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Human Capital: Global Trends and the Impact of the COVID-19 Pandemic

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Main Messages

- Human capital—estimated as the present value of future earnings for the labor force, employed and self-employed—is the largest asset across all income groups, constituting 64 percent of total wealth in 2018, slightly higher than in 1995.
- Slower annual wage growth in high-income countries (roughly 1 percent) combined with aging of the labor force reduced their share of global human capital, while higher rates in some middle-income countries (up to 4 percent) increased their relative share.
- Significant disparity between male and female human capital persists across most regions and income groups, with great variation among regions: by 2018, females held 44 percent of human capital in Latin America and the Caribbean but only 13 percent in South Asia.
- Although the full, long-lasting effects of the COVID-19 pandemic are still unknown, the resulting economic downturn and associated unemployment and loss of earnings have already set back the long-term trajectory of poverty reduction. As a share of human capital, Sub-Saharan Africa and South Asia have suffered the greatest setbacks, losing 13 and 6 percent of their human capital, respectively.

Introduction

The previous edition of *The Changing Wealth of Nations* (CWON), in 2018, provided the first global set of comparable, estimated human capital based on expected lifetime earnings. It was derived from a time series of household surveys for 141 countries over two decades, from 1995 to 2014 (Lange, Wodon, and Carey 2018). Before that, previous editions of the CWON (World Bank 2006, 2011) measured human capital indirectly as a component of the unexplained residual, called "intangible capital." This edition's direct estimates of human capital allow for a deeper analysis of the role it plays in economic development and a clearer understanding of the underlying factors that drive human capital over time. This edition of the CWON builds on the human capital methodology established in CWON 2018 by expanding coverage to 146 countries from 1995 to 2018 and introducing a region- and income-specific approach to future wage growth.

The chapter is organized as follows. First, the estimation of human capital is summarized, and data sources and methodology are brieflly discussed. (The detailed methodology is included in the annex to this chapter.) The next section provides an overview of trends in human capital at the global, income group, and geographic region levels. This is followed by a more detailed look at trends in gender disparity. Finally, the potential effects of the COVID-19 pandemic on human capital are discussed, recognizing that its long-term impacts on human capital are currently unknown.

Estimating Human Capital

The World Bank estimates human capital by following the lifetime income approach developed by Jorgenson and Fraumeni (1989, 1992a, 1992b). According to this approach, human capital is estimated as the total present value of the expected future labor income that could be generated over the lifetime of the current working population. There are a number of different approaches to measuring human capital (box 7.1), but here human capital is considered to be an asset that generates a stream of future economic benefits. The same conceptual approach is applied to other assets in the wealth accounting framework.

The choice of the lifetime income approach for measuring the human capital stock reflects its advantages in bringing together a broad range of factors that shape the stock of human capital of the population. These factors include not only the total population and population structure but also the expected lifespan of people (a measure that reflects health conditions), their educational attainment, and their labor market experiences in terms of employment probabilities and earnings. An additional advantage of the lifetime income approach is that it allows changes in human capital to be described in terms of investment. These can include such things as formal and informal education; depreciation, such as deaths; and revaluation, such as changes in the labor market premiums of education (Liu 2011).

BOX 7.1 Different Approaches to Measuring Human Capital

Human capital consists of the knowledge, skills, and health that people accumulate over their lives. In addition to its intrinsic importance, human capital is a key driver of sustainable growth and poverty reduction. There are two broad approaches to measuring human capital. The first is an indicators-based approach, and the second is a monetary measure–based approach. The indicators-based approach estimates human capital based on measures of population characteristics, such as years of schooling, educational attainment, and test scores (Boarini, Mira d'Ercole, and Liu 2012). Single indicators cannot capture the various dimensions of human capital, and some indicators-based measures—like the United Nations Development Programme's Human Development Index or the World Bank's Human Capital Index—combine multiple components to produce more comprehensive human capital indexes. However, it can be challenging for composite indexes to produce an overall measure, since they must aggregate across indicators that lack a common metric (Boarini, Mira d'Ercole, and Liu 2012).

The monetary value approach calculates the total stock of human capital either indirectly or directly. The indirect approach estimates human capital residually, as the difference between the total discounted value of each country's future consumption flows (which is taken as a proxy for total wealth) and the sum of the tangible components of that wealth: that is, produced capital and the market-component of natural capital (Boarini, Mira d'Ercole, and Liu 2012). While a useful method, it has some drawbacks. First, since it is measured residually, estimates for human capital may be biased by measurement error in all the terms entering the accounting identities. Second, it does not take into account the nonmarket benefits of the various capital stocks (Liu 2011).

Direct monetary approaches to calculating the stock of human capital include the cost-based approach (for example, Kendrick 1976 and Eisner 1985) and the income-based approach (for example, Jorgenson and Fraumeni, 1989, 1992a, 1992b). The cost-based approach takes into account all the costs that are incurred when producing the human capital. Therefore, human capital wealth stock is the stream of past investments in human capital. Even though the cost-based approach is easy to apply, it relies only on production costs and does not take into account demand and supply (Boarini, Mira d'Ercole, and Liu 2012). The income-based approach takes into account future earnings that human capital investment generates, and hence human capital wealth stock is a function of these future earnings. While the cost-based approach measures human capital wealth stock from the input side, the income-based approach measures the stock of human capital from the output side (Boarini, Mira d'Ercole, and Liu 2012).

This concept of human capital differs from that of human development or human capabilities and complements the World Bank's Human Capital Project, which compiles a wide range of nonmonetary indicators of human capital (box 7.2). The CWON's measures of human capital focus on the economic benefits that a well-educated and healthy workforce generates. Although this approach emphasizes the role of human capital in generating income through wages and earnings, other essential

BOX 7.2 The Human Capital Index and the CWON's Measure of Human Capital

The World Bank's Human Capital Index (HCI) is an international metric measuring the human capital that a child born today can expect to attain by her 18th birthday, given the risks of poor health and poor education prevailing in her country. The HCI incorporates key dimensions of human capital: health (child survival, stunting, and adult survival rates) and the quantity and quality of schooling (expected years of school and international test scores). Using global estimates of the economic returns to education and health, these components are combined into an index that captures the expected productivity of a child born today as a future worker, relative to a benchmark of complete education and full health (World Bank 2020).

In The Changing Wealth of Nations (CWON), human capital is measured as the expected future earnings of the entire labor force. It is estimated as the total present value of the expected future labor income that could be generated over the lifetime of the current working population. In other words, human capital is considered an asset that generates a stream of future economic benefits. The CWON's measure of human capital focuses on the economic benefits that a well-educated and healthy workforce generates.

The HCI uses a broader concept of human capital than CWON, incorporating several nonmonetary indicators of health and education outcomes. Conceptually, however, the two measures have much in common, as both are anchored in the development-accounting literature and measure human capital in terms of expected future earnings. The main difference between the two measures is that the HCI measures expected *future earnings of a child born today,* while the CWON measure estimates expected *future earnings of the entire labor force*. In addition, while the CWON reports estimates in monetary terms, the HCI is expressed relative to a benchmark of complete education and full health: a child born in a country with an HCI value of 0.5 will be only half as productive as a future worker as she would be if she enjoyed complete education and full health.

The CWON measure of human capital complements the HCI, using human capital outcomes that derive indirectly from factors such as educational attainment and health (probability of survival) to provide an understanding of the current stock of human capital in countries. The CWON measure also importantly accounts for labor market outcomes, such as the probability of employment and labor market premiums across countries. While the HCI does not include labor market outcomes, the 2020 update to the index introduced the Utilization-Adjusted HCI. This analytical extension accounts for the underutilization of human capital, based on the fraction of the working-age population that is employed or is in the types of jobs that might better enable them to use their skills and abilities to increase their productivity.

The HCI constitutes one pillar of the World Bank's Human Capital Project (HCP) that aims to help countries make effective investments in the human capital of their citizens, a core strategy to increase productivity and foster growth. The second pillar of the HCP aims to scale up measurement and research on human capital formation and the programs and policies that support this process. The third pillar, focused on country engagement, supports governments in identifying national priorities for human capital development and implementing policies that tackle the barriers preventing countries from reaching their goals (World Bank 2018). To this end, CWON estimates of the current stock of human capital complement the HCI's forward-looking measure to further the World Bank's agenda on human capital.

Sources: World Bank (2018, 2020); the Human Capital Project.

benefits from investments in human development are recognized, such as the intrinsic value of a good education and good health. But for financial wealth accounting purposes, the focus remains strictly on the monetary estimates of wealth associated with human capital. Therefore, human capital is an underestimate, since it leaves out positive externalities, the public good benefits of an educated population, such as building social capital and trust, which are discussed in chapter 15.

Because this approach builds on the concepts and measurement of labor earnings in the System of National Accounts (SNA), the CWON human capital estimates have a major omission: human capital that produces household services such as childcare, food preparation, and home repair. The SNA accounts for household production of goods, such as food for own consumption, but does not include household production of services. Consequently, the human capital associated with production of household services is not measured, an omission that disproportionately affects the measure of women's human capital.

Data and Methodology

Data Sources

To compute human capital as the discounted value of expected future labor income, data on the population, employment, annual earnings, survival rates, gross domestic product (GDP), and labor shares are needed from different data sources. The International Income Distribution Database (I2D2), a unique database developed by the World Bank containing more than 1,500 household surveys, is used for calculating annual earnings, educational attainment, and employment rates. As population data are retrieved from the United Nations World Population Prospects, the United Nations National Accounts database is used for GDP data.

