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METHODOLOGY OF THE 2020 ILO-UNICEF GLOBAL ESTIMATES OF CHILD LABOUR

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ACRONYMS AND ABBREVIATIONS

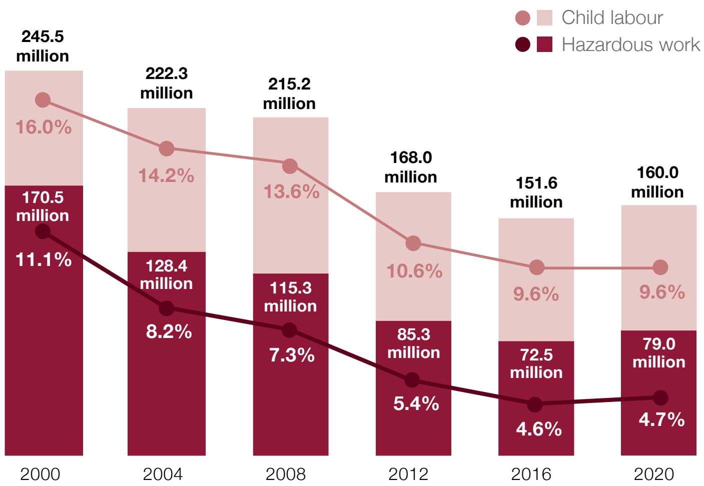
CiE	Children in employment
CL	Child labour
CLS	Child Labour Surveys
DHS	Demographic and Health Surveys
DW	Domestic work
EA	Economic activity
EU-LFS	European Union Labour Force Survey
GDP	Gross domestic product
HW	Hazardous work
ICLS	International Conference of Labour Statisticians
ILO	International Labour Organization
ILO-IPEC	ILO International Programme on the Elimination of Child Labour
LFS	Labour Force Surveys
MICS	Multiple Indicator Cluster Surveys
PPP	Purchasing power parity
RMSE	Root mean square error
SDG	Sustainable Development Goal
SDG GPB	Sustainable Development Goal general production boundary
SDG SNA PB	Sustainable Development Goal System of National Accounts production boundary
SNA	System of National Accounts
STE	Status in employment
STU	School attendance
UNICEF	United Nations Children's Fund
UN-WPP	United Nations World Population Prospects

EXECUTIVE SUMMARY OF KEY STATISTICS

Trends

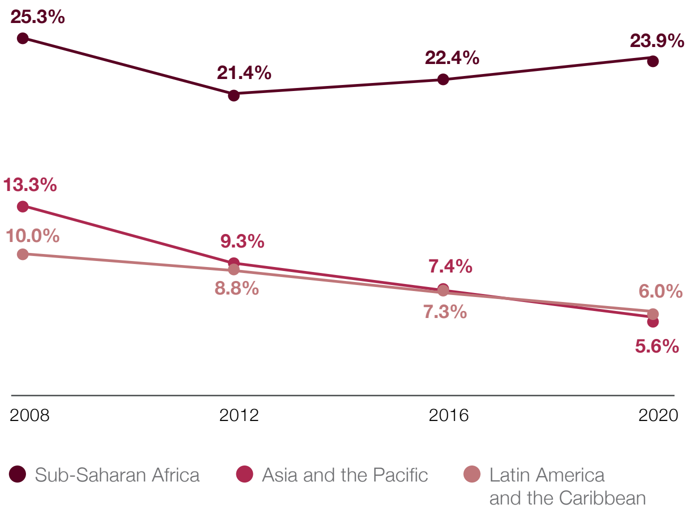
Global progress against child labour has stalled since 2016

Percentage and number of children aged 5 to 17 years in child labour and hazardous work



Asia and the Pacific and Latin America and the Caribbean have seen steady progress on child labour since 2008; similar progress has eluded sub-Saharan Africa

