) is as follows:

$$QAYH_C^S = Tertiary\ attainment_c^{age\ 30-34} \times 3.5 \times \left(\frac{Literacy_c^{age\ 30-34}}{400} + \frac{Numeracy_c^{age\ 30-34}}{400}\right)\frac{1}{2}$$

The detailed calculation formula for the input-based quality-adjusted years of higher education (*QAYH*) is as follows:

$$QAYH_c^U = Tertiary\ attainment_c^{age\ 30-34} \times 3.5 \times 0.787 \times e^{0.0024 \times Q_c} \tag{9}$$

where *Q* is the aggregate quality score for higher education for country *c*.

The correlation between the skill-based and input-based QAYH is very high ($\rho = 0.98$) when computed for countries for which both measures are available, the main difference being a constant value (Fig. 6). The average skill-based QAYH is 1.17 years, while the average input-based QAYH is 1.34 years. This difference reflects that, on average, countries are slightly closer to the high-quality benchmark in the input-quality dimension than in the skills-quality dimension.

QAYH, both in the skill-based version as in the input-based version, correlate positively with learning-adjusted years of basic education (Fig. 7). There is some dispersion, however, as the comparison of ranks based on both education outcomes shows (Fig. 8). For instance, Denmark and the Czech Republic have almost the same level of learning-adjusted years of basic education (about 11.1) but very different levels of QAYH (1.76 for Denmark and 1.04 for the Czech Republic in the input-based version; 1.53 for Denmark and 0.99 for the Czech Republic in the skill-based version). Armenia and Italy have similar levels of QAYH (between 0.68 and 0.69 in the skill-based version and between 0.80 and 0.8 in the input-based version) but very different levels of learning-adjusted years of basic education (8 for Armenia and 10.5 for Italy). These patterns suggest that the factors driving quality in basic and higher education at the country level may operate somewhat independently.

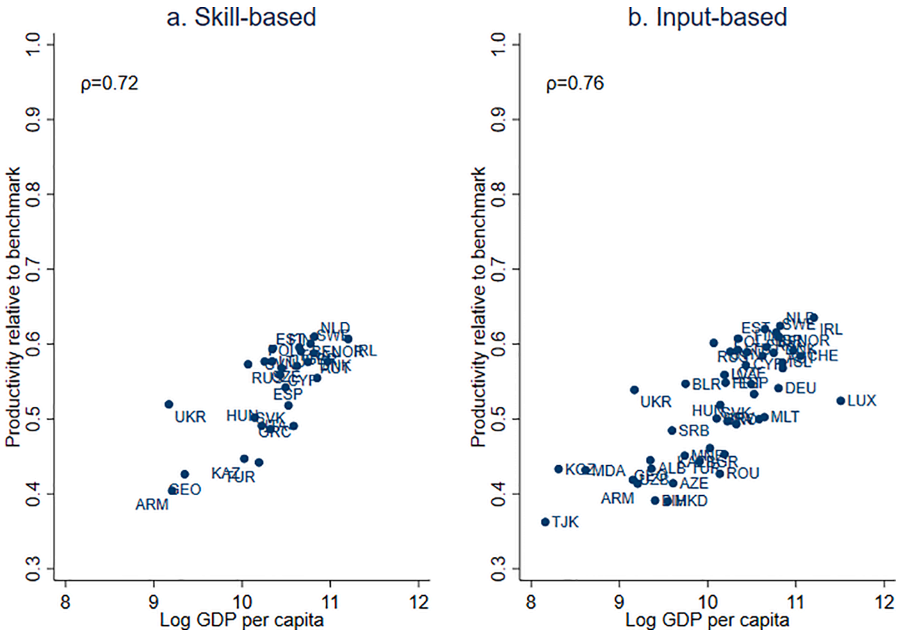

Figure 9. Contribution of education to relative productivity (ECA-HCI)
Note: This graph plots, for every country with available data, the value of the education component of the ECA-HCI expressed as a ratio with respect to the full-education productivity benchmark (vertical axis) and the log of GDP per capita at PPP in 2019 (horizontal axis). Panel *a* plots the value of the skill-based education component and panel *b* plots the value of the input-based education component.

2.4. Contribution of education to relative productivity in the ECA-HCI

To calculate the education component of the ECA-HCI, we need to establish the returns to one additional year of tertiary education. We rely on the evidence presented by Montenegro and Patrinos (2014), who suggest that an average return of an additional year of tertiary education is 0.152. For basic education, as stated before, we will rely on the same productivity parameter as the original HCI – a value of 0.08 for any additional year of basic education. The benchmarks for full education are set at 14 years of basic education and 3.5 years of higher education. We present to estimates of the education component, one based on a skill-based quality adjustment of higher education, available only for a set of 27 countries, and a second one based on an input-based quality adjustment, available for the full set of 45 countries in the region. Country and subregion estimates are presented in Table 6.

Fig. 9 plots the education component of the ECA-HCI estimated by both quality adjustment measures. The distance between a given value and 1 indicates the productivity lost as a result of the average level of education falling short of the benchmark. For both types of quality adjustment there is a positive association between a country's income level and the contribution of education to relative productivity, although the association is looser at lower income levels. The dispersion in the education component by income levels suggests that countries should not expect to see better quality of higher education just as a result of income growth.

How different are the values of the education component in the ECA-HCI and the original HCI? By design, the value corresponding to the ECA-HCI is systematically lower than the value corresponding to the original HCI, as the ECA-HCI includes an additional term accounting for differences in higher education. The correlation between the two values is positive and strong -about 0.96 for both the skill-based and input-based ECA-HCI -, also by design, as the education component of the ECA-HCI is an augmentation of the same component of the HCI. There is some re-ranking across countries. Serbia and Luxembourg, for instance, have almost the same value in the original version of the HCI, but in the ECA-HCI (input-based), Luxembourg's value is higher than Serbia's, because of Luxembourg's considerably higher level of tertiary attainment (50% versus 33%), and a higher quality of tertiary education (the average standardized quality score for Luxembourg's universities is 28.0 versus 22.6 for Serbian universities).

These figures suggest that good indicators of basic education, as captured in the original HCI, do not necessarily translate into good indicators of tertiary education. In some cases, indicators of relatively poor outcomes of basic education are partly compensated by better outcomes in higher education. For example, the education component of the original HCI is higher for Spain than for Ukraine. The level of tertiary attainment is very high in Ukraine, where 56% of people 30–34 hold a tertiary degree, compared with 40% in Spain. For this reason, the Ukrainian value of the education component of the ECA-HCI is almost the same as Spain's (0.518 and 0.519 respectively in the skill-based version; 0.533 and 0.538 respectively in the input-based version), even though the skill proficiency of university graduates and the average quality score of universities is lower in Ukraine than in Spain. From a productivity perspective, then, both countries show a similar gap with respect to the benchmark. Closing that gap, however, may involve different policy strategies for each country – one focusing on the extensive margin of education, like extending enrollment, the other focusing on the intensive margin, like improving quality.

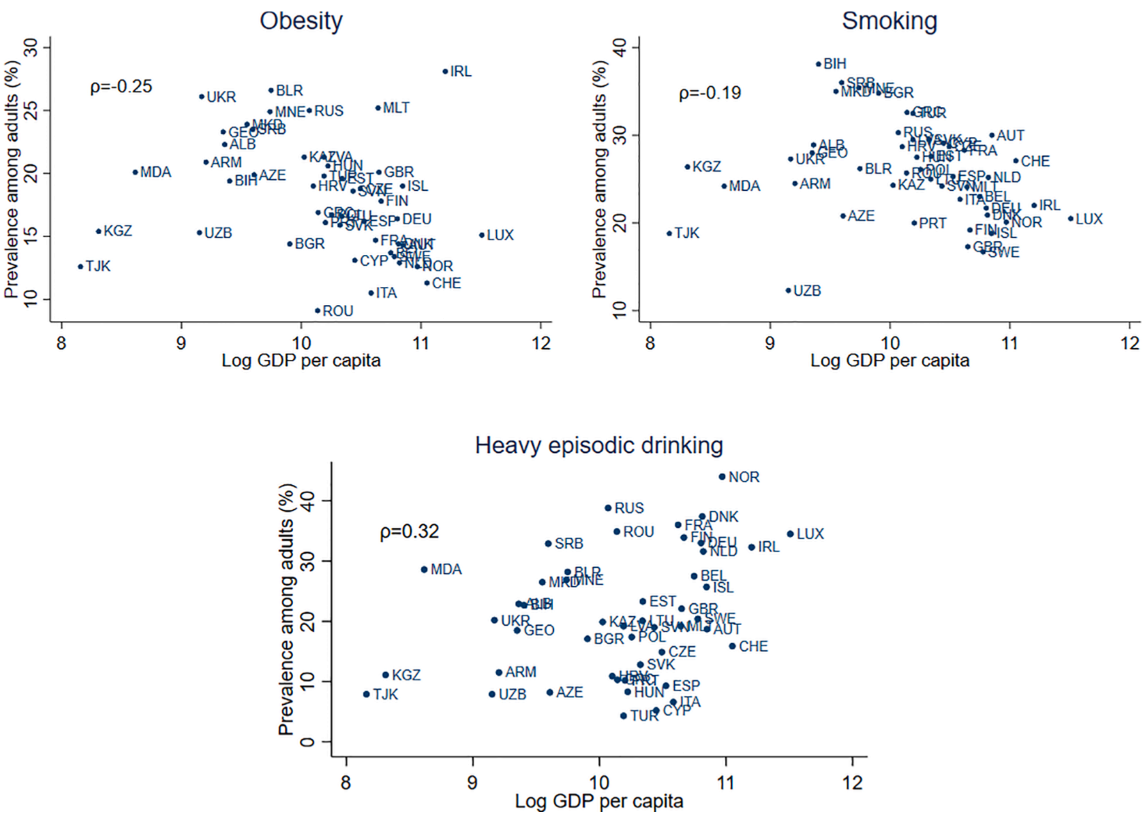

Figure 10. Prevalence of health risk factors among adult population
Note: This graph plots, for every country, the log of GDP per capita at PPP in 2019 (horizontal axis) and the prevalence among adults of three different health risk factors (obesity in panel a, smoking in panel b, heavy episodic drinking in panel c). *Sources:* European Health Interview Survey 2014 and World Health Organization.

3. Health component

The health component of the HCI seeks to measure the productivity losses associated with poor health that a child born today will face later in life as an adult. The original HCI calculates this component based on two variables: the child stunting rate and the adult survival rate (the chance that a 15-year-old survives to age 60). These variables are understood to be good proxies for unobserved latent health status in a global context. Their effects on productivity are measured by the returns to adult height.

The ECA-HCI takes a different approach. It starts by assuming that good health means the absence of disease and bad health means the presence of disease. To measure latent health status, the ECA-HCI focuses on the factors that may cause disease. A low prevalence of these risk factors implies a lower disease burden; a high prevalence could imply a higher disease burden. The risk factors that are relevant as indirect measures of latent health status depend on the types of disease prevalent in each context. Smith and Nguyen (2013) show that in Europe and Central Asia, cardiovascular disease, followed by external causes (mainly alcohol-related road traffic injuries), explains most of the differences in adult life expectancy. Data from the COVID-19 pandemic also show that people with underlying cardiovascular conditions have a higher mortality rate than people without them (Wu and McGoogan 2020; Zhou and others 2020). In view of these findings, the ECA-HCI uses the prevalence of three health risk factors associated with cardiovascular disease: obesity, tobacco smoking, and heavy alcohol consumption. The higher the prevalence of these risk factors, the higher the probability of disease and the worse the health status. The prevalence of these risk factors increases the probability of suffering from noncommunicable diseases and increases the mortality and morbidity consequences of some infectious diseases like COVID-19. The health benchmark in the ECA-HCI with which countries are compared is zero prevalence of obesity, smoking, and heavy drinking.

The impact on productivity of specific health conditions is difficult to estimate. There is more evidence on the productivity effects associated with the risk factors behind such health conditions. The literature has quantified the effects on productivity of obesity, tobacco smoking, and heavy drinking, making it possible to incorporate their prevalence directly into the ECA-HCI without the intermediating factor of adult height, as in the original version of the index.

Focusing only on risk factors has its limitations, however. Between risk factors and morbidity lies a mediating institutional factor: health care systems. The capacity of health care systems to manage the consequences of increased risk factors—and the diseases associated with them—ultimately determines whether that increased risk ends in increased morbidity and, eventually, mortality. Good health care systems strongly alleviate the morbidity and mortality consequences of the increased prevalence of risk factors.