The World Bank's I2D2 database is used for the information on the number of people, their earnings, school enrollment rates, and employment rates. The Mincerian coefficients are obtained from Mincerian wage regressions utilizing the I2D2 database. Based on the results of the Mincerian regressions, a matrix of expected earnings is constructed. Therefore, the matrix accounts for labor earnings of the population by age, gender, and education level.

For simplification, the lifetime for working is assumed to be a maximum of 50 years, starting at age 15 and ending with retirement at age 65, for all countries. All individuals younger than age 15 are assumed to be in school. Individuals between ages 15 and 24 are enrolled in school or part of the labor force. Individuals in the labor force are then expected to work until age 65, after which labor income is assumed to be zero. In calculating the net present value, a uniform discount rate of 4 percent is used for human capital, in line with all resources and countries within the wealth accounting framework.

Survival rates are not readily available from the data sources. To calculate survival rates, death rates obtained from the Global Burden of Disease Study 2019 are utilized. The shares of compensation of employees and the self-employed in the national accounts are retrieved from the Penn World Table 9.1 to control the estimated wages. Finally, employment data from the International Labour Organization are used for controlling and scaling up total employment from the I2D2 database. Where some data are missing for a country in a given year, gap-filling measures are employed. The data and methods are described further in annex 7A at the end of this chapter.

Labor Income Growth Rates

A critical factor in human capital valuation is the expected change in wage rates over time. The estimates in CWON 2018 assumed the same constant wage growth rate in all countries, 2.46 percent, because of a lack of data. However, this is not realistic, because wage growth rates vary greatly across countries. CWON 2021 introduces region- and income group–specific annual real labor wage growth rates capped at 4 percent (table 7.1). The growth rates are derived from the World Bank's macroeconomic and fiscal model based on historical data and long-term projections based on potential output in each country, which builds on total factor productivity growth, capital stocks, and employment growth. These growth rates were estimated in October 2020 and include the initial negative effects of the COVID-19 pandemic on economic activity and wage growth for 2020–22. For the period after 2023, a recovery in the labor income growth rates is assumed aligned with the

TABLE 7.1 Labor Income Growth Rates, by Region and Income Level

Region	Countries	Wage growth (%)
East Asia and Pacific, high-income	4	1.08
East Asia and Pacific (excluding high-income)	11	4.00
Europe and Central Asia, high-income	27	1.08
Europe and Central Asia (excluding high-income)	17	2.83
Latin America and the Caribbean, high-income	4	1.08
Latin America and the Caribbean (excluding high-income)	20	0.96
Middle East and North Africa, high-income	7	1.08
Middle East and North Africa (excluding high-income)	10	1.34
North America	2	0.91
South Asia	6	3.60
Sub-Saharan Africa	38	1.41
Total	**146**	

Source: World Bank staff calculations.
Note: All countries in North America are high-income; all countries in South Asia and Sub-Saharan Africa are low- or middle-income.

recovery in total factor productivity growth. In addition, real labor wage growth rates are differentiated by region and income group, reflecting factors such as underlying labor market characteristics and productivity. Grouping wage growth rates by region and income group allows for a more transparent and simpler calculation, given the vast size of the database. In a later section, this chapter explores the impact of this short-term COVID-19-related loss on human capital.

Adjustments to the National Accounts and Population Data

Because the survey data do not capture the entire world population, the data from the surveys are adjusted to population estimates from the United Nations to ensure that the estimates are adequate. In addition, the earnings profiles are not compatible with the published data from the SNA because the earnings profiles from the surveys do not include any benefits other than wages, including social security payments and other wage-related payments. Hence, the estimated earnings profiles from the surveys are benchmarked to the compensation of employees and self-employed that is obtained from the Penn World Table. Therefore, expected labor earnings from the surveys are scaled up to the labor earnings in the national accounts.

Generating the Lifetime Income

After the lifetime income profiles for a representative individual cross-classified by age, gender, and education are generated, they are multiplied by the corresponding number of people in a country, and thereby the human capital stock by age, gender, and education is calculated. Summing up the stocks of human capital across all classified categories generates the estimate of the aggregate value of the human capital stock for each country.

Estimates of Human Capital

This section focuses on human capital across countries and trends in human capital over 1995–2018. The estimates of human capital are summarized at the global, income, and regional levels, with an additional discussion on the self-employed portion of human capital.

Human Capital by Income Group

Human capital is a critical component of a nation's wealth, accounting for the largest share of wealth for most countries. On average, human capital constitutes about two-thirds of total wealth at the global level, rising from 62 percent in 1995 to 64 percent in 2018 (table 7.2). The share of human capital in total wealth changes steadily with the level of development—human capital's share of total wealth generally increases as countries achieve higher levels of economic development. Human capital was greater than 60 percent of wealth in middle-income and high-income Organisation for Economic Co-operation and Development (OECD)

TABLE 7.2 Trends in Wealth per Capita, by Income Group, 1995–2018

Income group	1995	2000	2005	2010	2015	2018	Total growth (%)
Low-income							
Total wealth per capita (2018 US$)	9,379	9,121	9,250	10,228	11,306	11,462	22
Human capital per capita (2018 US$)	3,580	3,548	3,812	4,266	5,163	5,726	60
Human capital as share of total wealth (%)	38	39	41	42	46	50	n.a.
Lower-middle-income							
Total wealth per capita (2018 US$)	15,253	15,516	17,721	22,066	24,896	27,108	78
Human capital per capita (2018 US$)	8,570	8,926	10,387	13,092	14,961	16,847	97
Human capital as share of total wealth (%)	56	58	59	59	60	62	n.a.
Upper-middle-income							
Total wealth per capita (2018 US$)	50,744	58,872	74,317	100,114	128,136	141,682	179
Human capital per capita (2018 US$)	28,827	35,579	46,108	62,489	83,305	93,794	225
Human capital as share of total wealth (%)	57	60	62	62	65	66	n.a.
High-income: non-OECD							
Total wealth per capita (2018 US$)	315,088	334,226	367,631	410,083	450,258	400,891	27
Human capital per capita (2018 US$)	123,878	125,885	119,946	130,637	135,468	134,604	9
Human capital as share of total wealth (%)	39	38	33	32	30	34	n.a.
High-income: OECD							
Total wealth per capita (2018 US$)	468,398	522,668	545,341	564,426	597,897	621,278	33
Human capital per capita (2018 US$)	299,270	337,303	344,467	349,834	378,100	396,222	32
Human capital as share of total wealth (%)	64	65	63	62	63	64	n.a.
World							
Total wealth per capita (2018 US$)	111,174	120,431	128,122	140,129	153,631	160,167	44
Human capital per capita (2018 US$)	68,450	75,524	79,227	85,448	95,971	101,797	49
Human capital as share of total wealth (%)	62	63	62	61	62	64	n.a.

Source: World Bank staff calculations.
Note: OECD = Organisation for Economic Co-operation and Development; n.a. = not applicable.

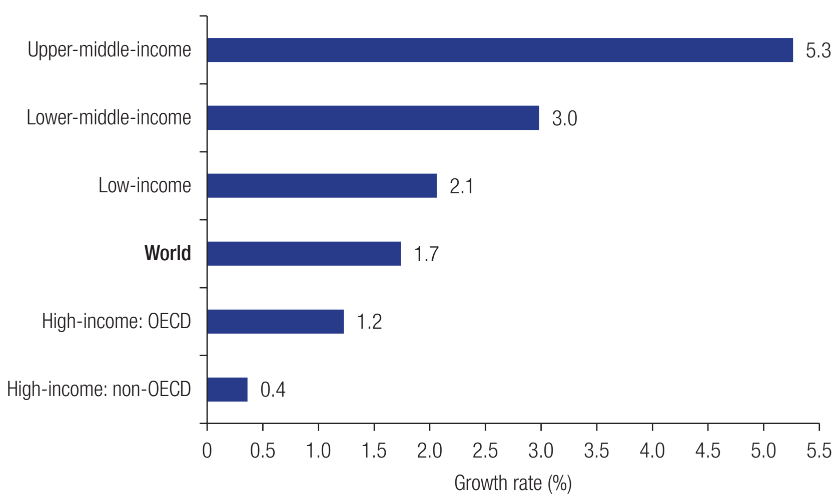
countries in 2018 but only 50 percent in low-income countries. High-income non-OECD countries—countries that are heavily dependent on fossil fuel wealth—had the lowest share, only 34 percent of wealth. It is a challenge for oil-rich countries to build human capital quickly, despite the abundant financial resources provided by oil.

Trends in human capital differ over time between high-income OECD countries and low- and middle-income countries. On average, the share of human capital in high-income countries plateaued during 1995–2018, while it increased in all other income groups. This can be explained in part by the share of labor earnings in GDP, which anchors the human capital estimates. Labor earnings as a share of GDP and per capita human capital grew rapidly in the 1990s, but much more slowly since 2000 because of technological change, stagnating wages, and in many countries, a reduction in the share of the population in the labor force, which resulted from the aging of the population. But in many middle- and low-income countries, educational attainment and returns to education are still growing, and hence human capital is growing fast.

Inequality in total wealth across income groups extends to human capital as well. Per capita human capital in high-income OECD countries in 2018 was 69 times of that in low-income countries. In high-income OECD countries, human capital per capita was close to US$400,000, while it was only US$5,726 in low-income countries (table 7.2). This significant difference between human capital in low-income and high-income countries reflects the difference in incomes.