Percentage of children aged 5 to 17 years in child labour, by region

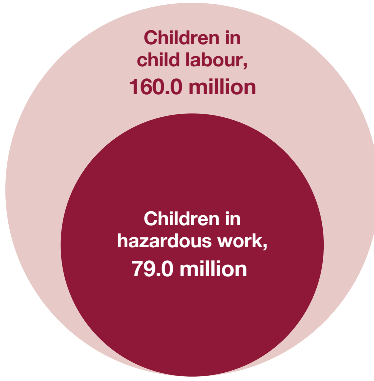


Notes: The figure shows regional groupings used for ILO reporting. Comparable historical data prior to 2016 were not available for other regions.

Current situation

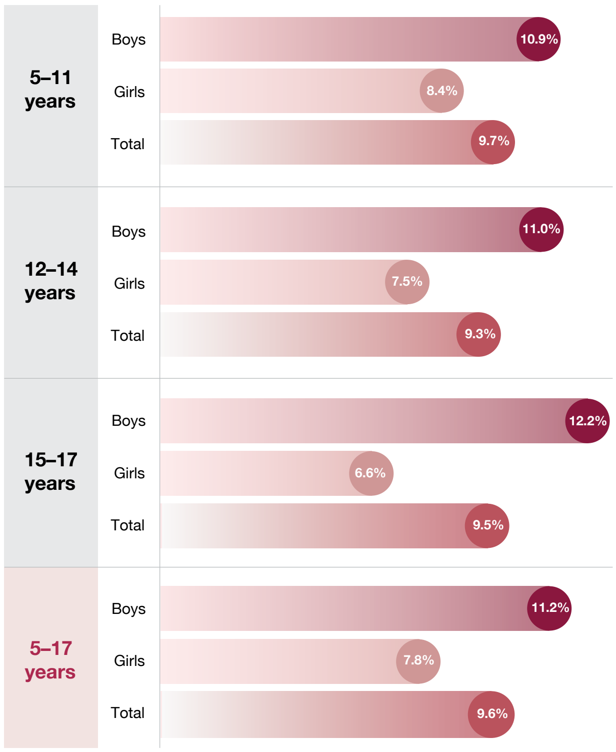
Worldwide, 160 million children are engaged in child labour; 79 million of them are performing hazardous work

Number of children aged 5 to 17 years in child labour and hazardous work



Child labour is more prevalent among boys than girls at every age

Percentage of children aged 5 to 17 years in child labour, by age and sex



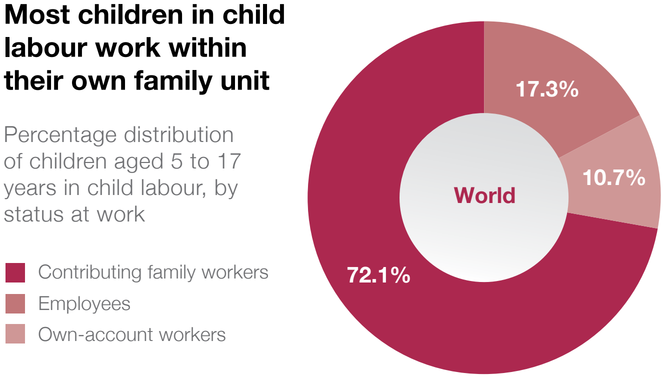
Sub-Saharan Africa stands out as the region with the highest prevalence and largest number of children in child labour

Percentage and number of children aged 5 to 17 years in child labour, by region

Notes: The size of the bubbles is proportionate to the absolute number of children in child labour. The figure shows regional groupings used for SDG reporting. The region of Oceania is omitted because of low data coverage. For this reason, region-specific numbers do not add up to the global total.