To account for the effects of health care systems, the model uses a health outcome measure as a proxy for latent health status—the child stunting and adult survival rates used in the original HCI. The health component of the ECA-HCI uses the average of a risk factor–based proxy of health status and an outcome-based proxy. The productivity effects of child stunting and adult survival rates are retained, as in the original HCI. The health component of the ECA-HCI has the following basic formulation:

$$ECA - HCI_{Health} = e^{\frac{\gamma_{RF}(RF-RF^*)+\gamma_O(O-O^*)}{2}} \tag{10}$$

where γ_{RF} is the productivity effect associated to the prevalence of risk factors *RF; RF** is the benchmark rate of zero prevalence of risk factors; and γ_O is the productivity effect of health outcomes *O*, with the benchmark of "full" health outcomes being *O**. For risk factors, the ECA-HCI uses the share of non-obese adults (*NOB*), the share of nonsmokers among adults (*NSM*), and the share of adults not reporting heavy drinking (*NAL*). The productivity effects of these risk factors (γ_{OB}, γ_{SM}, γ_{AL}) are assumed to be additive.[6] For health outcomes, the ECA-HCI uses the adult survival rate (*ASR*) and the share of children not stunted (*NSTNT*). As in the original HCI, these rates are intended to proxy the same variable: latent health status. Their productivity effects (γ_{ASR}, γ_{STNT}) are therefore averaged. The equation for the health component is the following:

$$ECA - HCI_{Health} = e^{\frac{[\gamma_{OB}(NOB-1)+\gamma_{SM}(NSM-1)+\gamma_{AL}(NAL-1)]+[\gamma_{ASR}(ASR-1)+\gamma_{STNT}(NSTNT-1)]/2}{2}} \tag{11}$$

The values of γ_{STNT} and γ_{ASR}, the productivity effects associated with child stunting the adult survival rate, are kept as in the original HCI. They are derived from the correlation of these rates with adult height, for which the literature provides reliable microeconometric estimations of productivity. These values are assumed to be 0.35 for γ_{STNT} and 0.65 for γ_{ASR} (for more details on the estimation of these parameters see Kraay, 2019). Adult survival rates are widely available; child stunting rates are available only for a few countries in the region. For countries for which estimates of child stunting are not available, only the adult survival rate is used to estimate the outcome-based productivity proxy.

A literature review was carried out to obtain estimates of the productivity effects of the prevalence of the risk factors (see appendix B). The median values for all the average effects found was chosen as the parameter for use in the ECA-HCI. These values are 0.0993 for obesity (γ_{OB}), 0.096 for smoking (γ_{SM}), and 0.1995 for heavy drinking (γ_{AL}). These values represent the negative productivity effects associated with each risk factor. The prevalence of the three health risk factors among the adult population across Europe and Central Asia is plotted in Fig. 10 in comparison with country income levels.

Country and subregional estimates of the health component are presented in Table 3. Fig. 11 plots the values of the health component with respect to countries' income level. In contrast to the education component, there is no clear correlation between income and the contribution of health status to relative productivity.

Fig. 12 compares the health component estimated by the original HCI and the ECA-HCI. For most countries, the value of the health component in the ECA-HCI is lower than the value in the original index—only eight countries have a higher value in the ECA-HCI. The main reason for this result is that the productivity gap emerging from the prevalence of adult health risk factors is larger than the one emerging from the adult survival and child stunting rates, the sole indicators used for almost all the countries in the region in the original index. These results show that estimates of productivity lost to bad health in Europe and Central Asia can be underestimated if the focus is on indicators of child health or proxies of it, as the burden of disease in the region is skewed towards pathologies that affect adults.

The health component of the ECA-HCI is an average of the productivity gap of risk factors and health outcomes. It takes into account that countries with similar prevalence of risk factors—such as heavy episodic drinking in the Nordic countries, the Russian Federation, and Ukraine—can have very different adult mortality rates because of differences in the capacity of health care systems to manage the consequences of those risk factors.

4. Estimation of the ECA-HCI

The ECA-HCI is the product of three components:

$$ECA - HCI = Survival \times Education \times Health$$

The three components are defined as follows:

$$Survival \equiv \frac{1 - Under\ 5\ Mortality\ rate}{1}$$

$$Education \equiv e^{0.08(LAYS-14)+0.152(QAYH-3.5)}$$

$$Health \equiv e^{\frac{[0.0993(NOB-1)+0.096(NSM-1)+0.1995(NAL-1)]+[0.65(ASR-1)+0.35(NSTNT-1)]/2}{2}}.$$

[6] Perfectly additive productivity effects imply that the productivity effect of smoking and obesity (combined) is simply the summation of the productivity effect of smoking and the productivity effect of obesity. This figure can be understood as an upper-bound estimation of the combined productivity effects of risk factors.

Table 3
Health component of the Europe and Central Asia extension of the Human Capital Index (ECA-HCI)

Subregion/country	Obese adult population (%)	Heavy episodic drinkers (%)	Current smokers (%)	Adult survival rate	Children under 5 not stunted (%)	Health component, ECA-HCI
Central Asia	**16.6**	**11.5**	**17.8**	**0.859**	**88.9**	**0.941**
Kazakhstan	21.3	19.9	24.3	0.845	92.0	0.928
Kyrgyz Republic	15.4	11.1	26.4	0.849	88.2	0.936
Tajikistan	12.6	7.9	18.8	0.871	82.5	0.942
Uzbekistan	15.3	7.9	12.3	0.866	89.2	0.949
Central Europe and Baltic Countries	**15.9**	**19.3**	**27.3**	**0.890**	–	**0.928**
Bulgaria	14.4	17.1	34.8	0.866	93.0	0.934
Croatia	19.0	10.9	28.7	0.917	–	0.941
Czech Republic	18.8	14.9	28.7	0.922	–	0.939
Estonia	19.6	23.3	27.6	0.897	–	0.924
Hungary	20.6	8.3	27.5	0.880	–	0.932
Latvia	21.3	19.2	29.5	0.844	–	0.910
Lithuania	16.6	20.1	25.0	0.844	–	0.913
Poland	16.7	17.4	26.1	0.894	–	0.930
Romania	9.1	34.9	25.7	0.878	–	0.913
Slovak Republic	15.9	12.8	29.5	0.898	–	0.934
Slovenia	18.6	19.0	24.2	0.935	–	0.941
Eastern Europe	**25.8**	**22.0**	**26.9**	**0.822**	–	**0.901**
Belarus	26.6	28.2	26.2	0.853	93.6	0.903
Moldova	20.1	28.6	24.2	0.836	–	0.921
Ukraine	26.1	20.2	27.3	0.815	–	0.899
Northern Europe	**14.4**	**31.5**	**18.8**	**0.941**	–	**0.936**
Denmark	14.4	37.4	20.9	0.932	–	0.926
Finland	17.8	33.9	19.2	0.930	–	0.928
Iceland	19.0	25.7	18.8	0.955	–	0.943
Norway	12.6	44.0	20.1	0.945	–	0.925
Sweden	13.4	20.4	16.7	0.950	–	0.950
Russian Federation	**25.0**	**38.8**	**30.3**	**0.804**	–	**0.879**
South Caucasus	**20.8**	**11.1**	**23.1**	**0.876**	–	**0.934**
Armenia	20.9	11.5	24.5	0.886	90.6	0.941
Azerbaijan	19.9	8.2	20.8	0.882	82.2	0.939
Georgia	23.3	18.5	28.0	0.853	–	0.913
Southern Europe	**13.6**	**8.2**	**24.3**	**0.947**	–	**0.957**
Cyprus	13.1	5.2	29.1	0.952	–	0.960
Greece	16.9	10.3	32.6	0.933	–	0.945
Italy	10.5	6.6	22.7	0.953	–	0.963
Malta	25.2	19.2	24.1	0.951	–	0.943
Portugal	16.1	10.2	20.0	0.933	–	0.952
Spain	16.2	9.3	25.3	0.946	–	0.954
Turkey	**19.8**	**4.3**	**32.5**	**0.911**	**94.0**	**0.952**
Western Balkans	**22.5**	**27.9**	**35.0**	**0.906**	**92.4**	**0.925**
Albania	22.3	22.9	28.9	0.929	88.7	0.933
Bosnia and Herzegovina	19.4	22.7	38.1	0.914	91.1	0.930
Kosovo	–	–	–	0.906	–	–
Montenegro	24.9	26.9	35.4	0.906	90.6	0.923
North Macedonia	23.9	26.5	35.0	0.909	95.1	0.928
Serbia	23.5	32.9	36.0	0.893	94.0	0.919
Western Europe	**16.5**	**29.7**	**23.0**	**0.933**	–	**0.932**
Austria	14.3	18.7	30.0	0.937	–	0.941
Belgium	13.7	27.5	23.0	0.931	–	0.935
Germany	14.7	36.0	28.3	0.926	–	0.922
France	16.4	33.0	21.7	0.931	–	0.929
Ireland	28.1	32.3	22.0	0.944	–	0.928
Luxembourg	15.1	34.5	20.5	0.942	–	0.932
Netherlands	12.9	31.6	25.2	0.946	–	0.935
Switzerland	11.3	15.9	27.1	0.954	–	0.952
United Kingdom	20.1	22.1	17.3	0.933	–	0.940
ECA (country average)	**18.0**	**21.1**	**25.9**	**0.904**	**90.3**	**0.932**
ECA (population-weighted average)	**18.4**	**22.5**	**25.6**	**0.894**	**91.4**	**0.927**

Source: Data on obesity, smoking, and alcohol consumption are from the European Health Interview Survey, Health Equity and Financial Protection Indicators, and the World Health Organization. The ECA average for the share of children not stunted is calculated based on countries for which data are available only.
Note: ECA-HCI = Europe and Central Asia extension of the HCI.
- Not available.
a. Includes consumption of smokeless tobacco.

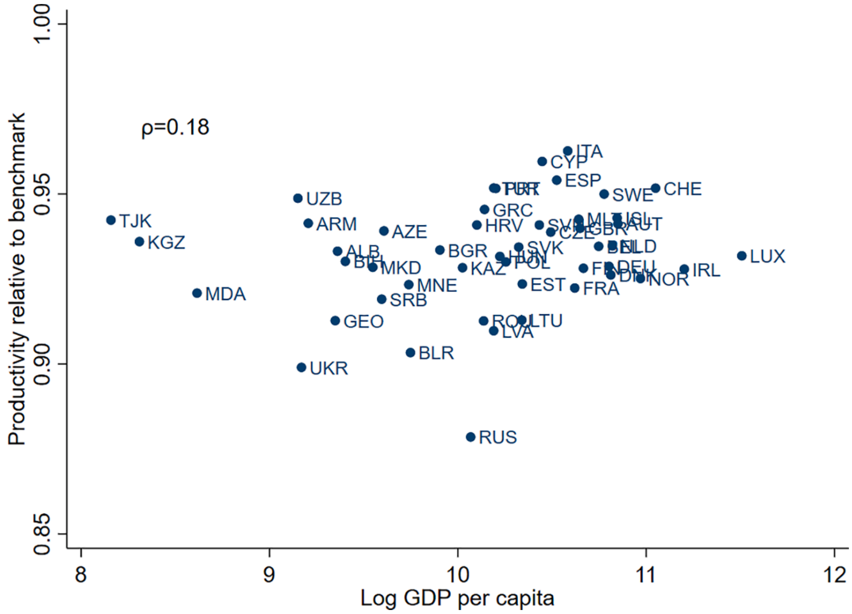

Figure 11. Contribution of health to relative productivity in Europe and Central Asia
Note: This graph plots, for every country, the value of the health component of the ECA-HCI expressed as a ratio with respect to the full-health productivity benchmark (vertical axis) and the log of GDP per capita at PPP in 2019 (horizontal axis).