Growth of human capital tends to be higher in middle-income countries, at 5.3 percent per year in upper-middle-income countries and 3.0 percent per year in lower-middle-income countries. The lowest growth is seen in high-income countries, at 0.4 percent per year in high-income non-OECD countries and 1.2 percent per year in high-income OECD countries (figure 7.1). This is mostly because of the differences in labor income growth rates and GDP growth rates. Labor income growth in high-income countries is significantly lower than that in low-income and middle-income countries. Moreover, on average, GDP growth rates of high-income countries are lower than GDP growth rates of low- and middle-income countries.

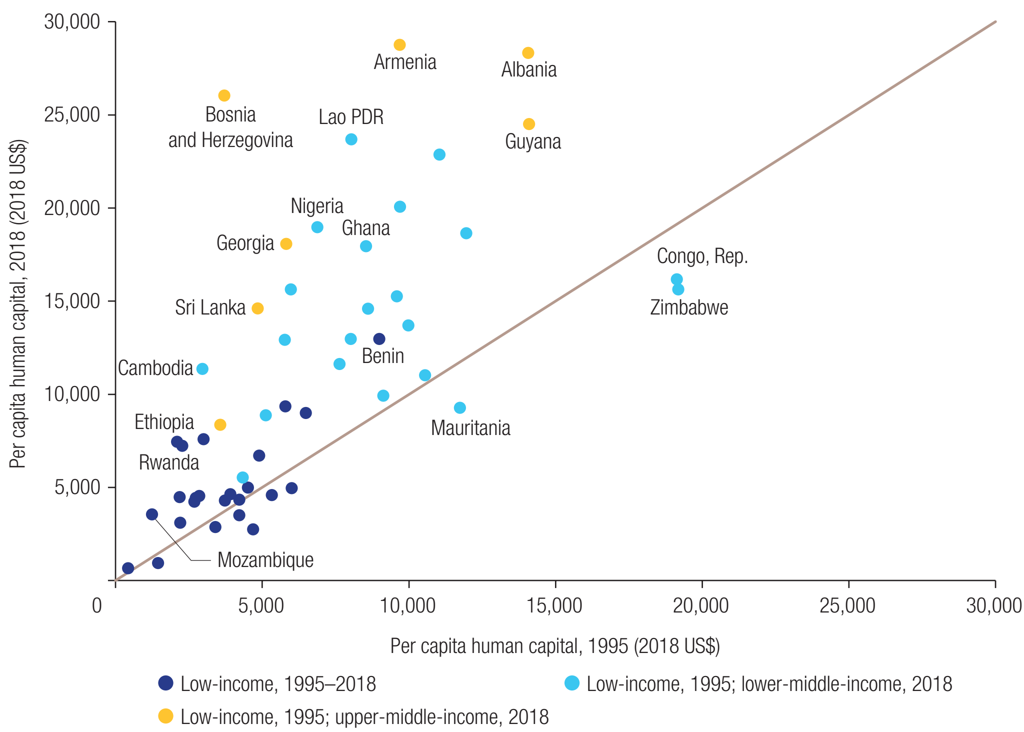
FIGURE 7.1 Annual Growth Rates of Human Capital per Capita, by Income Group, 1995–2018



Source: World Bank staff calculations.
Note: OECD = Organisation for Economic Co-operation and Development.

Of particular interest is the pattern of growth of countries that were classified as low-income in 1995 but grew to become middle-income by 2018 (and are thus classified as middle-income in the CWON database). The transition of all these countries involved accelerated investment in and accumulation of human capital. However, there were three exceptions—countries that became middle-income largely because of fossil fuel and mineral wealth: Mauritania, Zimbabwe, and the Republic of Congo. The Republic of Congo and Zimbabwe are considered fragile and conflict-affected states in which building human capital becomes very difficult. The Republic of Congo's heavy dependence on oil created further difficulties after 2014 when oil prices fell. Although it is not a fragile and conflict-affected state, Mauritania is an example of the potential demographic dividend from population growth not being achieved, a result of underinvestment in human capital. Total human capital increased from 1995 to 2018, but the increase was not enough to compensate for the country's rapid population growth (figure 7.2).

FIGURE 7.2 Change in Per Capita Human Capital in Low-Income Countries, 1995–2018



Source: World Bank staff calculations.
Note: Although China was a low-income country in 1995 and became an upper-middle-income country in 2018, its per capita human capital is not included in the figure because of scaling. The figure includes all countries with per capita human capital less than US$30,000 in 2018. Since China's per capita human capital is far above this threshold, the figure doesn't include China while it was a low-income country in 1995, because it would distort the figure. China's per capita human capital was US$25,556 in 1995, and it skyrocketed to US$127,685 in 2018.

In general, countries that sustained their low-income status from 1995 to 2018 did not experience a meaningful change in their human capital (dark blue dots in figure 7.2). Among these countries, only Benin's per capita human capital exceeded US$10,000 from 1995 to 2018. Low-income countries that moved to middle-income status from 1995 to 2018 saw significant increases in human capital. Human capital per capita more than doubled from 1995 to 2018 in most of the current middle-income countries that were classified as low-income status in 1995 (light blue and yellow dots in figure 7.2). Per capita human capital increased by a factor of seven in Bosnia and Herzegovina, a factor of five in China, four in Cambodia, three and a half in Ethiopia, and about three in Rwanda, Georgia, Sri Lanka, Armenia, the Lao People's Democratic Republic, Mozambique, and Nigeria (figure 7.2). Furthermore, Bosnia and Herzegovina outperformed not only low-income countries but also countries at all income levels in the increase in per capita human capital. And China's per capita human capital exceeded US$100,000, reaching US$127,685 in 2018.

Regional Trends in Human Capital

Human capital constitutes a significant share of total wealth in all regions except the Middle East and North Africa, where human capital is less than one-third of total wealth. For all other regions, human capital is the largest share of total wealth. The share of human capital in total wealth increased from 1995 to 2018 in all regions except the Middle East and North Africa, where it decreased, and East Asia and Pacific, where it stayed the same (table 7.3).

There are significant variations in human capital per capita among regions. In 2018, the difference between the per capita human capital of the regions with the highest value and the lowest was 50 times. Although South Asia had the lowest per capita human capital in 1995, by 2018 Sub-Saharan Africa claimed the lowest per capita human capital. This was mostly the result of faster GDP growth in South Asian countries compared with Sub-Saharan African countries. For instance, average GDP growth in South Asia over 1995–2018 was 6.2 percent, while it was 4.2 percent in Sub-Saharan Africa. Thus, average per capita human capital in Sub-Saharan Africa in 2018 was US$12,278, while it was US$14,769 in South Asia. On the other end of the spectrum, North America had the highest per capita human capital of all regions, at US$612,452 in 2018—more than three times the per capita human capital of Europe and Central Asia. The main reason is that North America consists of only two high-income countries, while Europe and Central Asia includes countries in all income groups.

As a result of the differences in labor income growth rates, growth in human capital is higher in the South Asia and East Asia and Pacific regions, at 3.9 percent per year in both. As the methodology section suggests, labor income growth rates are higher in these regions. Moreover, most countries in these regions had the highest growth rates of the wage rate and GDP over the past 25 years, although these two regions include the two most populous countries in the world. The Middle East and North Africa,

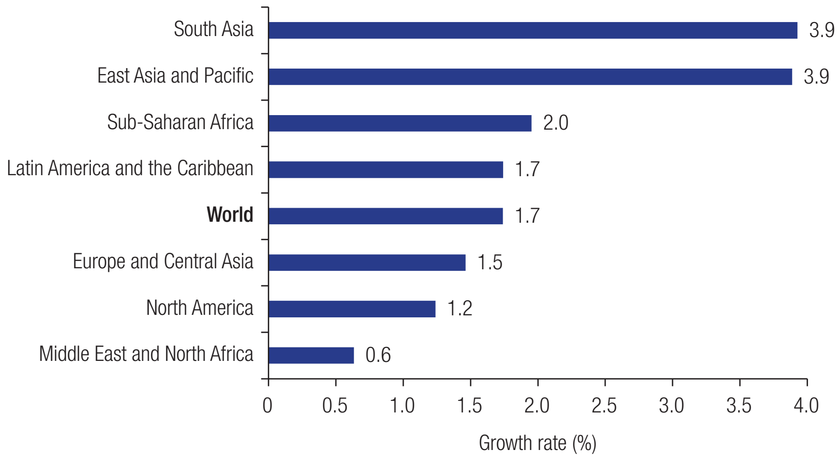
TABLE 7.3 Trends in Wealth per Capita, by Region, 1995–2018

Region	1995	2000	2005	2010	2015	2018	Total growth (%)
East Asia and Pacific							
Total wealth per capita (2018 US$)	73,518	84,441	99,076	126,270	158,301	176,125	140
Human capital per capita (2018 US$)	49,107	55,790	65,061	82,052	105,384	118,041	140
Human capital as share of total wealth (%)	67	66	66	65	67	67	n.a.
Europe and Central Asia							
Total wealth per capita (2018 US$)	237,608	257,762	276,580	296,021	309,672	322,739	36
Human capital per capita (2018 US$)	128,957	142,468	152,194	163,012	171,434	180,093	40
Human capital as share of total wealth (%)	54	55	55	55	55	56	n.a.
Latin America and the Caribbean							
Total wealth per capita (2018 US$)	75,547	78,567	83,210	94,677	106,246	107,229	42
Human capital per capita (2018 US$)	44,848	47,913	49,579	56,208	64,698	66,709	49
Human capital as share of total wealth (%)	59	61	60	59	61	62	n.a.
Middle East and North Africa							
Total wealth per capita (2018 US$)	74,030	75,920	88,615	109,212	116,929	102,927	39
Human capital per capita (2018 US$)	26,801	26,396	26,261	30,332	31,764	30,989	16
Human capital as share of total wealth (%)	36	35	30	28	27	30	n.a.
North America							
Total wealth per capita (2018 US$)	674,771	766,443	796,244	799,827	841,547	867,304	29
Human capital per capita (2018 US$)	461,403	536,869	546,905	537,602	585,338	612,452	33
Human capital as share of total wealth (%)	68	70	69	67	70	71	n.a.
South Asia							
Total wealth per capita (2018 US$)	9,648	10,964	12,944	16,168	19,791	22,680	135
Human capital per capita (2018 US$)	6,089	7,142	8,490	10,130	12,513	14,769	143
Human capital as share of total wealth (%)	63	65	66	63	63	65	n.a.
Sub-Saharan Africa							
Total wealth per capita (2018 US$)	17,273	15,528	16,018	19,527	21,003	20,473	19
Human capital per capita (2018 US$)	7,870	7,228	7,747	10,613	12,062	12,278	56
Human capital as share of total wealth (%)	46	47	48	54	57	60	n.a.