Most children in child labour work within their own family unit

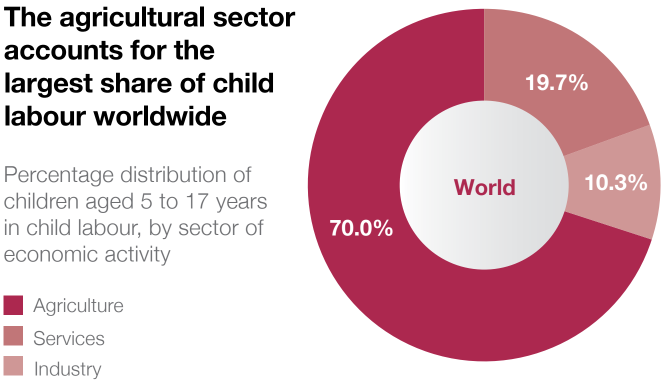
Percentage distribution of children aged 5 to 17 years in child labour, by status at work



Note: Due to rounding, figures in percentages do not add up to 100 per cent.

The agricultural sector accounts for the largest share of child labour worldwide

Percentage distribution of children aged 5 to 17 years in child labour, by sector of economic activity



Impact of COVID-19

Without mitigation measures, the number of children in child labour could rise from 160 million in 2020 to 168.9 million by the end of 2022

Number of children aged 5 to 17 years in child labour, projected to the end of 2022

206.2 million If austerity measures or other factors cause a slippage in social protection coverage

168.9 million Due to an increase in poverty and in the absence of additional mitigation measures

144.9 million If social protection coverage is increased

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1. INTRODUCTION

The International Labour Organization (ILO) produced Global Estimates of Child Labour for the first time in 1995, when it estimated the total number of children engaged in child labour at 250 million.[1] Since then, the ILO has released five comprehensive editions of Global Estimates of Child Labour.[2] A steady decline in child labour was reported worldwide over this period, from 245.5 million in 2000, to around 152 million in 2016. These figures played a crucial role in bringing to public attention the size and nature of the phenomenon, helping governments, social partners and civil society formulate and monitor policies for combating child labour throughout the world.

The current sixth edition of the Global Estimates of Child Labour provides updated estimates for 2020 and has been produced for the first time in partnership with the United Nations Children's Fund (UNICEF). These estimates are based on a wide range of nationally representative household surveys, covering fully or partially the target population of children aged 5 to 17 years old.

The ILO-UNICEF estimates are based on the international standards concerning statistics on child labour, which were adopted by the 20th International Conference of Labour Statisticians (ICLS) in October 2018.[3] These standards outline statistical definitions of child labour and its components, hazardous work by children and the worst forms of child labour other than hazardous work.

In the present edition of the Global Estimates of Child Labour, an attempt has been made to improve the imputation methodology of child labour data for countries without surveys. To gauge trends in child labour and other related indicators at the regional and global levels, a series of econometric models were developed to account for the non-randomness in missing data. These efforts will improve accuracy of the estimates and also ensure replicability of the estimation process, thereby facilitating updates and the development of subsequent global estimates.

The purpose of this report is to present the methodological protocols used for the development of the 2020 Global Estimates of Child Labour. Section 2 outlines the measurement framework and defines the main concepts and classifications. Section 3 describes the scope and coverage of the global and regional estimates in relation to the underlying national datasets. Section 4 explains the approach adopted for harmonizing the national datasets. Section 5 describes the statistical modelling strategy implemented. Section 6 details the process of going from country data to regional and global aggregates. Finally, section 7 is a sensitivity analysis of the data.

2.MEASUREMENT FRAMEWORK

The measurement framework for producing the 2020 Global Estimates of Child Labour aligns with the international standards on child labour statistics adopted by the 18th ICLS in 2008. Hosted by the ILO, the conference takes place every five years. Participants include experts from governments, mostly from labour ministries and offices of national statistics, as well as specialists from employers' and workers' organizations. Although the 20th conference in 2018 adopted a more recent resolution on child labour statistics, most countries still use the previous framework. Once the 2018 framework becomes the principal method for household surveys, the global and regional estimates will be produced with these newer statistical standards.