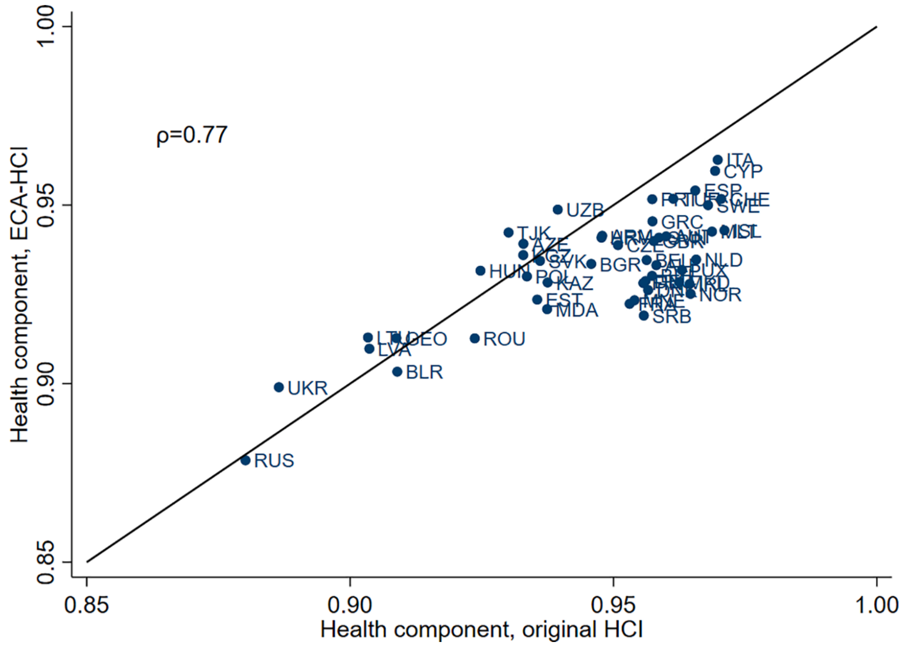

Figure 12. Health component, ECA-HCI and original HCI
Note This graph plots, for every country, the value of the health component of the ECA-HCI expressed as a ratio with respect to the full-health productivity benchmark (vertical axis) and the value of the health component of the original HCI also expressed with respect to the same benchmark (horizontal axis).

Table 4
Full estimates of the Europe and Central Asia extension of the Human Capital Index (ECA-HCI)

Subregion/country	Probability of survival to age 5	Education component		Health component	ECA-HCI	
		Input based	Skills based		Input based	Skills based
Central Asia	**0.980**	**0.424**		**0.941**	**0.391**	
Kazakhstan	0.990	0.461	0.447	0.928	0.424	0.411
Kyrgyz Republic	0.981	0.433	–	0.936	0.398	–
Tajikistan	0.965	0.362	–	0.942	0.330	–
Uzbekistan	0.979	0.419	–	0.949	0.389	–
Central Europe and Baltic countries	**0.995**	**0.526**	**0.552**	**0.928**	**0.486**	**0.512**
Bulgaria	0.993	0.443	–	0.934	0.411	–
Croatia	0.995	0.501	–	0.941	0.469	–
Czech Republic	0.997	0.547	0.542	0.939	0.511	0.507
Estonia	0.997	0.607	0.593	0.924	0.559	0.546
Hungary	0.996	0.497	0.491	0.932	0.461	0.455
Latvia	0.996	0.559	–	0.910	0.506	–
Lithuania	0.996	0.592	0.577	0.913	0.538	0.525
Poland	0.996	0.590	0.577	0.930	0.546	0.534
Romania	0.993	0.427		0.913	0.387	
Slovak Republic	0.994	0.493	0.486	0.934	0.458	0.452
Slovenia	0.998	0.572	0.558	0.941	0.537	0.524
Eastern Europe	**0.992**	**0.534**	–	**0.901**	**0.477**	–
Belarus	0.997	0.547	–	0.903	0.492	–
Moldova	0.984	0.432	–	0.921	0.391	–
Ukraine	0.991	0.539	0.520	0.899	0.480	0.463
Northern Europe	**0.997**	**0.605**	**0.591**	**0.936**	**0.564**	**0.551**
Denmark	0.996	0.609	0.588	0.926	0.562	0.542
Finland	0.998	0.596	0.590	0.928	0.552	0.547
Iceland	0.998	0.575	–	0.943	0.541	–
Norway	0.997	0.591	0.577	0.925	0.545	0.532
Sweden	0.997	0.616	0.600	0.950	0.583	0.569
Russian Federation	**0.993**	**0.601**	**0.573**	**0.879**	**0.525**	**0.500**
South Caucasus	**0.983**	**0.421**	**0.416**	**0.934**	**0.386**	**0.381**
Armenia	0.988	0.414	0.404	0.941	0.385	0.376
Azerbaijan	0.978	0.414		0.939	0.381	
Georgia	0.990	0.445	0.426	0.913	0.402	0.385
Southern Europe	**0.997**	**0.518**	**0.503**	**0.957**	**0.494**	**0.480**
Cyprus	0.998	0.589	0.568	0.960	0.564	0.544
Greece	0.996	0.519	0.502	0.945	0.488	0.472
Italy	0.997	0.500	0.491	0.963	0.480	0.471
Malta	0.993	0.502		0.943	0.470	
Portugal	0.996	0.548	–	0.952	0.520	–
Spain	0.997	0.533	0.518	0.954	0.507	0.493
Turkey	**0.989**	**0.453**	**0.442**	**0.952**	**0.426**	**0.416**
Western Balkans	**0.993**	**0.442**	–	**0.925**	**0.406**	–
Albania	0.991	0.434	–	0.933	0.401	–
Bosnia and Herzegovina	0.994	0.391	–	0.930	0.362	–
Kosovo	0.985	–	–	–	–	–
Montenegro	0.997	0.451	–	0.923	0.415	–
North Macedonia	0.990	0.390	–	0.928	0.359	–
Serbia	0.994	0.485	–	0.919	0.443	–
Western Europe	**0.996**	**0.583**	**0.568**	**0.932**	**0.541**	**0.527**
Austria	0.996	0.568	0.555	0.941	0.533	0.520
Belgium	0.996	0.588	0.576	0.935	0.548	0.536
France	0.996	0.584	0.571	0.922	0.537	0.524
Germany	0.996	0.541	0.532	0.929	0.501	0.493
Ireland	0.996	0.635	0.607	0.928	0.587	0.561
Luxembourg	0.998	0.524	–	0.932	0.487	–
Netherlands	0.996	0.624	0.610	0.935	0.581	0.568
Switzerland	0.996	0.584	–	0.952	0.553	–
United Kingdom	0.996	0.620	0.596	0.940	0.580	0.557
ECA (country average)	**0.993**	**0.520**	**0.540**	**0.932**	**0.481**	**0.501**
ECA (population-weighted average)	**0.993**	**0.539**	**0.538**	**0.927**	**0.496**	**0.494**

Source: Authors' calculations.
Note: – Not available.

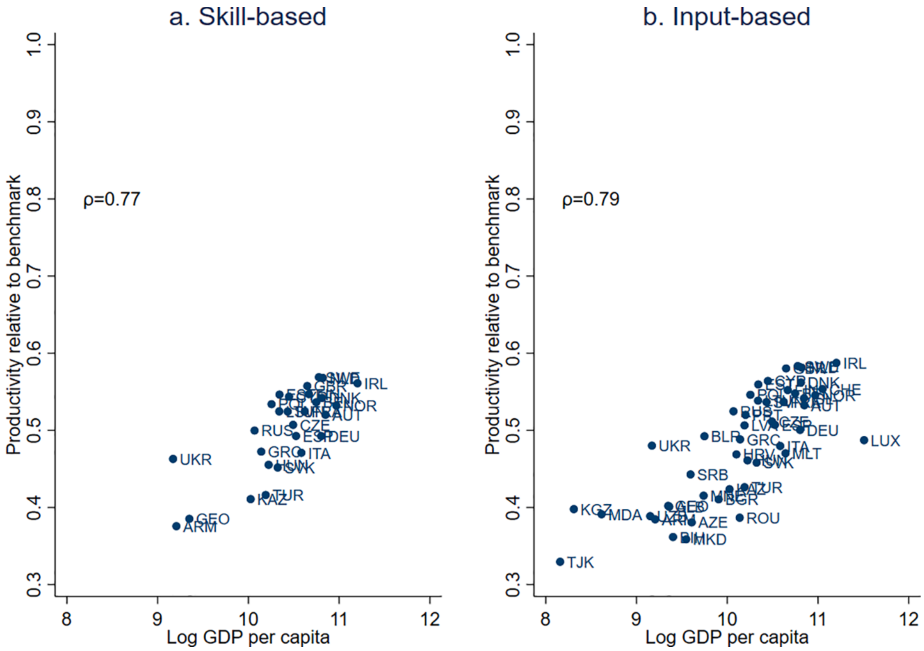

Figure 13. Estimates of ECA-HCI and country income levels
Note: This graph plots, for every country, the value of the ECA-HCI expressed as a ratio with respect to the full-health and complete education productivity benchmark (vertical axis) and the log of GDP per capita in 2019 (horizontal axis). Panel *a* plots the value of the skill-based ECA-HCI and panel *b* plots the value of the input-based ECA-HCI

The estimates of the ECA-HCI in Table 4 [7] show that countries in the region can achieve large increases in their long-run productivity if they reduce the distance between the expected educational attainment and adult health status of children born today and the benchmarks of complete education and full health. Looking at the version of the ECA-HCI with the widest coverage -the one using the input-based quality measure of higher education-, the results show that the average country has a value of 0.481, meaning that children born today in the average country in the region will be almost half as productive as they would have had they reached the benchmark of complete education and full health (14 years of basic education; 3.5 years of higher education; no obesity, tobacco smoking, or heavy drinking; no statistically significant child stunting; and 100% adult survival rate to age 60). The skill-based version of the ECA-HCI, which is available for only 27 countries in the region, has an average value of 0.501 – similar to that of the input-based version. The correlation between income levels and the ECA-HCI in its two versions is positive, as it is for the original HCI (Fig. 13).

Ireland, Sweden, and the Netherlands have the highest values (tied at about 0.58 in the input-based version of the ECA-HCI and at about 0.56 in the skill-based version), implying a long-run increase in productivity of above 70% if these countries were to close the gap to the benchmark. The country with the lowest value is Tajikistan (0.33), which would enjoy a long-run increase in productivity of about 200% if it were to close the gap. Substantial variation across subregions exists, with the highest values reported in Northern Europe and the lowest values in Central Asia and the South Caucasus. Differences in the education component explain most of the overall differences in ECA-HCI, although variations in the health component are not trivial.

Unlike in the original HCI, the correlation between the education and health components in the ECA-HCI is almost nonexistent (Fig. 14). Countries with relatively good education indicators are not necessarily those with relatively good health indicators; good performance in basic and higher education is not informative of a low prevalence of adult health risk factors and vice versa. The Russian Federation is a clear example. It has one of the region's highest values of the education component and lowest values of the health component. Belarus and Portugal have the same productivity gap when looking only at child mortality and education but bringing health to the analysis increases substantially Belarus' productivity gap vis-á-vis that of Portugal, which has systematically better adult health indicators.

The value of the ECA-HCI is consistently below that of the original HCI, because the full education benchmark of the ECA-HCI includes higher education. However, there is considerable correlation between the two values, although some re-ranking occurs (Fig. 15). Like the original HCI, the ECA-HCI is measured with some imprecision, so small differences across countries do not represent meaningful differences in education and health environments.

The weights attributed to the education and health component of the ECA-HCI result from the calibrated returns to education and health (η, ω, γ_{RF}, γ_O). The values of these returns are sourced from the academic literature. However, one could arbitrarily assume that

[7] The estimates of ECA-HCI are available for download in the journal's website. Alternatively, readers can request them to the corresponding author (Iván Torre) at itorre@worldbank.org.