Source: World Bank staff calculations.
Note: n.a. = not applicable.

North America, and Europe and Central Asia saw the lowest growth rates in human capital, at 0.6, 1.2, and 1.5 percent per year, respectively (figure 7.3). Compared with South Asia and East Asia and Pacific, these regions consist mostly of high-income countries, where labor income growth and GDP growth tend to be lower. Moreover, most countries in the Middle East and North Africa are resource-rich countries and reliant

FIGURE 7.3 Annual Growth Rates of Human Capital per Capita, by Region, 1995–2018



Source: World Bank staff calculations.

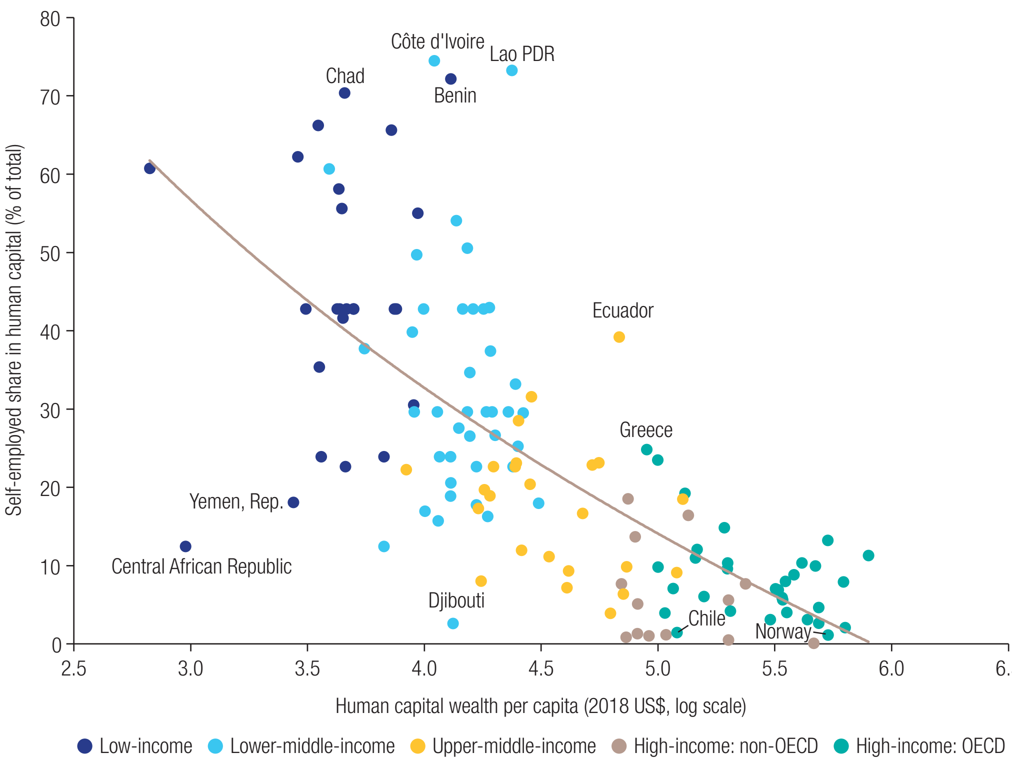
on fossil fuel energy resources, and these countries face unique development challenges to transform an exhaustible resource into assets that can continue to generate income and employment.

Human Capital and the Self-Employed

Self-employment is an important part of the labor market in many countries, but especially in low-income countries. However, estimation of the earnings of the self-employed reported in national surveys is underrepresented and poorly captured, because surveys tend to focus only on formal employment. In addition, most self-employed workers are active in agriculture, and earnings as measured in a labor force or household survey may not adequately account for these workers. This makes it difficult to estimate the share of human capital attributed to self-employment in a systematic way across countries (given differences in survey designs and questionnaires among countries). As is explained in annex 7A, the Penn World Table provides estimates of the income of the self-employed by drawing on additional data (for example, national accounts' mixed income and value added from agriculture). Therefore, disaggregating earnings by employment is done by using the Penn World Table estimates for the purpose of this chapter.

Self-employed workers account for only 13 percent of global human capital. However, the human capital of the self-employed is a large share of the total in many of the poorest countries, where the agriculture sector and informal employment are significant. In more recent years, the growth of self-employment has been increasing in higher-income-level economies. In particular, technological improvement, artificial intelligence, and automation have been paving the way for the increasing number of self-employed people in those countries.

FIGURE 7.4 Self-Employed Share in Human Capital, 2018



Source: World Bank staff calculations.
Note: OECD = Organisation for Economic Co-operation and Development.

Figure 7.4 illustrates the strong downward relationship between the level of human capital and the share of human capital attributed to the self-employed. In general, countries with lower levels of human capital have higher shares of wealth attributed to the self-employed. This is an expected result, because self-employment (including subsistence farmers and small businesses in the informal sector) constitutes a more substantial part of total labor inputs than wage employment in these countries. By contrast, the share of human capital attributed to the self-employed in high-income countries is meaningfully low. For instance, the share of human capital attributed to the self-employed is only 1.1 percent in Norway and 1.5 percent in Chile.

Gender and Human Capital

The human capital estimates reveal a significant disparity between the male and female shares of human capital. Unfortunately, little progress has been made toward greater gender parity in human capital over the past 25 years. Globally, as shown in table 7.4, women accounted for only

TABLE 7.4 Shares of Human Capital, by Gender, 1995–2018

	Male share (%)						Female share (%)					
Income group and region	**1995**	**2000**	**2005**	**2010**	**2015**	**2018**	**1995**	**2000**	**2005**	**2010**	**2015**	**2018**
Income group												
Low-income	66	66	66	67	67	68	34	34	34	33	33	32
Lower-middle-income	74	75	76	75	77	78	26	25	24	25	23	22
Upper-middle-income	63	62	62	63	63	64	37	38	38	37	37	36
High-income: non-OECD	71	70	70	72	71	71	29	30	30	28	29	29
High-income: OECD	64	64	63	62	62	62	36	36	37	38	38	38
Region												
East Asia and Pacific	70	69	67	67	67	67	30	31	33	33	33	33
Europe and Central Asia	62	62	61	61	60	61	38	38	39	39	40	39
Latin America and the Caribbean	61	58	58	57	56	56	39	42	42	43	44	44
Middle East and North Africa	75	75	75	75	74	74	25	25	25	25	26	26
North America	62	63	61	59	59	59	38	37	39	41	41	41
South Asia	88	88	87	87	87	87	12	12	13	13	13	13
Sub-Saharan Africa	56	57	62	67	67	67	44	43	38	33	33	33
World	**65**	**64**	**63**	**63**	**63**	**63**	**35**	**36**	**37**	**37**	**37**	**37**

Source: World Bank staff calculations.
Note: OECD = Organisation for Economic Co-operation and Development.

37 percent of human capital in 2018, which was only 2 percentage points greater than the 1995 level.

Although higher levels of economic development are generally associated with a higher share of women in human capital, women account for less than 40 percent of human capital at all levels of development. While women account for less than one-third of human capital in low-income, lower-middle-income, and high-income non-OECD countries, the share of women is slightly greater than one-third of human capital in upper-middle-income and high-income OECD countries.

The differences between regions are even more striking. As shown in table 7.4, women accounted for only 13 percent of human capital in South Asia in 2018, while 44 percent of human capital was attributed to women in Latin America and the Caribbean. The share of women in Europe and Central Asia and North America was about 40 percent of human capital, while about one-third of human capital was attributed to women in East Asia and Pacific and Sub-Saharan Africa.

These results demonstrate that women's role in human capital tends to increase as countries achieve higher levels of economic development. This is an expected outcome because higher educational attainment, better quality of education, higher participation of women in the labor force, and more competitive wages are associated with economic development. However, as the results suggest, there is still substantial gender disparity between men and women even in high-income countries and regions with high economic development. There are several other factors causing the gender disparity in human capital, including (1) careers that are interrupted for childbearing; (2) penalties for childcare, as women work part-time to meet family needs and as employers question the commitment of women to their career; (3) preferences on the part of women for occupations that may be lower paid, an effect that is often reinforced by preferences for fields of study that lead to such occupations; (4) barriers that prevent women from attaining similar economic opportunities as men; and (5) a lack of women in leadership positions in the workforce. Gender discrimination fosters and reinforces many of these negative influences on women's earnings.