2.1 Regional classification systems used

The global child labour estimates use different geographic classification systems to present figures. The main body of the report employs the regional classification system of the Sustainable Development Goals (SDGs), unless otherwise indicated.[4] However, child labour figures in the statistical annex are categorized using the ILO[5] and UNICEF[6] geographic classification systems.

2.2 Age of a child

Children are defined as "all persons in the age group from 5 to 17 years, where age is measured as the number of completed years at the child's last birthday" (para. 9 of Resolution II: Resolution concerning statistics of child labour). All global and regional estimates are presented for the 5–17 year age group, as well as subgroups 5–11 years, 12–14 years and 15–17 years. Child labour statistics are disaggregated by sex and, for the first time, also by urban or rural area of residence.

2.3 Children in employment

Children in employment are "those engaged in any activity falling within the production boundary of the UN System of National Accounts (SNA) for at least one hour during the reference period."[7] The production boundary includes all activities undertaken to produce goods and services for pay or profit, as well as activities to produce goods for own use, such as subsistence foodstuff production. It excludes, however, activities for own-use production of services, and those that do not involve the production of goods or services (such as begging or stealing).

It is important to note that the concept of employment used in the international standards concerning statistics of child labour[8] has now been superseded by the new international standards on statistics of work, employment and labour underutilization,[9] where employment is defined more narrowly to refer to "any activity to produce goods or provide services for pay or profit." This new definition thus excludes subsistence foodstuff production and, more generally, own-use production of goods from the scope of employment. The data presented here, however, continue to refer to the broader definition of employment for comparability purposes.

2.4 Child labour

According to Resolution II concerning statistics of child labour,[10] children engaged in child labour include "all persons aged 5 to 17 years who, during a specified time period, were engaged in one or more of the following categories of activities: (a) worst forms of child labour […]; (b) employment below the minimum age […]; and (c) hazardous unpaid household services […]", as detailed in the resolution.

The concept of child labour includes the 'worst forms of child labour other than hazardous work', such as all forms of slavery and trafficking, the recruitment of child soldiers, and the use of children for prostitution or other illicit activities,[11] as well as 'hazardous work by children'.[12] It is important to note that only estimates of 'hazardous work by children' due to long hours of work and in designated hazardous industries and occupations are included in this document. Estimates of commercial sexual exploitation of children and forced labour of children are calculated separately and will be included as part of the Alliance 8.7 Global Estimates of Modern Slavery: Forced Labour and Forced Marriage, 2021, to be published in 2022.

2.5 Hazardous work by children

Hazardous work by children is "statistically defined in terms of the engagement of children in activities of a hazardous nature (designated industries and occupations) […], or work under hazardous conditions, for example, long hours of work in tasks and duties which by themselves may or may not be of a hazardous nature for children."

The international standards specify that hazardous work by children involves "(a) work which exposes children to physical, psychological or sexual abuse; (b) work underground, under water, at dangerous heights or in confined spaces; (c) work with dangerous machinery, equipment and tools, or which involves the manual handling or transport of heavy loads; (d) work in an unhealthy environment, which may, for example, expose children to hazardous substances, agents or processes, or to temperatures, noise levels or vibrations damaging to their health; (e) work under particularly difficult conditions such as work for long hours or during the night or work where the child is unreasonably confined to the premises of the employer."