Figure 14. Education and Health components of the ECA-HCI
Note: This graph plots, for every country, the value of the education component of the ECA-HCI expressed as a ratio with respect to the full-health productivity benchmark (vertical axis) and the value of the health component of the ECA-HCI also expressed with respect to the same benchmark. Panel *a* plots the value of the skill-based education component and panel *b* plots the value of the input-based education component

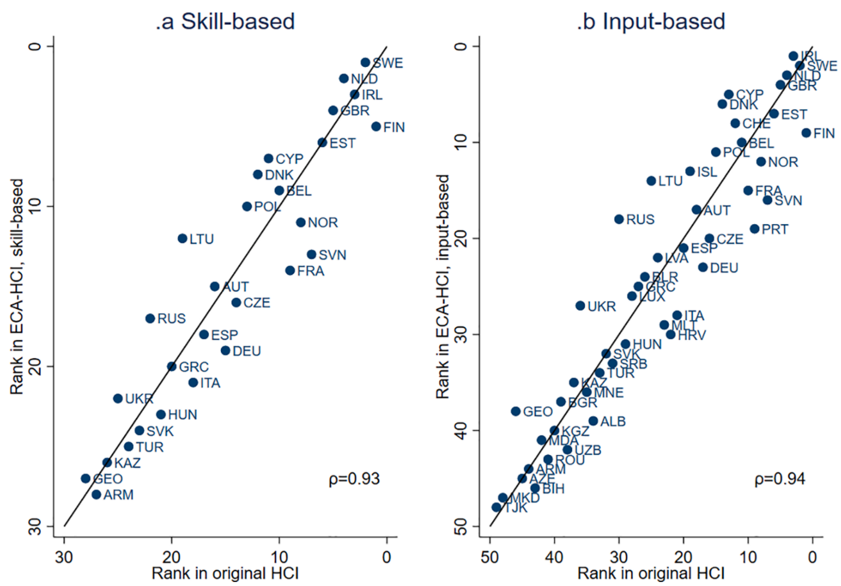

Figure 15. Correlation between the ranks of original HCI and ECA-HCI
Note: This graph plots each country's rank based on their value of the ECA-HCI (skill-based, vertical axis in panel a; input-based, vertical axis in panel b) and on their value of original HCI (horizontal axis, both panels). The rank in the original HCI is calculated only for the sample of countries which have a non-missing value in the skill-based ECA-HCI (panel a) and in the input-based ECA-HCI (panel b).

education and health should contribute equally to the productivity gap. Following Kraay (2019), this could be represented by a situation in which moving from the bottom to the top of the distribution of education outcomes in the region (a variation of 4.9 years in learning-adjusted years of basic education and of 1.44 years in quality-adjusted years of education, input-based version) should account for the same change in the productivity gap as moving from the top to the bottom of the distribution of health outcomes in the region (a variation of 19% in the prevalence of adult obesity, 25.8% in adult smoking rate, 39.7% in the heavy drinking rate and 15.1% in the adult survival rate). The correlation of this alternative estimate with the baseline one is 0.89, lower than the one reported by

Table 5
Gender-disaggregated estimates of the Europe and Central Asia extension of the Human Capital Index (ECA-HCI)

	Probability of survival to age 5		Education component Input based		Skill based		Health component		ECA-HCI Input based		Skill based	
Subregion/country	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*
Central Asia	**0.978**	**0.983**	**0.433**	**0.434**			**0.920**	**0.961**	**0.390**	**0.411**		
Kazakhstan	0.989	0.991	0.449	0.474	0.436	0.458	0.900	0.956	0.399	0.449	0.388	0.434
Kyrgyz Republic	0.979	0.983	0.424	0.442	–	–	0.909	0.962	0.378	0.418	–	–
Tajikistan	0.961	0.969	–	–	–	–	–	–	–	–	–	–
Uzbekistan	0.976	0.982	0.426	0.411	–	–	0.933	0.964	0.388	0.389	–	–
Central Europe and Baltic countries	**0.995**	**0.995**	**0.503**	**0.549**	**0.527**	**0.577**	**0.909**	**0.957**	**0.456**	**0.524**	**0.482**	**0.552**
Bulgaria	0.992	0.994	0.431	0.457	–	–	0.914	0.953	0.391	0.432	–	–
Croatia	0.995	0.996	0.479	0.525	–	–	0.921	0.961	0.439	0.502	–	–
Czech Republic	0.996	0.997	0.523	0.570	0.520	0.565	0.921	0.957	0.480	0.544	0.477	0.539
Estonia	0.997	0.998	0.579	0.641	0.568	0.623	0.894	0.954	0.516	0.610	0.506	0.593
Hungary	0.995	0.996	0.487	0.509	0.482	0.501	0.910	0.953	0.441	0.483	0.436	0.476
Latvia	0.996	0.996	0.521	0.600	–	–	0.873	0.945	0.453	0.565	–	–
Lithuania	0.996	0.996	0.562	0.625	0.549	0.606	0.873	0.952	0.488	0.592	0.478	0.575
Poland	0.995	0.996	0.557	0.622	0.547	0.605	0.923	0.964	0.512	0.597	0.503	0.581
Romania	0.992	0.993	0.418	0.436	–	–	0.877	0.949	0.364	0.411	–	–
Slovak Republic	0.994	0.995	0.470	0.518	0.465	0.509	0.911	0.958	0.426	0.494	0.421	0.485
Slovenia	0.998	0.998	0.533	0.614	0.524	0.596	0.923	0.959	0.491	0.588	0.483	0.571
Eastern Europe	**0.991**	**0.993**	**0.517**	**0.551**	–	–	**0.860**	**0.942**	**0.441**	**0.515**	–	–
Belarus	0.996	0.997	0.534	0.560	–	–	0.863	0.943	0.459	0.526	–	–
Moldova	0.982	0.986	0.419	0.443	–	–	0.888	0.953	0.366	0.416	–	–
Ukraine	0.990	0.992	0.521	0.558	0.504	0.536	0.857	0.940	0.443	0.520	0.428	0.500
Northern Europe	**0.997**	**0.997**	**0.570**	**0.643**	**0.559**	**0.625**	**0.921**	**0.950**	**0.523**	**0.610**	**0.513**	**0.593**
Denmark	0.995	0.996	0.575	0.647	0.558	0.620	0.912	0.940	0.522	0.606	0.507	0.581
Finland	0.998	0.998	0.553	0.644	0.549	0.636	0.907	0.949	0.500	0.611	0.497	0.603
Iceland	0.998	0.998	0.536	0.621	–	–	0.934	0.953	0.500	0.591	–	–
Norway	0.997	0.998	0.557	0.630	0.545	0.611	0.911	0.939	0.506	0.590	0.496	0.573
Sweden	0.997	0.998	0.584	0.648	0.572	0.630	0.939	0.962	0.546	0.622	0.535	0.604
Russian Federation	**0.992**	**0.994**	**0.582**	**0.623**	**0.557**	**0.590**	**0.840**	**0.917**	**0.485**	**0.568**	**0.464**	**0.538**
South Caucasus	**0.981**	**0.985**	**0.417**	**0.426**	**0.405**	**0.430**	**0.908**	**0.958**	**0.371**	**0.402**	**0.355**	**0.409**
Armenia	0.986	0.989	0.401	0.427	0.393	0.417	0.912	0.967	0.361	0.409	0.353	0.398
Azerbaijan	0.976	0.981	0.416	0.412	–	–	0.921	0.957	0.374	0.387	–	–
Georgia	0.989	0.991	0.431	0.461	0.414	0.440	0.871	0.954	0.371	0.436	0.356	0.417
Southern Europe	**0.997**	**0.997**	**0.503**	**0.534**	**0.490**	**0.516**	**0.945**	**0.968**	**0.473**	**0.515**	**0.462**	**0.498**
Cyprus	0.997	0.998	0.574	0.604	0.556	0.580	0.944	0.974	0.541	0.586	0.523	0.563
Greece	0.995	0.996	0.499	0.540	0.485	0.521	0.929	0.961	0.462	0.517	0.448	0.498
Italy	0.997	0.997	0.481	0.519	0.475	0.507	0.953	0.969	0.457	0.502	0.451	0.490
Malta	0.992	0.994	0.478	0.530	–	–	0.930	0.956	0.441	0.504	–	–
Portugal	0.996	0.997	0.529	0.568	–	–	0.933	0.969	0.492	0.549	–	–
Spain	0.997	0.997	0.524	0.542	0.510	0.526	0.942	0.967	0.492	0.523	0.479	0.507
Turkey	**0.989**	**0.990**	**0.453**	**0.452**	**0.442**	**0.442**	**0.939**	**0.965**	**0.421**	**0.432**	**0.410**	**0.422**
Western Balkans	**0.993**	**0.994**	**0.429**	**0.460**			**0.904**	**0.947**	**0.385**	**0.432**		
Albania	0.991	0.992	–	–	–	–	0.910	0.957	–	–	–	–
Bosnia and Herzegovina	0.994	0.995	0.378	0.405	–	–	0.910	0.951	0.341	0.384	–	–
Kosovo	0.983	0.988	–	–	–	–	–	–	–	–	–	–
Montenegro	0.997	0.998	0.443	0.458	–	–	0.904	0.943	0.400	0.431	–	–
North Macedonia	0.989	0.991	0.375	0.407	–	–	0.909	0.949	0.337	0.383	–	–
Serbia	0.994	0.995	0.469	0.502	–	–	0.897	0.941	0.418	0.470	–	–
Western Europe	**0.996**	**0.996**	**0.571**	**0.595**	**0.557**	**0.579**	**0.914**	**0.949**	**0.520**	**0.563**	**0.507**	**0.547**
Austria	0.996	0.997	0.564	0.572	0.551	0.559	0.927	0.956	0.520	0.545	0.509	0.532
Belgium	0.996	0.997	0.567	0.611	0.557	0.597	0.919	0.950	0.519	0.579	0.510	0.565
France	0.996	0.996	0.558	0.610	0.548	0.593	0.897	0.948	0.499	0.576	0.489	0.560
Germany	0.996	0.997	0.537	0.545	0.529	0.536	0.913	0.945	0.488	0.514	0.481	0.505
Ireland	0.996	0.997	0.613	0.655	0.588	0.623	0.917	0.951	0.560	0.621	0.537	0.591
Luxembourg	0.997	0.998	0.501	0.547	–	–	0.916	0.948	0.458	0.517	–	–
Netherlands	0.996	0.997	0.601	0.649	0.588	0.633	0.916	0.955	0.548	0.618	0.536	0.602
Switzerland	0.996	0.996	0.575	0.593	–	–	0.942	0.962	0.539	0.568	–	–
United Kingdom	0.995	0.996	0.615	0.625	0.592	0.599	0.927	0.952	0.568	0.592	0.546	0.568
Simple average	**0.993**	**0.994**	**0.507**	**0.545**	**0.521**	**0.559**	**0.911**	**0.954**	**0.459**	**0.517**	**0.473**	**0.531**
Population-weighted average	**0.993**	**0.994**	**0.527**	**0.556**	**0.524**	**0.551**	**0.905**	**0.950**	**0.473**	**0.524**	**0.471**	**0.520**

Source: Authors' calculations.
Note: – Not available.

Kraay (2019) but still substantially high – the difference clearly emanating from the fact that the education and health components are less correlated between countries in ECA than between countries across the world. In this alternative exercise, however, the productivity losses to bad health would be implausibly high – more than five times higher than the ones identified in the literature.

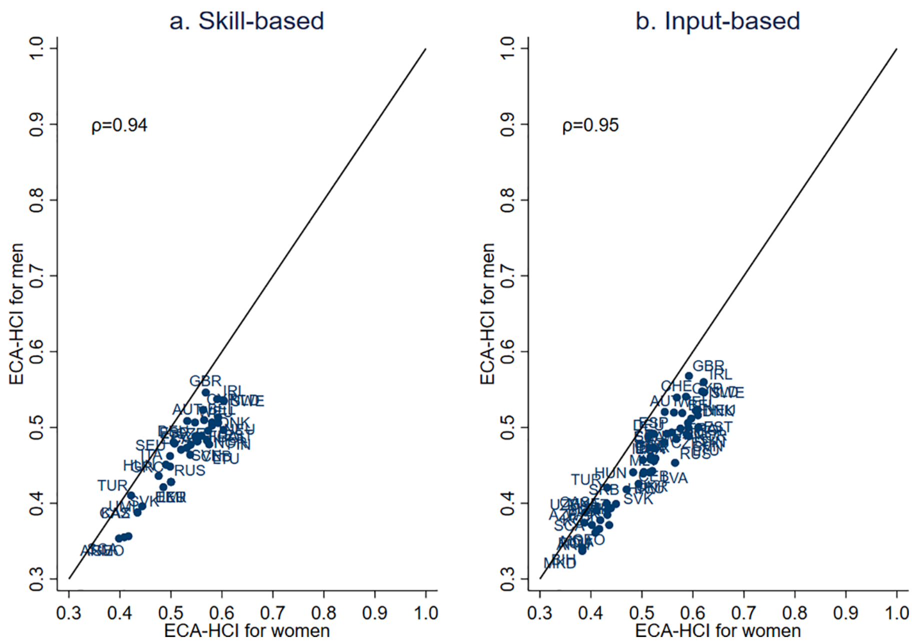

Figure 16. Gender-disaggregated values of ECA-HCI

Note: This graph plots, for every country, the value of the ECA-HCI for men (vertical axis) and the value of ECA-HCI for women (horizontal axis). Panel *a* plots the value of the skill-based ECA-HCI and panel *b* plots the value of the input-based ECA-HCI).