To capture the magnitude of gender-based disparities in human capital over time, table 7.5 provides a simple measure of the gender gap in human capital, defined as the ratio of the human capital of women divided by that of men in a country. In 2018, the global gender gap in human capital was 57 percent, meaning the remaining gap to close is 43 percent. Although there was progress from 1995 to 2018, the global

TABLE 7.5 Potential Gains in Human Capital from Gender Equity, by Income Group and Region, 1995–2018

	Gender gap ratio (x100) (ratio of human capital by gender)						Potential gain from gender equity (% increase from base)					
Income group and region	**1995**	**2000**	**2005**	**2010**	**2015**	**2018**	**1995**	**2000**	**2005**	**2010**	**2015**	**2018**
Income group												
Low-income	51	51	52	49	48	47	25	24	24	25	26	27
Lower-middle-income	36	33	32	34	29	28	32	33	34	33	35	36
Upper-middle-income	59	62	62	60	58	57	20	19	19	20	21	21
High-income: non-OECD	41	43	42	40	41	41	29	28	29	30	30	30
High-income: OECD	56	56	59	62	62	62	22	22	21	19	19	19
Region												
East Asia and Pacific	44	46	48	50	49	49	28	27	26	25	25	25
Europe and Central Asia	62	62	63	64	65	64	19	19	18	18	17	18
Latin America and the Caribbean	64	74	73	77	78	79	18	13	13	12	11	11
Middle East and North Africa	34	34	34	34	36	36	33	33	33	33	32	32
North America	60	59	64	69	69	69	20	20	18	15	15	15
South Asia	14	14	15	15	15	15	43	43	42	42	42	42
Sub-Saharan Africa	78	74	62	49	49	49	11	13	19	26	25	25
World	**55**	**55**	**57**	**59**	**58**	**57**	**23**	**22**	**21**	**21**	**21**	**21**

Source: World Bank staff calculations.
Note: OECD = Organisation for Economic Co-operation and Development.

progress has been minimal: only 2 percentage points. In low-income, lower-middle-income, and high-income non-OECD countries, the gender gap ratio is particularly low, below 50 percent. In other words, women's presence and contribution to human capital is still extremely limited at these levels of economic development. In countries at higher levels of economic development, the gender gap ratio is higher, but still well below parity. Interestingly, only high-income OECD countries made progress toward gender equality over 1995–2018, narrowing the gap by 6 percentage points. In contrast, the gender gap worsened in countries at all other levels of development. One possible reason why the gender gaps are widening outside high-income OECD countries could be that women's wages tend to be lower than men's wages even as women's labor force participation is increasing. However, further research is needed for a full explanation.

The gender gap in human capital across regions is even more noticeable. The gender gap ratio has a wide range, from 15 percent in South Asia to 79 percent in Latin America and the Caribbean. South Asia's large gender gap is mostly caused by a male-dominated labor force and many barriers that prevent women from attaining similar economic opportunities as men. In contrast, female labor force participation is higher in Latin America and the Caribbean. Although the gender gap ratio is higher in North America and Europe and Central Asia compared with other regions, it is still far from parity, at below 70 percent.

The gender gap in human capital can be used to conduct simple simulations of the gains that could be achieved from greater equity in earnings and thereby human capital by gender. Assume for simplicity that the working-age population is equally divided between men and women, each with a 50 percent share. Then, if the earnings of women were on par with those of men, women's human capital would rise considerably. Assuming no decrease in the human capital of men, the resulting gains in human capital (NG) can be estimated as $NG = (100 - \text{gender gap ratio}) \times 0.50/100$. As shown in table 7.5, human capital worldwide could increase by 21 percentage points with gender parity. In low-income, lower-middle-income, and high-income non-OECD countries where the gender gaps in human capital are more pronounced, the gains from gender equity would be larger. Meanwhile, countries at all levels of economic development benefit from gender equity.

Because the gender gaps are substantially larger in some regions, the gains from gender equity in these regions are stunning. The region with the largest difference in human capital by gender is South Asia. If gender parity were achieved in South Asia, this could increase human capital nationally by roughly 42 percentage points (table 7.5). These simple simulations do not account for the general equilibrium impact that an influx of women into the labor market might generate, and thereby tend to overestimate the benefits that could result from gender equity. Still, the estimates show that major gains in human capital per capita could be achieved if women were able to work more and earn more and that deeper analysis is needed on the components driving women's human capital compared to men's.

Impact of COVID-19 on Human Capital

Impact of COVID-19 on Wage Growth Rates

While the COVID-19 pandemic has had an immediate and devastating impact on all people and countries, the magnitude of its effects in the medium to long term is still unknown and complex because of its multidimensional effects. For instance, its harmful effects include but are not limited to wage growth losses resulting from the global economic recession, productivity losses of affected people, and interrupted education of the next generation of workers (particularly in low- and middle-income countries).

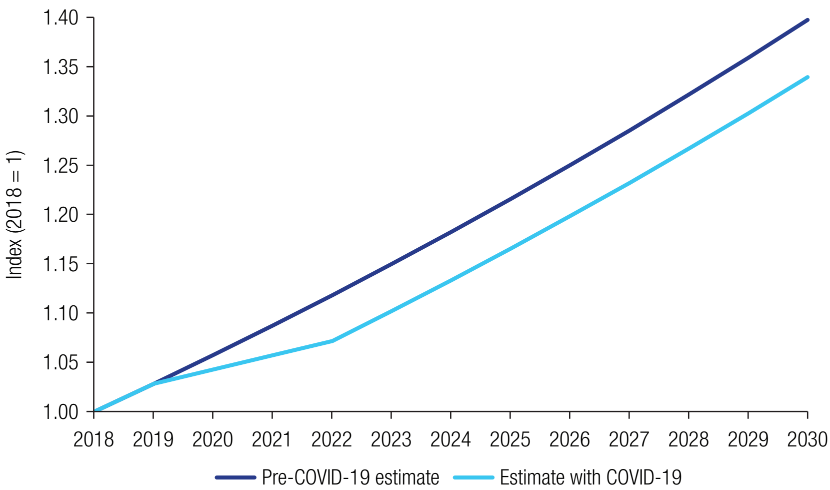
This section focuses on the impact of COVID-19 on only wage growth rates because all other impacts of COVID-19 on human capital are still limited to a few studies. Estimated labor income growth rates before COVID-19 are compared with estimates made in October 2020, when the pandemic was well under way (table 7.6). The COVID-19-related economic recession will cause a significant drop in the number of jobs, and it will take some time for employment to get back on track. Therefore, it is presumed that the COVID-19 recession has an effect on wages during the first three years of the pandemic, after which the annual wage growth rates will return to pre-COVID-19 levels (figure 7.5). Since human capital is estimated following the lifetime income approach, a drop in wage growth during the COVID-19 pandemic has a substantial impact on human capital through the discounted lifetime earnings to the base year.

TABLE 7.6 Annual Wage Growth Rates, Pre-COVID-19 and Post-COVID-19

Region	Countries	Wage growth pre-COVID-19 (%)	Wage growth post-COVID-19 (%)	Change (percentage points)
East Asia and Pacific, high-income	4	1.21	1.08	–0.13
East Asia and Pacific (excluding high-income)	11	4.00	4.00	0.00
Europe and Central Asia, high-income	27	1.21	1.08	–0.13
Europe and Central Asia (excluding high-income)	17	3.03	2.83	–0.20
Latin America and the Caribbean, high-income	4	1.21	1.08	–0.13
Latin America and the Caribbean (excluding high-income)	20	1.15	0.96	–0.19
Middle East and North Africa, high-income	7	1.21	1.08	–0.13
Middle East and North Africa (excluding high-income)	10	1.48	1.34	–0.14
North America	2	1.07	0.91	–0.16
South Asia	6	4.00	3.60	–0.40
Sub-Saharan Africa	38	2.31	1.41	–0.90
Total	**146**			

Source: World Bank staff calculations.
Note: All countries in North America are high-income; all countries in South Asia and Sub-Saharan Africa are low- or middle-income.

FIGURE 7.5 Index of the Wage Growth Trajectory: Impact of the COVID-19 Pandemic



Source: World Bank staff calculations.

Since the wage growth trajectory is affected only during the first three years of the pandemic, the changes in longer-term average wage growth rates are smaller, ranging from 0.13 percentage points in high-income countries to 0.9 percentage points in Sub-Saharan Africa. There is virtually no change in the long-term average wage growth rate in the middle-income East Asia and Pacific region, dominated by China.

At the global level, it is estimated that human capital declined about 1.9 percent in 2018 because of COVID-19, corresponding to US$14 trillion (in 2018 US dollars). At the global level, it is estimated that per capita human capital declined on average US$1,959 in 2018 because of COVID-19 (table 7.7). The most severely affected region is Sub-Saharan Africa, where per capita human capital declined by about 13.3 percent in 2018 (table 7.7; figure 7.6). The other most severely affected region is South Asia, where per capita human capital declined by about 6.3 percent in 2018. East Asia and Pacific is the least negatively affected region because only high-income countries in this region are badly affected by declining wage growth.