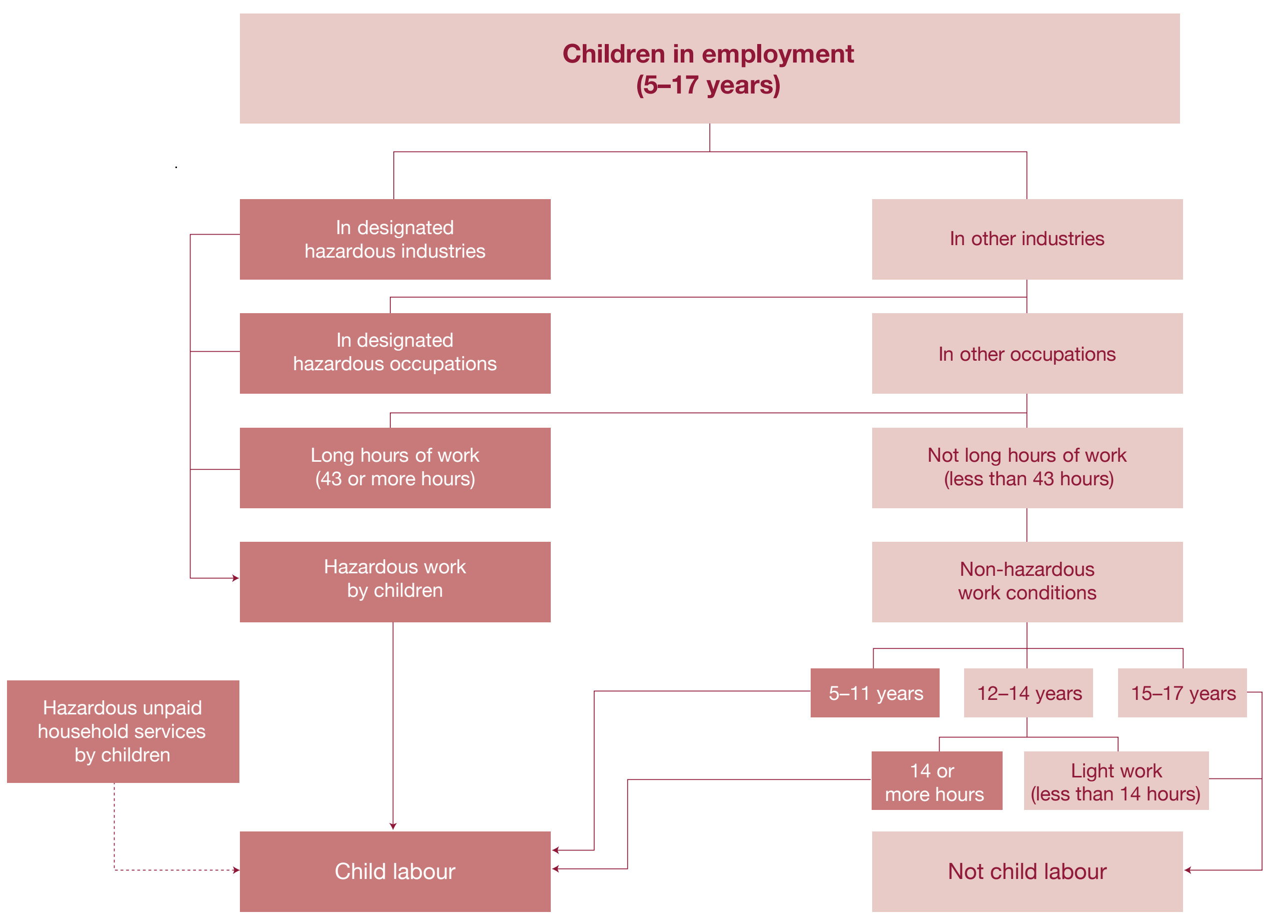
2.6 Hazardous unpaid household services

Hazardous unpaid household services by children are "those performed in the child's own household under conditions corresponding to those defined in paragraph 20 above [of the resolution]; that is, unpaid household services performed (a) for long hours, (b) in an unhealthy environment, involving unsafe equipment or heavy loads, (c) in dangerous locations, and so on."

The operational definitions of the components of child labour estimated under the present measurement framework are shown in schematic form in Figure 1.

The starting point for measuring child labour is calculating the number of children aged 5–17 years in employment. Among children in employment, those in designated hazardous industries are first separated from those employed in other branches of economic activity. In the present context, designated hazardous industries are mining and quarrying and construction.[13]

Figure 1: Conceptual framework of the ILO-UNICEF global estimation of child labour



Source: 18th ICLS, *Resolution concerning statistics of child labour*, ILO, Geneva, 2008.