4.1. Gender disaggregation of ECA-HCI

Like the original HCI, the ECA-HCI can be disaggregated by gender. The values of learning-adjusted years of schooling can be disaggregated by gender in terms of quantity (expected years of basic education) and quality (test score performance); the values of QAYH can be disaggregated by gender in quantity (expected years of higher education) and quality in the skill-based version, but the disaggregation in quality is not possible for the input-based version as there is no gender variation in the quality measure used for higher education (university rankings). The prevalence of adult risk factors (obesity, smoking, and heavy drinking) is available for men and women for almost all countries in the region.

The results can be disaggregated by gender for 38 countries (Table 5). For the average country, the value of the input-based ECA-HCI is 0.459 for men and 0.517 for women (0.473 for men and 0.531. for women in the skill-based version, only available for 26 countries). In all countries, the value is lower for men than women (Fig. 16). The gender gap is largest in Finland and Latvia (about 11 percentage points) and smallest in Uzbekistan and Turkey (1 percentage point or below).

4.2. Uncertainty intervals of ECA-HCI

The components of the ECA-HCI are measured with some error; just as in the original HCI, an uncertainty interval can be calculated to provide a measure of the precision of the estimates. This uncertainty interval is not a statistical estimation but rather a calculation of the ECA-HCI under worst- or best-case scenarios. The worst-case scenario indicates that all the components take the lower-bound values; the best-case scenario indicates that all the components take the upper-bound values. As Kraay (2019) points out, this approach is conservative, equivalent to assuming that the measurement error is highly correlated across components. The variables for which lower- and upper-bound values are available are the probability of survival to age five; quality-adjustment factors for basic education (harmonized learning outcomes) and higher education (aggregate quality score); the prevalence of adult health risk factors (obesity, smoking, and heavy drinking); the adult survival rate; and the share of stunted children.

For the probability of survival to age five, harmonized learning outcomes, the adult survival rate, and the share of stunted children, we use the same bounds as in the original HCI (for details, see Kraay 2019). For the input-based quality adjustment factor for higher education, we bootstrap the standard errors in the same way as the Harmonized Learning Outcomes in the original HCI - 200 random draws are taken from the distribution of the normalized scores of the university rankings at the country level, assuming that the country-level mean score (across rankings) is normally distributed. Then the quality adjustment factor is calculated using the 200 samples of original scores, and the 2.5th and 97.5th percentiles of the resulting bootstrapped adjustment factors are. For the skill-based quality score for higher education, we perform as similar procedure but using the jackknife resampling method and the 80 replications already provided by the PIAAC dataset. For the adult health risk factors, the determination of the bounds depends on the data source. For countries whose values are sourced from the European Health Interview Survey, the bounds represent the limits of the 95% confidence interval, as detailed in the European Health Interview Survey round 2 quality report (Eurostat, 2018). For countries whose values are sourced from the World Health Organization, the bounds are that institution's low and high estimates.

The ECA-HCI values range from 0.31 to 0.60 (see Table 6). The median size of the uncertainty intervals is about 0.017 in the skill-based version and 0.016 in the input-based version—somewhat smaller to that of the original HCI (0.030). For some countries with less precise component data, the interval can range up to 0.04. Fig. 17 plots the uncertainty intervals of the ECA-HCI.

Table 6
Uncertainty intervals for the Europe and Central Asia extension of the Human Capital Index (ECA-HCI)

	ECA-HCI – Input based			ECA-HCI – Skill based		
Subregion/country	Point estimate	Lower bound	Upper bound	Point estimate	Lower bound	Upper bound
Central Asia	**0.391**	**0.380**	**0.402**	–	–	–
Kazakhstan	0.424	0.416	0.432	0.411	0.404	0.418
Kyrgyz Republic	0.398	0.390	0.405	–	–	–
Tajikistan	0.330	0.314	0.343	–	–	–
Uzbekistan	0.389	0.377	0.401	–	–	–
Central Europe and Baltic countries	**0.486**	**0.478**	**0.494**	**0.512**	**0.504**	**0.520**
Bulgaria	0.411	0.403	0.419	–	–	–
Croatia	0.469	0.462	0.475	–	–	–
Czech Republic	0.511	0.503	0.517	0.507	0.498	0.514
Estonia	0.559	0.551	0.568	0.546	0.538	0.555
Hungary	0.461	0.455	0.467	0.455	0.449	0.462
Latvia	0.506	0.496	0.516	–	–	–
Lithuania	0.538	0.531	0.546	0.525	0.516	0.534
Poland	0.546	0.539	0.553	0.534	0.525	0.542
Romania	0.387	0.377	0.397	–	–	–
Slovak Republic	0.458	0.452	0.464	0.452	0.445	0.458
Slovenia	0.537	0.531	0.542	0.524	0.518	0.530
Eastern Europe	**0.477**	**0.462**	**0.490**	–	–	–
Belarus	0.492	0.478	0.506	–	–	–
Moldova	0.391	0.381	0.402	–	–	–
Ukraine	0.480	0.465	0.494	0.463	0.449	0.476
Northern Europe	**0.564**	**0.556**	**0.573**	**0.551**	**0.542**	**0.560**
Denmark	0.562	0.554	0.570	0.542	0.534	0.550
Finland	0.552	0.544	0.560	0.547	0.539	0.555
Iceland	0.541	0.534	0.549	–	–	–
Norway	0.545	0.538	0.553	0.532	0.523	0.541
Sweden	0.583	0.574	0.592	0.569	0.558	0.579
Russian Federation	**0.525**	**0.509**	**0.545**	**0.500**	**0.482**	**0.522**
South Caucasus	**0.386**	**0.375**	**0.397**	**0.381**	**0.372**	**0.389**
Armenia	0.385	0.376	0.393	0.376	0.367	0.384
Azerbaijan	0.381	0.368	0.393	–	–	–
Georgia	0.402	0.393	0.411	0.385	0.376	0.394
Southern Europe	**0.494**	**0.488**	**0.499**	**0.480**	**0.474**	**0.486**
Cyprus	0.564	0.555	0.573	0.544	0.535	0.552
Greece	0.488	0.480	0.497	0.472	0.463	0.482
Italy	0.480	0.474	0.485	0.471	0.464	0.477
Malta	0.470	0.463	0.477			
Portugal	0.520	0.513	0.526			
Spain	0.507	0.502	0.511	0.493	0.488	0.498
Turkey	**0.426**	**0.421**	**0.432**	**0.416**	**0.410**	**0.422**
Western Balkans	**0.406**	**0.396**	**0.416**	–	–	–
Albania	0.401	0.393	0.410	–	–	–
Bosnia and Herzegovina	0.362	0.352	0.371	–	–	–
Montenegro	0.415	0.396	0.427	–	–	–
North Macedonia	0.359	0.353	0.365	–	–	–
Serbia	0.443	0.432	0.453	–	–	–
Western Europe	**0.541**	**0.533**	**0.549**	**0.527**	**0.518**	**0.536**
Austria	0.533	0.525	0.540	0.520	0.511	0.530
Belgium	0.548	0.540	0.556	0.536	0.528	0.545
France	0.537	0.529	0.545	0.524	0.516	0.533
Germany	0.501	0.493	0.509	0.493	0.484	0.501
Ireland	0.587	0.579	0.596	0.561	0.552	0.570
Luxembourg	0.487	0.480	0.494	–	–	–
Netherlands	0.581	0.570	0.592	0.568	0.557	0.579
Switzerland	0.553	0.545	0.562	–	–	–
United Kingdom	0.580	0.573	0.588	0.557	0.549	0.567
Simple average	**0.481**	**0.472**	**0.490**	**0.501**	**0.492**	**0.510**
Population-weighted average	**0.496**	**0.486**	**0.506**	**0.494**	**0.485**	**0.505**

Note: – Not available

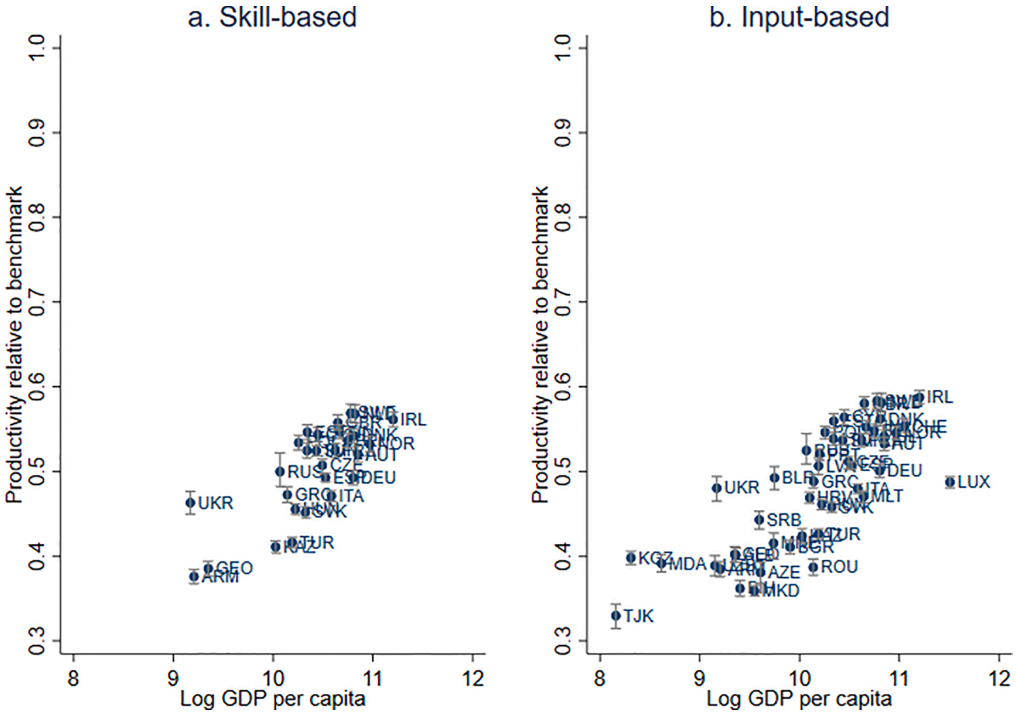

Figure 17. Uncertainty intervals for ECA-HCI

Note: This graph plots, for every country, the value of the ECA-HCI expressed as a ratio with respect to the full-health and complete education productivity benchmark (vertical axis) and the log of GDP per capita in 2019 (horizontal axis). Panel *a* plots the value of the skill-based ECA-HCI and panel *b* plots the value of the input-based ECA-HCI. Grey lines indicate the upper and lower bounds estimates.

5. Concluding remarks

This paper provides an extension of the Human Capital Index to better account for the education and health challenges that drive the productivity gaps faced by high- and middle-income countries like those in Europe and Central Asia. Specifically, the extension incorporates two elements that are particularly important for the region. First, there is an additional focus on quality adjusted years of tertiary education, in addition to basic education. Second, health status is captured by including risk factors such as obesity, smoking and heavy alcohol consumption, all of which are prevalent in the region. This exercise highlights the importance of investing in tertiary education for many countries in the region, as well as the importance of preventing risk factors for noncommunicable and infectious diseases in the aging societies of the region. The average country for which the input-based ECA-HCI is calculated has a value of 0.481, and the average country for which the skill-based ECA-HCI is calculated has a value of 0.501. In both cases, this means that children born today in the average country in the region will be almost half as productive as they would have had they reached the benchmark of complete education and full health.

The estimates of the ECA-HCI show, in the realm of education, that good indicators of basic education do not necessarily correlate with good indicators of higher education, and that the associated productivity gaps can be substantial. Attending a university does not imply learning valuable knowledge, as the quality of higher education is uncorrelated from tertiary degree attainment levels. This mirrors the global "learning crisis" in basic education where, similarly, schooling is not learning (Pritchett, 2013; World Bank, 2018). Also, the productivity gap emerging from lags in education according to the ECA-HCI is uncorrelated with the one emerging from bad health indicators. Some countries in the region -particularly in Eastern Europe- see their relatively good performance in education obscured by especially bad performance in adult health. In fact the ECA-HCI shows that productivity gaps due to bad health can be underestimated if the factors driving the burden of disease in the region, skewed towards pathologies that affect adults rather than children, are not taken into account.