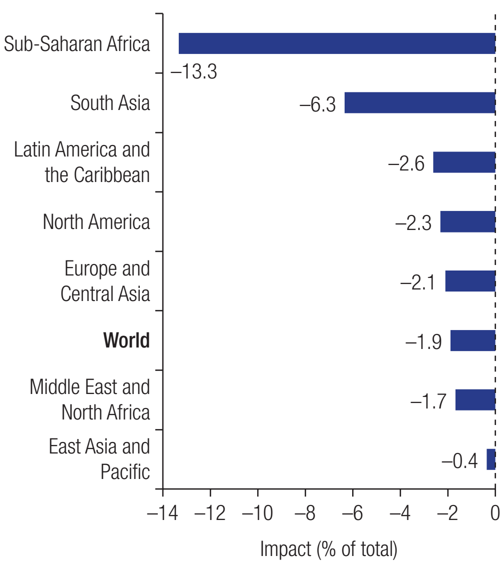
Looking at the change in human capital by income level, the results indicate that low-income (mostly Sub-Saharan African countries) and lower-middle-income countries (largely South Asian countries) are the most severely affected by the declining wage growth, while upper-middle-income countries are the least affected. In 2018, human capital per capita dropped by about 12.5 percent (US$821) in low-income countries and 5.6 percent (US$999) in lower-middle-income countries because of COVID-19. By contrast, the decline in per capita human capital in upper-middle-income countries is only about 0.8 percent (US$772).

TABLE 7.7 Drop in Per Capita Human Capital Because of COVID-19, by Income Group and Region
2018 US$

Income group and region	1995	2000	2005	2010	2015	2018
Income group						
Low-income	437	428	484	574	729	821
Lower-middle-income	425	464	563	751	898	999
Upper-middle-income	438	473	524	628	736	772
High-income: non-OECD	2,015	2,050	1,937	2,102	2,112	2,087
High-income: OECD	5,833	6,541	6,754	6,960	7,542	7,902
Region						
East Asia and Pacific	429	424	396	401	429	435
Europe and Central Asia	2,797	3,094	3,316	3,551	3,675	3,875
Latin America and the Caribbean	1,232	1,350	1,390	1,541	1,742	1,792
Middle East and North Africa	491	487	482	543	548	529
North America	10,534	12,066	12,500	12,679	13,894	14,530
South Asia	408	489	594	693	852	1,001
Sub-Saharan Africa	1,172	1,048	1,152	1,617	1,853	1,888
World	**1,428**	**1,540**	**1,596**	**1,712**	**1,869**	**1,959**

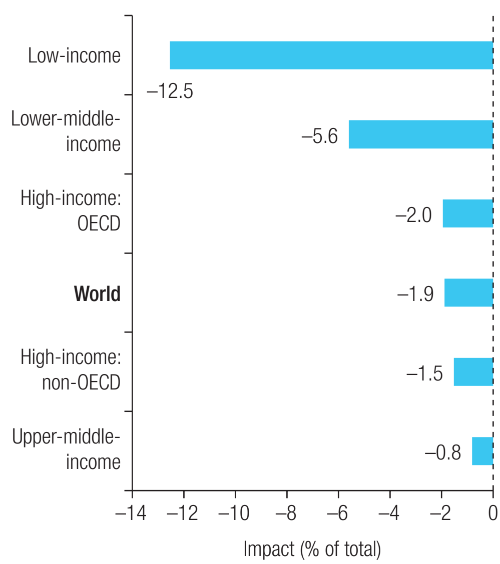
Source: World Bank staff calculations.
Note: Since human capital is estimated following the lifetime income approach, a drop in wage growth during the COVID-19 pandemic has a substantial impact on human capital through the discounted lifetime earnings to the base year. OECD = Organisation for Economic Co-operation and Development.

FIGURE 7.6 Impact of COVID-19 on Human Capital, by Region, 2018



Source: World Bank staff calculations.
Note: Since human capital is estimated following the lifetime income approach, a drop in wage growth during the COVID-19 pandemic has a substantial impact on human capital through the discounted lifetime earnings to the base year.

FIGURE 7.7 Impact of COVID-19 on Human Capital, by Income Group, 2018



Source: World Bank staff calculations.
Note: Since human capital is estimated following the lifetime income approach, a drop in wage growth during the COVID-19 pandemic has a substantial impact on human capital through the discounted lifetime earnings to the base year. OECD = Organisation for Economic Co-operation and Development.

For high-income OECD countries, the decline in per capita human capital is about 2 percent, although these countries are estimated to experience an average decline of US$7,902 in 2018 (table 7.7; figure 7.7).

Conclusion

This chapter provided a set of comparable estimates of human capital based on a time series of household surveys for 146 countries throughout 1995–2018. Human capital accounts for about two-thirds of total global wealth and typically a higher share in upper-middle-income and high-income OECD countries. On average, the share of human capital increases with higher levels of development and is highest in high-income and upper-middle-income countries.

Estimates by gender demonstrate the continued, significant disparity between men's and women's human capital, which is greater in some regions than others. Globally, the female share in human capital is only about one-third, and progress in closing the gender gap has been slow over the past 25 years. The COVID-19 pandemic and economic shutdown have had disproportionate impacts on women and may have set back progress toward gender equality even further.

The COVID-19 pandemic has clearly created immediate impacts on economic growth, jobs, and wages. Medium- to long-term effects on human capital resulting from the interrupted education of millions of students and negatively affected health of millions of people are still limited to a few studies (box 7.3). The partial impacts estimated for the

BOX 7.3 Impact of the COVID-19 Pandemic on Education and Health

The COVID-19 pandemic is of critical concern for human capital through tragic direct channels of health (mortality and morbidity) and indirect channels of household income, productivity, educational quality, health, and economywide impacts. Simulations conducted for the Human Capital Index 2020 Update (World Bank 2020) suggest that school closures combined with family hardship are significantly affecting the accumulation of human capital for the current generation of school-age children. Additionally, COVID-19's disruption of health services, losses in income, and worsened nutrition are expected to increase child mortality and stunting, with effects that will be felt for decades to come.

A recent paper by Azevedo et al. (2020) estimates that the potential short- and long-term impacts of school closures and remote learning could result in a loss of between 0.3 and 0.9 year of schooling adjusted for quality.

Roberton et al. (2020) estimate the additional maternal and under-5 child deaths stemming from the potential health systems disruption and worsened access to food because of COVID-19 in 118 low- and middle-income countries under two scenarios. The optimistic scenario suggests that COVID-19 will increase maternal deaths by 8.3 percent and child deaths by 9.8 percent, while the pessimistic scenario suggests that maternal deaths will increase by 38.6 percent and child deaths will increase by 44.7 percent.

short-term economic shutdown could be devastating, particularly for low- and middle-income countries, setting back gains in eradicating poverty. In addition, according to a recent report by UNESCO and the World Bank (2021), two-thirds of low-income and lower-middle-income countries have cut their education budgets since the onset of the COVID-19 pandemic. Moreover, there is a potential that the cuts will be higher in the future (UNESCO and World Bank 2021). The cuts in education budgets in low-income and lower-middle-income countries may further depress the value of human capital for those countries in the future.

The focus in this chapter was solely on human capital as a productive asset that produces a stream of benefits: future wages. This is not to deny that education, good health, and knowledge are sources of well-being in and of themselves, or that doing a job well is one of the great human pleasures. Development is about building human capital—some of that requires direct investment, such as education, while some requires broader investment in a healthy environment, water, sanitation, and clean air.

In future work, some improvements to the methodology used here could be undertaken, including the number of surveys needed and the methodology on filling gaps between surveys. In addition, the impact of COVID-19 on education and health can be incorporated into the methodology, and more precise estimates on the impact of COVID-19 could be made. Further research and analysis on the factors driving the large differences between men's and women's human capital are also important, especially for policy makers. Nevertheless, even with the data now available, additional analysis as well as simulations can be undertaken to inform policy.

Annex 7A: Methodology for Calculating Human Capital: Estimating Human Capital with the Lifetime Income Approach

Annex 7A explains how the lifetime income approach developed by Jorgenson and Fraumeni (1989, 1992a, 1992b) was implemented to estimate human capital. According to this approach, human capital is estimated as the total present value of the expected future labor income that could be generated over the lifetime of the women and men currently living in a country (Fraumeni 2008; Hamilton and Liu 2014).

The implementation of the lifetime income approach requires data by age and gender on population, employment and labor force participation, education, earnings profiles, and survival rates. The data sources for each variable are included in table 7A.1. The estimation is carried out in seven steps, as described in this annex.

In the equations, the country and gender dimensions of variables are omitted for ease of presentation.

Step 1. Estimating the Earnings Regressions

The World Bank's International Income Distribution Database (I2D2), a unique database of more than 2,000 household surveys maintained by the World Bank, is used to construct a database containing information on the number of people, their age, gender, earnings, educational attainment,

TABLE 7A.1 Data Sources for the Human Capital Calculations

Indicator or variable	Data source(s)	Notes
Annual earnings	I2D2	Annual earnings are calculated utilizing the Mincerian regression results. The (relative) earnings profile by age, education, and gender is derived for each country and year given the corresponding data availability.
Educational attainment	I2D2	Years of education by age and gender are derived for each country and year.
Employment rates	I2D2	The employment rate and self-employment rate by age, gender, and education level are calculated for each country and year. These rates are calculated for employed (or self-employed) persons divided by the whole population, which includes the employed, self-employed, unemployed, and the people out of the labor force.
School enrollment rates	I2D2	This indicates whether an individual by age, gender, and education is enrolled in school or not; used for the probability of remaining employed in future years.
Employment	ILO	The ILO employment data are used as control totals for scaling up employment from the I2D2 database. ILO employment data are also used for filling data gaps when necessary.
Compensation of employees, GDP	United Nations National Accounts database	The Compensation of Employees data are used as input to control totals for scaling up annual earnings estimates from the I2D2 database and for filling the data gaps. In addition, the GDP data are used for expressing variables as a percentage of GDP.
Labor share of earnings of the self-employed	Penn World Table database	Penn World Table estimates of the labor component of the earnings of the self-employed in total earnings of the self-employed. Used as input to control total labor earnings.
Total labor earnings	United Nations National Accounts database and Penn World Table database	Compensation of employees plus labor earnings of the self-employed. This combined labor earnings estimate is used as a control total for scaling up earnings estimates from I2D2 to the national level.
Population	United Nations World Population Prospects	By gender and age groups: The distribution of workers from the I2D2 database is scaled up using the population data.
Survival rates	GBD study from the Institute for Health Metrics and Evaluation	Survival rates are calculated utilizing the death rates obtained from the GBD study. The GBD database includes global, regional, and national age- and gender-specific mortality for 369 diseases and injuries in 204 countries and territories.