Among children engaged in other branches of economic activity, those engaged in designated hazardous occupations are identified next. Since the publication of the first Global Estimates of Child Labour in 2002, an ILO task force defined a set of 39 hazardous occupations for children at the three-digit level using ISCO-88 as a reference *(see Annex 1)*. As a large number of countries have adopted the new ISCO-08 classification system, the corresponding three- and four-digit ISCO-08 equivalents have been established in these global estimates *(see Annexes 1 and 2)*.

Next, among children not engaged in either hazardous industries or hazardous occupations, those who worked long hours during the reference week are identified. Long hours are defined, for the purpose of the global estimates, as 43 or more hours of work during the reference week. The 43-hour threshold was the same as that used in earlier ILO global estimates. It corresponds to approximately the mid-point of normal hours of work stipulated by national legislations, mostly in the range of 40 to 44 hours.

The total number of children in designated hazardous industries, children in hazardous occupations and children with long hours of work constitutes, in aggregate, the overall number of children in hazardous work.

As shown in Figure 1, the final estimate of child labour is obtained by adding two more categories to the number of children in hazardous work, namely children aged 5–11 years engaged in any form of employment, and children aged 12–14 years working 14 hours or more per week. For 12- to 14-year-olds, the 14-hour threshold distinguishes between permissible light work and other work that cannot be considered as permissible light work. The same threshold was used in the earlier ILO global estimates. It corresponds to two hours of work per day over a calendar week, covering both school days and holidays.

The child labour statistical framework by the ICLS also provides for the separate measurement of hazardous unpaid household services by children (18th ICLS, 2008). Specifically, and following the definition used in the context of SDG indicator 8.7.1, a child labour indicator is derived that considers the performance of household chores by children between 5 and 14 years of age for 21 or more hours per week.

3. NATIONAL DATASETS

In total, 106 national datasets from as many countries are used to produce the 2020 Global Estimates of Child Labour *(see Annex 3)*. This represents a similar number to the 105 national datasets used for the 2016 global estimates.