As in any cross-country benchmarking exercise, there are limitations. When analyzing the contribution to productivity from higher education, the ECA-HCI does not distinguish between types of disciplines and the measure of quality can be imprecise. Moreover, data on tertiary attainment and adult skill proficiency are missing for some countries. In terms of the health component, the contribution of adult health risk factors to productivity is based on estimates from the literature which can be imprecise. In any case, the ECA-HCI is not to be interpreted as a measure of welfare but as a reference for policy makers on the productivity gains that can be expected from investing in the different aspects of human capital in Europe and Central Asia. Despite these caveats, the extension of the Human Capital Index presented in this paper could be useful for all middle-income countries where investments in improving tertiary education and limiting health risk factors are likely to be priorities.

Regional or income group benchmarking exercises have the additional limitation that their relevance may be limited when applied to different contexts. However, in the case of an exercise measuring the productivity of human capital, regional differences may be necessary as the conditions in which human capital is put to productive use can be substantially different. Pennings (2020) extends the original Human Capital Index by adjusting for labor force participation and for the share of non-agricultural jobs (assumed to be "productive jobs") in each country. The measurement tool we present in this work takes a different approach by modifying the full-productivity benchmark to match the actual characteristics of employment and the conditions that make individuals healthy in a specific regional context. Further work could potentially establish a way of providing a global measurement tool that accounts for country and region specific differences in the potential human capital productivity.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jce.2022.05.007.

Appendix A

The quality of higher education is calculated under the assumption that a high-quality degree is a degree that makes its holders more productive in the labor market—the working assumption of the broad literature on the effects of college quality on earnings in the United States. Standard ordinary least squares (OLS) estimates of the impact of college quality (usually measured by the average SAT score of admitted students) on earnings show that there is a positive and significant association between them. Given the existence of a selection process into college—high school students decide which colleges to apply to—these estimates may suffer from a substantial selection bias.

To address this issue, the literature has followed two approaches. The first is a "selection-on-observables" approach, in which the decision to apply to a given type of college is modeled based on observable variables such as net college costs or high school grade point average (Breweret al., 1999; Andrews et al., 2016). This approach has confirmed the existence of a positive and significant return of the quality of college education on earnings.

The second is a "selection-on-unobservables" approach, in which, rather than modeling college choice, the researcher compares the outcomes of students who were admitted to the same set of colleges but chose to go to different ones (Dale and Krueger 2002, Dale and Krueger 2014). This approach is a "self-revelation" method, because it assumes that the set of students admitted to a given college share the same "unobservable" characteristics. This method shows that, for the average student, there is no significant effect of college quality on earnings. The effect is significant for minority students and those from poor backgrounds, however.

University rankings

Table A1 describes the six university rankings used in this analysis. The CWUR includes the largest number of universities (2000);

Table A1
Descriptions of six systems of university ranking

Item	Times Higher Education (THE)	Quacquarelly Symmonds (QS)	Academic Ranking of World Universities (ARWU)[a]	Center for World University Rankings (CWUR)[b]	U.S. News Global Universities Ranking	U-Multirank (UMR)[c]
Number of universities included	1,397	1,021	1,000	2,000	1,500	1,666
Of which in ECA	540	418	385	708	556	1,041
Number of countries	91	85	63	98	81	92
Of which in ECA	37	35	32	36	36	43
Ranking components covered						
Research/ innovation on outputs	✓	✓	✓	✓	✓	✓
Faculty performance	✓	✓	✓	✓	✓	✓
Internationalization	✓	✓			✓	✓
Reputation	✓	✓	✓	✓	✓	
STEM focus			✓			
Overall score						
Global mean	34.57	29.90	37.00	71.64	42.45	59.27
Dispersion	17.07	19.75	12.71	5.07	16.28	14.41
Range	16.4–95.4	10.7–100	26–100	65.8–100	15.5–100	16.7–100
Research, Teaching, and Citations score[d]						
Global mean	33.43	30.83	20.96	n.a.	n.a.	63.56
Dispersion	17.45	20.00	9.82	n.a.	n.a.	16.54
Range	9.3–96.4	10.7–99.9	8.2–92.7	n.a.	n.a.	20–100

Note: ECA = Europe and Central Asia; STEM = science, technology, engineering, and mathematics.
a. The overall score for the ARWU ranking is published only for the top 100 universities. For the remaining institutions, only the individual subcomponents are published.
b. The CWUR publishes only the overall score, not the subcomponent scores.
c. The UMR provides a letter-based, not a numeric, score. To estimate a numeric equivalent, the following scale was used: A = 100; B = 75; C = 50, D =2 5, E = 0. The overall score represents the average of the numeric score of all the UMR categories (teaching and learning, research, knowledge transfer, international orientation, and regional engagement).
d. The Research, Teaching, and Citations score is composed of the simple average of the components of research, faculty performance, and reputation.

Table A2
Partial correlation across US universities (n=98)

	Ov. THE	Ov. QS	RTC ARWU	Ov. CWUR	Ov. US News	Ov. UMR		RTC THE	RTC QS	RTC ARWU	Ov. CWUR	Ov. US News	RTC UMR
Overall THE	1						RTC THE	1					
Overall QS	0.9728	1					RTC QS	0.9544	1				
RTC ARWU	0.8762	0.8895	1				RTC ARWU	0.8771	0.8735	1			
Overall CWUR	0.9375	0.9492	0.9396	1			Overall CWUR	0.9384	0.9437	0.9396	1		
Overall US News	0.9395	0.9350	0.9381	0.9620	1		Overall US News	0.9386	0.9246	0.9381	0.9620	1	
Overall UMR	0.6886	0.7374	0.6486	0.7187	0.7274	1	RTC UMR	0.7230	0.7666	0.6412	0.7246	0.7476	1

Table A3
Partial correlation across country averages (n=54)

	Ov. THE	Ov. QS	RTC ARWU	Ov. CWUR	Ov. US News	Ov. UMR		RTC THE	RTC QS	RTC ARWU	Ov. CWUR	Ov. US News	RTC UMR
Overall THE	1						RTC THE	1					
Overall QS	0.9044	1					RTC QS	0.8833	1				
RTC ARWU	0.8514	0.8587	1				RTC ARWU	0.8436	0.8533	1			
Overall CWUR	0.8741	0.8443	0.8461	1			Overall CWUR	0.8819	0.8427	0.8461	1		
Overall US News	0.9272	0.8220	0.7975	0.8961	1		Overall US News	0.9144	0.7962	0.7975	0.8961	1	
Overall UMR	0.7453	0.7711	0.6977	0.7122	0.6387	1	RTC UMR	0.7354	0.7231	0.7210	0.7125	0.6138	1

the ARWU/Shanghai includes the smallest number (1000). The rankings include 385–1040 higher education institutions in Europe and Central Asia. The total number of countries covered ranges from 63 to 98; the number of countries in Europe and Central Asia ranges from 32 to 43. Five of the six rankings (THE, QS, ARWU, CWUR, and U.S. News rankings) have scores that (theoretically) range from 0 to 100, although no institution included in any of the rankings has a score of 0. The U-Multirank is a nonnumeric, multidimensional, user-defined ranking. To use it, we imputed numeric values (ranging from 0 to 100) to the letter-based scores assigned. The CWUR has the highest minimum score (65.8) and the lowest dispersion (5.07). The ARWU/Shanghai overall score is reported only for the world's top 100 universities.

Given that the six rankings include subcomponents on the quality of research, faculty performance, and reputation, an alternative score can be estimated as the simple average of the scores of those subcomponents—the research, teaching, and citations (RTC) quality score. This score captures the quality of the subcomponents that are common to all the rankings. This calculation is not possible for the CWUR and U.S. News rankings, which do not publish the scores on the subcomponents.

The correlation between these rankings is very high. Partial correlations across the rankings for a subset of 98 U.S. universities included in the six rankings range from 0.64 to 0.97 (Table A2). Partial correlations across the country averages for the 54 countries that have at least one university present in all six rankings are also high, ranging from 0.61 to 0.91 (Table A3).

A positive correlation also exists between the quality scores and the income level of countries (see Fig. 1). Singapore is ranked as the country with the highest quality score in the THE, QS and ARWU rankings, while for the CWUR ranking the highest ranked country is the Netherlands.

To create an aggregate quality score that combines the information from the six rankings, we first code as 0 the score for a country that is not present in the ranking (except for the CWUR ranking, for which we use a value of 60, given that the minimum score recorded in that ranking is 66.5). The scores for each ranking are then normalized to have a mean of 0 and a standard deviation of 1. The overall score is used for the THE, QS, CWUR, U.S. News, and U-Multirank rankings; the RTC score is used for the ARWU. The simple average of the six standardized scores is then rescaled to a 0–100 range for presentational purposes.

This procedure ranks countries in terms of the average quality of its universities, ignoring the distribution of students across universities. Given that this information is not available at a global scale, the simple average is used.

Estimation of the quality-adjustment factor

To estimate the productivity effect of university quality (parameters β and m in Eq. (8)), we rely on a cohort-college-level data set for 294 U.S. colleges. Focusing on the U.S. data allows us to control for parental income, one of the key drivers of individual income. The data set comes from the *Mobility Report Cards* constructed by Chetty et al. (2017), which combines college and administrative data that link the parental and post-college earnings of about 28.1 million students born between 1980 and 1991 for 2,463 colleges. The data set consists of cohort-college observations—that is, observations of the average characteristics of students born in a given year who studied at a given college. For each observation, the data set includes the students' average annual earnings in 2014 and the

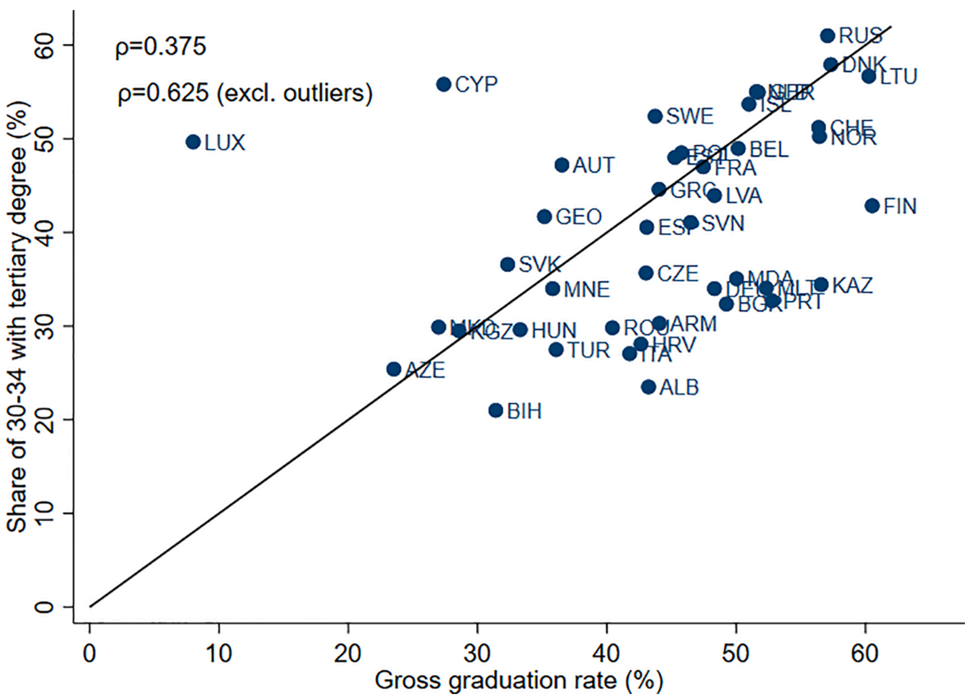

Figure A.1. Correlation between share of individuals age 30-34 with a tertiary degree and gross graduation rate

Note: This graph plots, for every country, the share of adults age 30-34 with a tertiary degree (vertical axis) and the tertiary gross graduation rate as defined by UNESCO (horizontal axis).