Source: World Bank.
Note: GBD = Global Burden of Disease; GDP = gross domestic product; I2D2 = International Income Distribution Database; ILO = International Labour Organization.

school enrollment rates, and employment rates. This database is used to estimate the Mincerian coefficients. The Mincerian wage regressions are estimated as

$$Ln(w_i) = \alpha + \beta_1 e_i + \beta_2 X_i + \beta_3 X_i^2 + \mu_i \,, \qquad (7A.1)$$

where $Ln(w_i)$ is the natural log of earnings of individual i, e_i is years of schooling (from 0 to 24), X_i is labor market working experience (estimated as AGE_i (from age 15 to 64) $- e_i - 6$), X_i^2 is working experience-squared, and μ_i is a random disturbance term reflecting unobserved abilities. The coefficient β_1 measures the return to an extra year of schooling, and the coefficients β_2 and β_3 measure the return to working experience. Since working experience shows a decreasing marginal return, in general the coefficient β_3 is expected to be a negative value. The constant, α, measures the average log earnings of individuals with zero years of schooling and working experience. Equation (7A.1) is estimated for each economy for each survey year for males and females separately.

Although the I2D2 includes the number of years of schooling for most countries, some countries have data on levels of education instead of number of years of schooling. Therefore, a conversion is needed to estimate the Mincerian coefficients. In this case, including the levels of education as dummy variables in the Mincerian equation, the Mincerian coefficients are estimated for each level of education. For example, if a country's schooling data are represented as primary, secondary, and tertiary, equation (7A.1) is converted to the following form,

$$Ln(w_i) = \alpha + \beta_{1p}e_{ip} + \beta_{1s}e_{is} + \beta_{1t}e_{it} + \beta_2 X_i + \beta_3 X_i^2 + \mu_i\,, \qquad (7A.2)$$

where the subscripts p, s, and t represent the levels of education (primary, secondary, and tertiary). Hence, the private rate of return to different levels of schooling (r) can be derived from the following equations:

$$r_p = \beta_{1p} S_p, \qquad (7A.3)$$

$$r_S = (\beta_{1s} - \beta_{1p}) \,/\, (S_s - S_p), \qquad (7A.4)$$

$$r_t = (\beta_{1t} - \beta_{1s}) \,/\, (S_t - S_s), \qquad (7A.5)$$

where S_p, S_s, and S_t stand for the total number of years of schooling for each successive level.

The wages/earnings profile by age, education, and gender, $AIN_{s,a,e}$, can be readily derived for each economy-year using the following equation:

$$AIN_{s,a,e} = \exp(\alpha + \beta_1 e + (\beta_2 + \beta_3\, X_{s,a,e})X_{s,a,e}). \qquad (7A.6)$$

Based on the results of the Mincerian regressions, a matrix of expected earnings, H, is constructed. Each cell in the matrix accounts for labor earnings of the population age a, gender s, and education level e. If $n_{s,a,e}$ is the number of workers of age a, gender s, and years of schooling e, each cell in the matrix is defined as

$$H_{s,a,e} = n_{s,a,e} AIN_{s,a,e}. \qquad (7A.7)$$

Step 2. Scaling Up Earnings and Estimating Labor Earnings of the Self-Employed

For the calculation of human capital, total earnings should include not only wages but also the value of any additional benefits provided to employees, such as social security payments, health insurance, housing, or other benefits in cash or in-kind. The earnings profiles from the surveys represent an underestimate of total earnings because they include only wages and not any additional benefits. To adjust for this underestimate, Compensation of Employees from the System of National Accounts (SNA) is used to benchmark survey earnings profiles. In this approach, the relative wages from the surveys matter rather than the absolute level values.

However, there is one more step needed to include all human capital. Total labor income consists of two components: the incomes of the employed and the self-employed. The earnings of employed workers are included in the SNA under Compensation of Employees. The earnings of the self-employed are included in the SNA under Mixed Income or a more general category, Gross Operating Surplus, which includes all incomes not accruing to employees, mostly returns to capital and natural resources. The estimation of each component and how it is used to benchmark survey earnings profiles are discussed in this section.

Earnings of Employees

The household surveys used for the computation of the earnings profiles—as well as the probability of working—are nationally representative. The surveys are in most cases of good quality, but they may still generate estimates that are not consistent with the Compensation of Employees in the SNA (EC et al. 2009). Compensation of Employees includes the economic value of benefits, such as housing or health insurance, in addition to wages, but household surveys typically report only the wages received, thus underestimating total compensation. In some countries, additional benefits, in cash or in-kind, can be substantial. Total earnings from the survey, and the resultant human capital, are expected to be too low in comparison with the share of labor earnings in gross domestic product (GDP) because they do not include other benefits. This is addressed by using Compensation of Employees as part of the control total to scale up earnings profiles from the surveys.

Estimating the Labor Income of the Self-Employed

The economic role of the self-employed can be especially important in many low- and middle-income countries, where subsistence agriculture and the informal economy are very common. However, the earnings of the self-employed are not well represented in the national accounts of many countries because, with few exceptions, Compensation of Employees includes only workers who are formally employed. The earnings of the self-employed are included as part of another category, Mixed Income or Gross Operating Surplus, which also includes income accruing to produced capital and natural resources (resource rents). Earnings of the self-employed workers may also be poorly represented in household surveys.

Correcting this omission requires (1) identifying the earnings that can be attributed to the self-employed and (2) distinguishing the labor component of earnings from returns to other factors of production, which are all combined. For human capital estimates, only the labor portion of the earnings of the self-employed should be included. The Penn World Table (PWT) database has made estimates of the labor component of the income of the self-employed (Feenstra, Inklaar, and Timmer 2015), which is described in the following text.

For the purpose of disaggregating earnings by employment, shares of labor income of employees and self-employed from the PWT data on total compensation of labor are used, except for China, for which the income group average is used.[1] The PWT data on total compensation of labor construct a "best estimate" labor share based on four options for adjustment, to estimate the shares of labor income of employees and the self-employed.

The first two adjustment estimation methods proposed by the PWT are used for the roughly 60 countries that report mixed income as a separate income category in the national accounts. Mixed income isolates total income earned by self-employed workers from resource rents and returns to produced capital by other producers. Mixed income combines capital and labor income accruing to the self-employed and can be considered as an upper bound of the amount of labor income earned by the self-employed. The two adjustment methods are as follows:

1. All mixed income is allocated to labor assuming self-employed workers use only labor input.
2. Half of the mixed income is allocated to labor assuming self-employed workers use labor and capital in the same proportion.

The third adjustment method assumes the self-employed earn the same average wage as employees. However, this method has some drawbacks for countries where the share of employees in the labor force is low. Assuming that the self-employed earn the same average wage as employees will overstate the labor income of the self-employed in those countries. In particular, agriculture employs about half of the self-employed in most low-income countries. This leads to the fourth adjustment method, which is based on the share of agriculture in GDP. Total value added in agriculture is considered a good enough proxy for the labor earnings of the self-employed.

As explained, all four methods have some drawbacks, and therefore the PWT data on total compensation of labor construct a "best estimate" labor share. Adjustments based on mixed income are applied where available because the mixed income captures the income of the self-employed. The second adjustment method is preferable since the first adjustment method assumes no use of produced capital by the self-employed. The third and fourth adjustment methods are used if there is no mixed income data and the share of labor compensation of employees is below 0.7.

Total Labor Earnings

The PWT-estimated labor component of the earnings of the self-employed is added to Compensation of Employees to produce the control total for total labor earnings to scale up survey-derived earnings profiles by age, gender, and years of education. This approach implicitly assumes that the demographic and earnings profiles of the self-employed are the same as those of employed workers in formal labor markets. Although this is a highly simplified approach, there are insufficient data with global coverage to refine treatment of the self-employed at this time.

The total labor compensation (W) consists of two parts: (*comp_employ*) plus (*comp_self*). By using the PWT data, it can be calculated as follows:

$$W = comp_{employ} + comp_{self} = LABSH * GDP, \tag{7A.8}$$

$$comp_{employ} = LABSH_{employ} * GDP, \tag{7A.9}$$

$$comp_{self} = LABSH_{self} * GDP, \tag{7A.10}$$

where $LABSH$,[2] $LABSH_{employ}$, and $LABSH_{self}$ represent the total labor share (including employees and the self-employed), labor share of employees, and labor share of the self-employed, respectively. Therefore, $comp_{employ}$ and $comp_{self}$ stand for total compensation of employees and the self-employed, respectively.

The annual labor income ($AIN_{s,a,e}$) is assumed to be the same for employees and the self-employed and is estimated by using information for employees in the I2D2 database (equation 7A.6). Then the following adjustment can be made:

$$\sum_{s,a,e}\left[\overline{AIN}_{s,a,e} * n_{s,a,e}\right] = W, \tag{7A.11}$$

where $n_{s,a,e}$, as before, includes the number of people for employees and the self-employed, and $\overline{AIN}_{s,a,e}$ is the after-adjustment annual income. $\overline{AIN}_{s,a,e}$ is estimated as follows:

$$\overline{AIN}_{s,a,e} = \frac{W}{\sum_{s,a,e}\left[AIN_{s,a,e} * n_{s,a,e}\right]} * AIN_{s,a,e}. \tag{7A.12}$$

After the lifetime income ($h_{s,a,e}$) for each cell (by gender s, age a, and education e) has been derived (as described in step 6), the I2D2 sample share of the self-employed can be applied to the corresponding population data to generate the human capital for the self-employed.