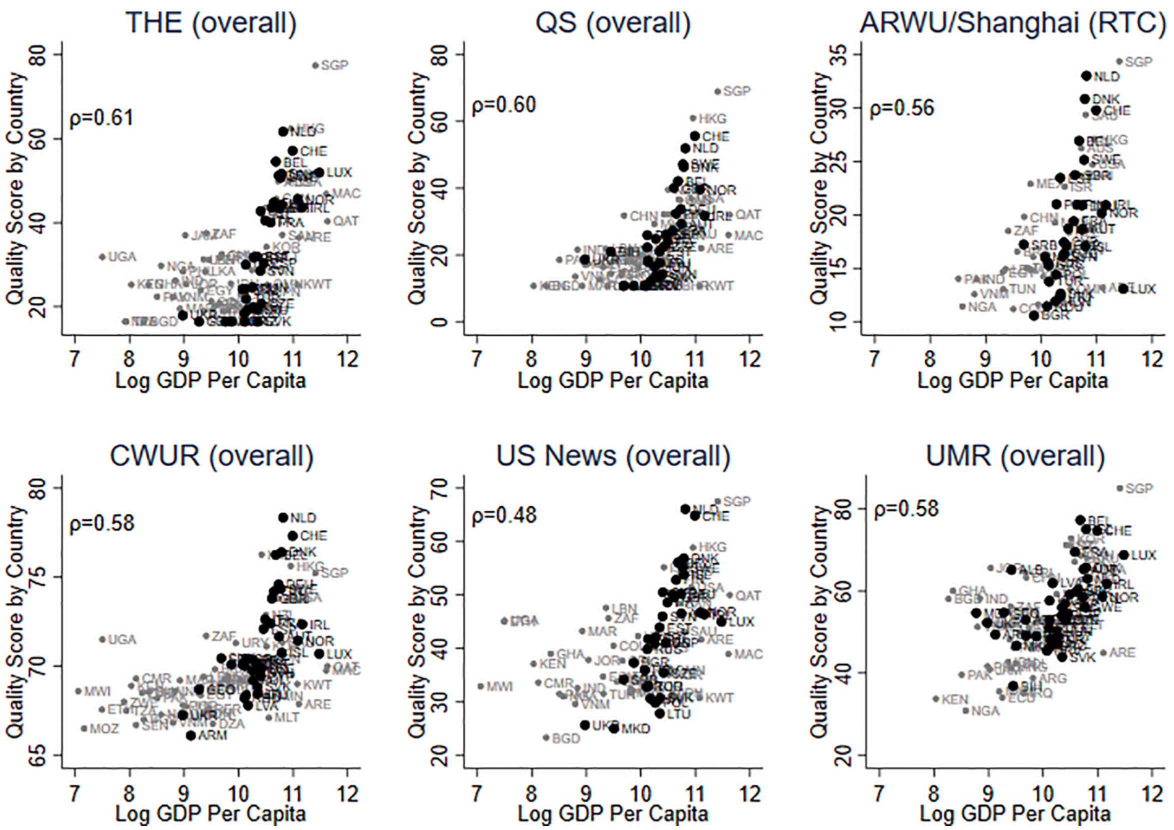

Figure A.2. University rankings (quality score) and income level
Note: This graph plots, for every country with available data, the university quality score according to each university ranking(vertical axis) and the log GDP per capita at PPP in 2019 (horizontal axis). Black points indicate countries in Europe and Central Asia.

Table A4
Ordinary least squares estimates of aggregate quality scores of universities

	Log annual earnings in 2014					
	Full sample			Common sample		
	Both genders	Men	Women	Both genders	Men	Women
Aggregate quality score	0.0024***	0.0031***	0.0016***	0.0044***	0.0052***	0.0036***
	(0.004)	(0.0004)	(0.0004)	(0.0009)	(0.0010)	(0.0008)
Log parental earnings	0.2986***	0.3142***	0.2646***	0.3202***	0.3597***	0.2543***
	(0.0136)	(0.0150)	(0.0134)	(0.0248)	(0.0283)	(0.0225)
Age	0.1074***	0.1237***	0.0894***	0.1157***	0.1295***	0.0979***
	(0.0013)	(0.0014)	(0.0013)	(0.0023)	(0.0024)	(0.0022)
STEM majors in college (0–100) (percent)	0.0058***	0.0053***	0.0049***	0.0046***	0.0043***	0.0032***
	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0010)
Constant	3.8250***	3.2798***	4.6636***	3.2758***	2.4979***	4.5139***
	(0.1679)	(0.1881)	(0.1606)	(0.3061)	(0.3469)	(0.2707)
Observations	3,784	3,689	3,738	1,159	1,159	1,156
Number of colleges	323	315	321	98	98	98

Note: The common sample is composed of universities that are present in all six rankings. Clustered standard errors at the college level are in parentheses. STEM = science, technology, engineering, and mathematics.
* $p < 0.10$, ** $p < 0.05$,
*** $p < 0.01$.

average parental earnings when the cohort was age 15–19. The data set also includes a series of college-level variables, such as the average attendance costs, instructional expenditure, and percentage of students in each type of major. We match this data set with the six university rankings. Among U.S. higher education institutions, 294 are present in at least one of the rankings, and 108 are present in all four (Fig. A.1).

The simple OLS regression estimated is the following:

$$\log(earnings)^{2014}_{b,g,c} = \alpha_g + \beta_g Q_c + \gamma_{1,g}\log(pearnings)_{b,g,c} + \gamma_{2,g}age_b + \gamma_{3,g}pct\_STEM_c + \varepsilon_{b,g,c} \quad \text{(A1)}$$

Table A5
Productivity effect of university quality

Panel a

	Dependent variable: log annual earnings in 2014											
Ranking	THE (Overall)			THE (RTC)			QS (Overall)			QS (RTC)		
	Both	Males	Females	Both	Males	Females	Both	Males	Females	Both	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Quality score (0-100)	0.0032***	0.0039***	0.0026***	0.0031***	0.0039***	0.0026***	0.0027***	0.0033***	0.0021***	0.0024***	0.0029***	0.0018***
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0006)
Log parental earnings	0.3222***	0.3526***	0.2650***	0.3194***	0.3489***	0.2628***	0.3035***	0.3327***	0.2466***	0.3076***	0.3365***	0.2507***
	(0.0221)	(0.0246)	(0.0216)	(0.0221)	(0.0247)	(0.0215)	(0.0235)	(0.0262)	(0.0235)	(0.0242)	(0.0271)	(0.0245)
Age	0.1097***	0.1242***	0.0919***	0.1097***	0.1242***	0.0919***	0.1120***	0.1270***	0.0934***	0.1121***	0.1271***	0.0935***
	(0.0018)	(0.0019)	(0.0017)	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0020)	(0.0019)	(0.0019)	(0.0020)	(0.0019)
% of STEM majors in college (0-100)	0.0056***	0.0053***	0.0046***	0.0057***	0.0054***	0.0046***	0.0057***	0.0051***	0.0047***	0.0058***	0.0053***	0.0049***
	(0.0005)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0007)
Constant	3.3955***	2.6932***	4.5220***	3.4290***	2.7378***	4.5480***	3.6132***	2.9394***	4.7470***	3.5621***	2.8922***	4.6973***
	(0.2640)	(0.2862)	(0.2509)	(0.2642)	(0.2972)	(0.2499)	(0.2910)	(0.3235)	(0.2896)	(0.3005)	(0.3342)	(0.3019)
Observations	1,823	1,823	1,816	1,823	1,823	1,816	1,708	1,696	1,705	1,708	1,696	1,705
Number of colleges	154	154	154	154	154	154	145	144	145	145	144	145

Panel b

	Dependent variable: log annual earnings in 2014											
Ranking	ARWU (RTC)			CWUR (Overall)			U-Multirank (overall)			U-Multirank (RTC)		
	Both	Males	Females	Both	Males	Females	Both	Males	Females	Both	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Quality score (0-100)	0.0045***	0.0056***	0.0035***	0.0073***	0.0102***	0.0045***	0.0040***	0.0047***	0.0031***	0.0032***	0.0035***	0.0028***
	(0.0007)	(0.0008)	(0.0008)	(0.0013)	(0.0013)	(0.0013)	(0.0007)	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0007)
Log parental earnings	0.3255***	0.3546***	0.2730***	0.3255***	0.3190***	0.2641***	0.3204***	0.3498***	0.2675***	0.3131***	0.3421***	0.2605***
	(0.0187)	(0.0216)	(0.0183)	(0.0187)	(0.0147)	(0.0143)	(0.0196)	(0.0230)	(0.0171)	(0.0202)	(0.0239)	(0.0172)
Age	0.1105***	0.1252***	0.0921***	0.1078***	0.1240***	0.0894***	0.1141***	0.1297***	0.0951***	0.1139***	0.1295***	0.0949***
	(0.0019)	(0.0021)	(0.0019)	(0.0013)	(0.0015)	(0.0013)	(0.0019)	(0.0021)	(0.0018)	(0.0019)	(0.0021)	(0.0018)
% of STEM majors in college (0-100)	0.0059***	0.0054***	0.0053***	0.0057***	0.0052***	0.0047***	0.0055***	0.0053***	0.0040***	0.0060***	0.0059***	0.0043***
	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0009)
Constant	3.3484***	2.6820***	4.4156***	3.2907***	2.5193***	4.3775***	3.1628***	2.4354***	4.3134***	3.2624***	2.5575***	4.3854***
	(0.2291)	(0.2655)	(0.2207)	(0.1774)	(0.2655)	(0.1701)	(0.2649)	(0.3107)	(0.2224)	(0.2690)	(0.3193)	(0.2204)
Observations	1,869	1,868	1,865	3,302	3,252	3,278	2,006	1,972	1,985	2,006	1,972	1,985
Number of colleges	158	158	158	279	275	278	170	167	169	170	167	169

Note: The common sample is composed of universities which are present in all the six rankings. Clustered standard errors at the college level in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Panel c

	Dependent variable: log annual earnings in 2014								
Ranking	US News (overall)			Aggregate Quality Score			Agg. Q. Score (common sample)		
	Both	Males	Females	Both	Males	Females	Both	Males	Females
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quality score (0-100)	0.0019***	0.0027***	0.0013**	0.0024***	0.0031***	0.0016***	0.0044***	0.0052***	0.0036***
	(0.0006)	(0.0006)	(0.0006)	(0.004)	(0.0004)	(0.0004)	(0.0009)	(0.0010)	(0.0008)
Log parental earnings	0.3440***	0.3701***	0.2934***	0.2986***	0.3142***	0.2646***	0.3202***	0.3597***	0.2543***
	(0.0206)	(0.0236)	(0.0202)	(0.0136)	(0.0150)	(0.0134)	(0.0248)	(0.0283)	(0.0225)
Age	0.1074***	0.1228***	0.0891***	0.1074***	0.1237***	0.0894***	0.1157***	0.1295***	0.0979***
	(0.0016)	(0.0018)	(0.0016)	(0.0013)	(0.0014)	(0.0013)	(0.0023)	(0.0024)	(0.0022)
% of STEM majors in college (0-100)	0.0059***	0.0059***	0.0050***	0.0058***	0.0053***	0.0049***	0.0046***	0.0043***	0.0032***
	(0.0004)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0010)
Constant	3.2374***	2.565***	4.2977***	3.8250***	3.2798***	4.6636***	3.2758***	2.4979***	4.5139***
	(0.2415)	(0.28001	(0.2293)	(0.1679)	(0.1881)	(0.1606)	(0.3061)	(0.3469)	(0.2707)
Observations	2,363	2,363	2,360	3,784	3,689	3,738	1,159	1,159	1,156
Number of colleges	199	199	199	323	315	321	98	98	98

Note: The common sample is composed of universities which are present in all the six rankings. Clustered standard errors at the college level in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.

where the dependent variable is the annual average log earnings in 2014 of the cohort born in year b of gender g that went to college c. The main regressor of interest is Q, the quality measure based on the six rankings for college c. Coefficient β is the productivity effect of quality; it is used as the quality-adjustment factor in Eq. (8) which feeds into the ECA-HCI. Other regressors are the log parental earnings of the cohort born in year b of gender g that went to college c when the individuals were 15–19; the age of cohort b in 2014; and percentage of STEM majors in college c in year 2000 (included to control for the STEM wage premium). Standard errors are clustered at the college level (Fig. A.2).

Table A4 provides the results for the aggregate quality score derived from the combination of the six rankings, shown for the sample of universities that are present in at least one of the rankings (323 universities in total) and for the common sample of 98 universities that are present in all the rankings. Table 1 summarizes the values of β and m (the implied productivity of a "zero-quality" institution) that arise from the results of the OLS estimations of Eq. (A1), focusing only on values that refer to both genders. Full results are available in Table A5.

Appendix B. Estimates of the effect of adult health risk factors on productivity

This appendix reports conditional estimates on log earnings. The characteristics controlled for may differ across papers, but they always include age, gender, and education (Tables B1–B3).

Table B1
Review of studies on effect of obesity on productivity

Paper	Estimate Low	High	Average	Comment	Source in paper
Averett and Korenman (1996)	–0.03	–0.15	–0.09	Coefficients compare obese people (BMI > 30) and people of ideal weight (BMI 20–25). Low estimate is for men, 1988 sample; high estimate is for women, 1981 sample.	Table 4
Cawley, Grabka, and Lillard (2005)	0	–0.1986	–0.0993	Coefficients compare obese people (BMI > 30) and people of ideal weight (BMI 20–25). Low estimate is for men in the United States (not significantly different from zero); high estimate is for women in the United States.	Table 2
Lundborg and others (2007)	–0.058	–0.074	–0.066	Coefficients compare obese people (BMI > 30) and non-obese people (BMI < 30); high estimate includes health status as control.	Table 9
Brunello and D'Hombres (2007)	–0.04	–0.105	–0.0725	Regression is linear specification with BMI as independent variable. Coefficients are multiplied by 5 to simulate a change from BMI 25 to BMI 30. Low estimate is for women, controlling for occupation and sector; high estimate is for men, not controlling for occupation and sector.	Table 3
Kline and Tobias (2008)	–0.0685	–0.153	–0.1108	Regression is nonlinear specification with BMI as independent variable. Low estimate corresponds to expected change between BMI 25 and BMI 30 for women; high estimate corresponds to same change for men.	Table IV
Lundborg, Nysted, and Rooth (2010)	–0.072	–0.153	–0.1125	Coefficients compare obese people (BMI > 30) and people of ideal weight (BMI 20–25). Low estimate is for specification controlling for noncognitive skills; high estimate is for specification not controlling for any skill.	Table 4.1, columns C, D, E
Bockerman and others (2019)	0	–0.355	–0.1775	Regression is linear specification with BMI as independent variable. Coefficients are multiplied by 5 to simulate a change from BMI 25 to BMI 30. Low estimate corresponds to genetic instrumental variable 97 SNP (not significantly different from zero). High estimate corresponds to genetic instrumental variable 32 SNP.	Table 1
Median			–0.0993		

Table B2
Review of studies on effect of smoking on productivity

Paper	Estimate Low	High	Average	Comments	Source in paper
Levine et al. (1997)	–0.04	–0.08	–0.06	Coefficients compare smokers (more than 1 cigarette a day) and nonsmokers. Low estimate is for 1984; high estimate is for 1991.	Table 4
Van Ours (2004)	–0.085	–0.119	–0.102	Coefficients compare smokers and nonsmokers. Low estimate is for average smokers; high estimate is for twice average smokers.	Table 10
Auld (2005)	–0.083	–0.268	–0.1755	Coefficients compare smokers and nonsmokers. Low estimate treats smoking as exogenous; high estimate treats smoking as endogenous.	Table 2
Grafova and Stafford (2009)	–0.076	–0.102	–0.089	Coefficient compare persistent smokers and people who never smoked. Low estimate is for 1986; high estimate is for 2001.	Table 7
Lokshin and Beegle (2011)	–0.19	–0.23	–0.21	Coefficient corresponds to (causal) difference in earnings of current smokers and nonsmokers. Low estimate is for LIV specification; high estimate is for 2SLS specification.	Table 2 and page 227
Bondzie (2016)	–0.043	–0.069	–0.056	Matching estimates of differences between smokers and nonsmokers. Low estimate corresponds to kernel ATT; high estimate corresponds to nearest neighbor ATT.	Table 5
Median			–0.096		

Table B3
Review of studies on effect of heavy drinking on productivity

Paper	Estimate Low	High	Average	Comments	Source in paper
Mullahy and Sindelar (1993)	–0.163	–0.176	–0.1695	Coefficients compare people diagnosed with alcoholism and people not diagnosed with alcoholism. Low estimate is for people ever diagnosed with alcoholism; high estimate is for people diagnosed with alcoholism in past year.	Table 3, all obs.
Hamilton and Hamilton (1997)	–0.254	–0.758	–0.506	Coefficients correspond to decomposition of wage differences attributed to differences in returns to characteristics of heavy drinkers (people who consume eight or more drinks on one or more days in the previous week) and nondrinkers. Low estimate is for wider definition of heavy drinker.	Table 4 and page 148
Zarkin and others (1998)	0.082	–0.021	0.0305	Coefficients compare heavy drinkers (people who consumed more than 94 drinks in past 30 days for men, 48 drinks for women) and nondrinkers. Low estimate is for men; high estimate is for women.	Table 2
Barrett (2002)	–0.08	–0.19	–0.135	Low estimate compares heavy drinkers (people who consumed eight or more drinks on one or more days the previous week) and nondrinkers. High estimate is for heavy drinkers versus moderate drinkers.	Table 4
Sloan and Grossman (2011)	0	–0.459	–0.2295	Coefficient compares heavy drinkers (people who consume more than 12 drinks a week) and nondrinkers. Low estimate is for whites and women (not significantly different from zero); high estimate is for black men.	Table 2
Bockerman et al. (2017)	–0.18	–0.424	–0.302	Coefficient corresponds compares heavy drinkers (men who consume more than 280 grams of alcohol a week and women who consume more than 190) and moderate drinkers (men who consume less than 280 grams of alcohol a week and women who consume less than 190). Low estimate is for twin differences in monozygotic twins; high estimate is for twin differences in dizygotic twins.	Table V
Median			–0.1995		

References

Andrews, R., Li, J., Lovenheim, M., 2016. Quantile treatment effects of college quality on earnings. Journal of Human Resources 51 (1), 201–238.
Angrist, N., Patrinos, H., 2018. Global Dataset on Education Quality: A Review and Update (2000-2017). Policy Research Working Paper n. 8592. Global Dataset on Education Quality: A Review and Update (2000-2017). Policy Research Working Paper n. 8592. World Bank, Washington, DC.
Angrist, N., Djankov, S., Goldberg, P., Patrinos, H., 2021. Measuring human capital using global learning data. Nature 592, 403–408.
Becker, G., 1964. Human Capital. Human Capital, 2nd ed. Columbia University Press, New York.
Brewer, D., Eide, E., Ehrenberg, R., 1999. Does it pay to attend an elite private college? Cross-cohort evidence of the effects of college type on earnings. Journal of Human Resources 34 (1), 104–123.
Chetty, R., Friedman, J., Saez, E., Turner, N., Yaggan, D., 2017. Mobility Report Cards: The Role of Colleges in Intergenerational Mobility. NBER Working Paper 23618.
Dale, S., Krueger, A., 2002. Estimating the payoff to attending a more selective college: an application of selection on observables and unobservables. Quarterly Journal of Economics 117 (4), 1491–1528.
Dale, S., Krueger, A., 2014. Estimating the effects of college characteristics over the career using administrative earnings data. Journal of Human Resources 49 (2), 324–350.
Eurostat, 2018. Quality report of the second wave of the European Health Interview survey. Eurostat statistical reports. Publications office of the European Union, Luxembourg.
Filmer, D., Rogers, H., Angrist, N, Sabarwal, S., 2020. Learning-adjusted years of schooling (LAYS): defining a new macro measure of education. Economics of Education Review 77, 101971.
Hanushek, E., Schwertd, G., Wiederhold, S, Woessmann, L., 2015. Returns to skills around the world: evidence from PIAAC. European Economic Review 73, 103–130.
Hanushek, E., Woessman, L., 2012. Schooling, educational achievement, and the Latin American growth puzzle. Journal of Development Economics 99, 497–512.
Kelly, T., Liaplina, A., Tan, S., Winkler, H., 2017. Reaping digital dividends: leveraging the internet for development in Europe and Central Asia. Europe and Central Asia studies. World Bank, Washington, DC.
Kraay, A., 2019. The World Bank Human Capital Index: A Guide. World Bank Research Observer 34 (1), 1–33.
Kupets, O., 2016. Education-job mismatch in Ukraine: too many people with tertiary education or too many jobs for low-skilled? Journal of Comparative Economics 44, 125–147.
Loyalka, P., others, 2019. Computer science skills across China, India, Russia and the United States. Proceedings of the National Academy of Sciences 116 (4), 6732–6736.
Montenegro, C., Patrinos, H., 2014. Comparable estimates of returns to schooling around the world. Policy Research Working Paper Series 7020. World Bank, Washington, DC.
Pennings, S., 2020. The Utilization-adjusted Human Capital Index (UHCI). Policy Research Working Paper n. 9375. World Bank, Washington, DC.
Pritchett, L., 2013. The Rebirth of Education: Schooling ain't Learning. CGD Books.
Sondergaard, L., Murthi, M., Abu-Ghaida, D., Bodewig, C., Rutkowski, J., 2012. Skills, Not Just Diplomas. Managing Education for Results in Eastern Europe and Central Asia. Directions in Development, Human Development, World Bank, Washington, DC.
Smith, O., Nguyen, S.N., 2013. Getting Better: Improving Health System Outcomes in Europe and Central Asia. Europe and Central Asia Reports. World Bank, Washington, DC.
World Bank, 2018. World Development Report 2018: Learning to Realize Education's Promise. World Bank, Washington, DC.
Wu, Z., McGoogan, J., 2020. Characteristics of and Important Lessons from the Coronavirus Disease 2019 (COVID-19) Outbreak in China. JAMA. Published online February 24, 2020.
Zhou, F., others, 2020. Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. The Lancet 395, 1054–1062.
Brunello, G., D'Hombres, B., 2007. Does body weight affect wages? Evidence from Europe. Economics & Human Biology 5 (1), 1–19.
Cawley, J., Grabka, M., Lillard, D., 2005. A comparison of the relationship between obesity and earnings in the U.S. and Germany. Schmollers Jahrbuch: Journal of Applied Social Science Studies /Zeitschrift für Wirtschafts–und Sozialwissenschaften 125 (1), 119–129.
Kline, B., Tobias, J., 2008. The wages of BMI: Bayesian analysis of a skewed treatment–response model with nonparametric endogeneity. Journal of Applied Econometrics 23, 767–793.

Lundborg, P., Bolin, K., Hojgard, S., Lindgren, B., 2007. Obesity and occupational attainment among the 50+ of Europe. Advances on Health Economics and Health Services Research 17, 219–251.
Lundborg, P., Nysted, P., Rooth, D.–O., 2010. No Country for Fat Men? Obesity, Earnings, Skills and Health among 450,000 Swedish Men." IZA Discussion Paper No. 4775. Institute of Labor Economics, Bonn.
Auld, C., 2005. Smoking, drinking and income. Journal of Human Resources 40 (2), 505–518.
Bondzie, E.A., 2016. Effect of Smoking and Other Economic Variables on Wages in the Euro Area." MPRA Paper No. 69230. University of Munich, Germany.
Grafova, I., Stafford, F.P., 2009. The wage effects of personal smoking history. Industrial and Labor Relations Review 62 (3), 381–393.
Levine, P.B., Gustafson, T.A., Velenchik, A.D., 1997. More bad news for smokers? The effect of cigarette smoking on wages. Industrial and Labor Relations Review 50 (3), 493–509.
Lokshin, M., Beegle, K., 2011. Foregone earnings from smoking: evidence for a developing country. Research in Labor Economics 33, 209–238.
Van Ours, J., 2004. A pint a day raises a man's pay; but smoking blows that gain away. Journal of Health Economics 23 (5), 863–886.
Averett, S., Korenman, S., 1996. The economic reality of the beauty myth. Journal of Human Resources 31 (2), 304–330.
Barrett, G., 2002. The effect of alcohol consumption on earnings. Economic Record 78 (1), 79–96.
Bockerman, P., Cawley, J., Viinikainen, J., Lehtimäki, T., Rovio, S., Seppälä, I., Pejkonen, J., Raitakari, O., 2019. The effect of weight on labor market outcomes: an application of genetic instrumental variables. Health Economics 28, 65–77.
Bockerman, P., Hyytinen, A., Maczulskij, T., 2017. Alcohol consumption and long–term labor market outcomes. Health Economics 26, 275–291.
Hamilton, V., Hamilton, B.H., 1997. Alcohol and earnings: does drinking yield a wage premium? Canadian Journal of Economics 30 (1), 135–151.
Mullahy, J., Sindelar, J.L., 1993. Alcoholism, work and income. Journal of Labor Economics 11, 494–519.
Sloan, F.A., Grossman, D.S., 2011. Alcohol consumption in early adulthood and schooling completed and labor market outcomes at midlife by race and gender. American Journal of Public Health 101 (11), 2093–2101.
Zarkin, G.A., French, M.T., Mroz, T., Bray, J.W., 1998. Alcohol use and wages: new results from the national household survey on drug abuse. Journal of Health Economics 17, 53–68.