In other words, the human capital for the total employed (employees plus self-employed) is calculated first by using the adjusted annual income profiles as shown in equation (7A.12). Then among the calculated total human capital, the part contributed by the self-employed can be separately estimated.

Step 3. Filling the Data Gaps

Since the estimations rely on labor force and household surveys, it is important to have at least one survey for each year and each country. Unfortunately, this is not the case for most countries. Moreover, some countries have only one survey for the entire period (table 7A.2). Therefore, filling the data gaps is a crucial step for the human capital calculations. Although the current method for filling the gap has some drawbacks, it is useful.

To fill the data gaps, the estimated Mincer parameters and I2D2 sample employment and enrollment rates for the survey year are held constant until the next available survey year, and control totals for earnings for each of the intervening years are used to generate the human capital estimates for the years between two survey years. For example, if there exists only one survey for a country, the parameters of this one survey are used for the entire period. If there exist three surveys (for example, 1995, 2000, and 2010) for 1995–2018, the parameters from 1995 are used for 1995–99, the parameters from 2000 are used for 2000–2009, and the parameters from 2010 are used for 2010 and onward.

Obviously, there are significant problems associated with this method. First, an occasional jump occurs between human capital estimates from a nonsurvey year to a survey year. For example, if there are surveys for 1995 and 2010, all the data gaps until 2009 are filled with the parameters from the 1995 survey. A jump could occur between the human capital estimates of 2009 to 2010. In addition, if there is only one survey, all the periods must be estimated with the data from one survey, and this does not allow policy makers to see the effects of policy changes, if any.

TABLE 7A.2 Number of I2D2 Surveys among Countries

Survey count	Countries
1	29
2	15
3	12
4	14
5	5
6	7
7	6
8	3
9–11	8
12	11
13	15
14–19	10
20 or more	11
Total	**146**

Source: World Bank.
Note: I2D2 = International Income Distribution Database.

Step 4. Scaling Up the Employment and Population

Since the survey data do not capture the entire population, the data from the surveys are adjusted to population estimates from the United Nations to ensure that the estimates are adequate.

If $n_{s,a,e}$ is the number of workers age a, gender s, and years of schooling e, and P is the total population of a country from the United Nations World Population Prospects, the scale parameter a is calculated as

$$\alpha = \frac{P}{\sum_{s,a,e}\left[n_{s,a,e}\right]}. \tag{7A.13}$$

Thus, the scaled number of workers age a, gender s, and years of schooling e, $N_{s,a,e}$, is calculated as

$$N_{s,a,e} = \alpha * [n_{s,a,e}]. \tag{7A.14}$$

Step 5. Calculating Survival Rates for Each Country

Survival rates utilize death rates obtained from the Global Burden of Disease Study (GBD).[3] The GBD database includes global, regional, and national age- and gender-specific mortality for 369 diseases and injuries in 204 countries and territories for 1990–2019. Survival rates are calculated as

$$v_{a+1} = 1 - death_{a}, \tag{7A.15}$$

where v_{a+1} is the probability of surviving one more year at age a, and $death_a$ is the death rate at age a. Equation (7A.15) is calculated for each country for each survey year for males and females separately.

Step 6. Calculating Lifetime Income

Two stages in the life cycle of an individual of working age are distinguished: ages 15–24 and ages 25–65. The main assumption here is that individuals ages 15–24 have the possibility to receive further education, while those ages 25–65 are assumed to have no such possibility. Based on this assumption, the lifetime labor income of an individual is calculated as follows:

- Persons ages 25–65

$$h_{s,a,e} = p^{m}_{s,a,e} w^{m}_{s,a,e} + p^{s}_{s,a,e} w^{s}_{s,a,e} + \left[\frac{1+g}{1+d}\right] * v_{s,a+1} * h_{s,a+1,e} \tag{7A.16}$$

- Persons ages 15–24

$$h_{s,a,e} = p^m_{s,a,e} w^m_{s,a,e} + p^s_{s,a,e} w^s_{s,a,e} + \left(1 - r^{e+1}_{s,a,e}\right) * \left[\frac{1+g}{1+d}\right] * v_{s,a+1} * h_{s,a+1,e} + r^{e+1}_{s,a,e} * \left[\frac{1+g}{1+d}\right] * v_{s,a+1} * h_{s,a+1,e+1}\,. \tag{7A.17}$$

In these equations $h_{s,a,e}$ is the present value of the lifetime income for an individual age a, gender s, and education e, $p^m_{s,a,e}$ is the probability to be employed, $w^m_{s,a,e}$ is the received compensation of employees when employed, $p^s_{s,a,e}$ is the probability to be self-employed, $w^s_{s,a,e}$ is the received compensation of employees when self-employed, $r^{e+1}_{s,a,e}$ is the school enrollment rate for taking one more year of education from education e to one year higher level of e+1, d is the discount rate, g is the annual wage growth rate, and $v_{s,a+1}$ is the probability of surviving one more year.

Equations (7A.16) and (7A.17) suggest that the lifetime income of a representative individual consists of the current labor income and the lifetime income in the next year. The current labor income is adjusted by the probabilities of being employed or self-employed, and the lifetime income in the next year is adjusted by a discount factor and the corresponding survival rate. In addition, for an individual age 15–24, there are two courses of action: first, holding the same education level and continuing to work, and second, taking one more year of education and earning income after completing the education.

The probabilities of being employed ($p^m_{s,a,e}$) or self-employed ($p^s_{s,a,e}$) can be approximated by the employment rate or self-employment rate for people age a, gender s, and education e. These rates have to be calculated by the employed (or self-employed) persons divided by the entire population that includes the employed, self-employed, unemployed, and people out of the labor force. The sample ratios from the I2D2 database are used.

The empirical implementation of equations (7A.16) and (7A.17) is based on backward recursion. This suggests that the lifetime labor income of a representative individual age 65 is zero since it is presumed that there is no working life after age 65. Therefore, the lifetime labor income of a person age 64 is her current labor income. Likewise, the lifetime labor income of a representative individual age 63 is the sum of her current labor income and the present value of the lifetime labor income of a person age 64. Hence, the present value of the lifetime income matrix is created for an economy by applying backward recursion to equations (7A.16) and (7A.17).

Human capital is calculated under the assumption that labor earnings grow at a constant rate g over the working lifetime. Because of the efficiency differences among the income groups and regions, region- and income group–specific annual real labor earnings growth rates are applied. The growth rates are derived from the World Bank's macroeconomic and fiscal model based on historical data and long-term projections based on potential output in each country, which builds on total factor productivity growth, capital stocks, and employment growth. In addition, average long-term wage growth rates are capped at 4 percent. Furthermore, it is assumed

TABLE 7A.3 Labor Income Growth Rates, by Region and Income Level

Region	Countries	Wage growth (%)
East Asia and Pacific, high-income	4	1.08
East Asia and Pacific (excluding high-income)	11	4.00
Europe and Central Asia, high-income	27	1.08
Europe and Central Asia (excluding high-income)	17	2.83
Latin America and the Caribbean, high-income	4	1.08
Latin America and the Caribbean (excluding high-income)	20	0.96
Middle East and North Africa, high-income	7	1.08
Middle East and North Africa (excluding high-income)	10	1.34
North America	2	0.91
South Asia	6	3.60
Sub-Saharan Africa	38	1.41
Total	**146**	

Source: World Bank staff calculations.

that real labor wage growth rates are constant over time during the lifetime.

In addition, labor income growth for 2020–22 is revised down to adjust for the short-run effects of the COVID-19 pandemic on wages. For the period after 2023, a recovery in the labor income growth rates is assumed to be aligned with the recovery in total factor productivity growth. The growth rates for labor income used in the human capital calculations are provided in table 7A.3.

In addition, in calculating the net present value, a uniform discount rate of 4 percent is used for human capital in line with all resources and countries within the wealth accounting framework.

Step 7. Generating the Lifetime Income for All People in an Economy

The calculations from step 1 to step 6 generate the lifetime income profiles for a representative individual cross-classified by age, gender, and education. The lifetime income profiles for a representative individual are multiplied by the corresponding number of people in a country, and thus the human capital stock by age, gender, and education is calculated.

Summing up the stocks of human capital across all classified categories generates the estimate of the aggregate value of the human capital stock for each country:

$$HC = \Sigma_{s,a,e}[h_{s,a,e}] * pop_{s,a,e}, \tag{7A.18}$$

where HC is the human capital stock, $h_{s,a,e}$ is the present value of the lifetime income for an individual age a, gender s, and education e, and $pop_{s,a,e}$ is the population of age a, gender s, and education level e.

Notes

1. Official data on labor income for China include income of employed and self-employed workers.
2. The LABSH variable in the PWT is expressed as a share of GDP at basic prices. Therefore, when incorporated in the human capital calculations, LABSH is multiplied by an adjustment factor, reflecting the ratio of GDP at basic prices to GDP at market prices. Thus, the resulting LABSH is expressed as a share of GDP at market prices and used accordingly in equations 7A.8 to 7A.10.
3. The Global Burden of Disease Study 2019 database is used for the human capital calculations. http://www.healthdata.org/gbd/2019.

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