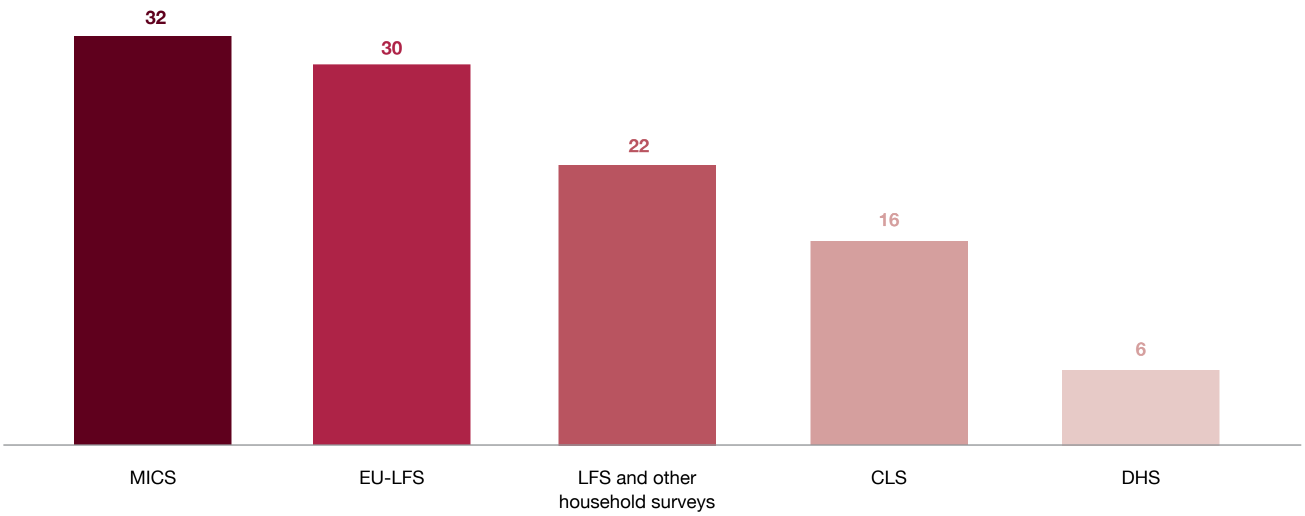
3.1 Data sources

Figure 2 shows the distribution of national datasets by type of source: 32 national datasets from the Multiple Indicator Cluster Surveys (MICS), implemented with the assistance of UNICEF; 30 datasets limited to children aged 15–17 years from national Labour Force Surveys (LFS) conducted under Eurostat regulations (EU-LFS); 22 further datasets from national LFS or other national household surveys; 16 national datasets derived from Child Labour Surveys (CLS), with the assistance of the ILO; and six other datasets from Demographic and Health Surveys (DHS), implemented mostly with funding from the United States Agency for International Development (USAID).

3.2 Multiple Indicator Cluster Surveys

The Multiple Indicator Cluster Survey (MICS) is an international household survey programme developed by UNICEF in the 1990s.[14] MICS is designed to collect statistically sound, internationally comparable estimates of about 130 indicators to assess the situation of children, women and men in the areas of health, education and child protection. MICS is a rich source of data on the SDGs, collecting about 33 SDG indicators. The MICS6 questionnaire contains a section on child labour comprising 13 questions, covering

Figure 2: National datasets by type of data source



economic activities, fetching water, collecting firewood, unpaid household services and the hours that children work in these activities. In addition, the MICS questionnaire includes a series of questions to assess hazardous work, including hazardous exposures, carrying heavy loads, working with dangerous tools and operating heavy machinery. The section on child labour collects information for children aged 5 to 17 years old.

3.3 European Union Labour Force Surveys

European Union Labour Force Surveys (EU-LFS), implemented under Eurostat regulations, are highly standardized national surveys carried out in most cases on a quarterly basis, with data collection spread over all weeks of the quarter. The survey questionnaires are designed to collect harmonized data on a set of data requirements specified by EU Council regulations. The surveys cover the working-age population aged 15 years and over, and rarely the child population below that age. In the Global Estimates of Child Labour, the Eurostat LFS were used for the first time to obtain estimates of child employment in the 15–17 year age group in EU, EU candidate and European Free Trade Association countries.

3.4 Labour Force Surveys and other household surveys

Labour Force Surveys (LFS) are generally large-scale household-based surveys conducted by national statistical offices to collect data on the current employment and unemployment situation of the country's working-age population. They often provide the main source of official statistics on the unemployment rate and other major indicators of the labour market. Many LFS, especially in developing countries, collect data not only on the working-age population aged 15 years and over, but also on the economic activity of children below that age. In most cases, the questionnaire covers a rich set of information, including on labour force status in the past week, status in employment, occupation, branch of economic activity, sector of employment, and hours of work in main and secondary jobs. The other household surveys used for the Global Estimates of Child Labour include national surveys on living conditions measurement surveys, household budget surveys, and household income and expenditure surveys.

3.5 Child Labour Surveys

The ILO Child Labour Surveys (CLS) are specialized household-based sample surveys implemented by

Member States with the support of the ILO.[15] The main objectives of the survey are to measure the prevalence of child labour and to obtain data on the socioeconomic characteristics of the children involved, with a view to identifying the causes and consequences of child labour in the implementing country. If it is a stand-alone survey, a typical CLS has a sample size of about 5,000 to 15,000 households. If the survey is a module attached to a national child labour survey, it has the sample size of the mother survey. Specialized CLS allow for an in-depth characterization of the phenomenon, by exploring in detail the different forms of work performed by children in line with the Resolution on child labour statistics adopted by the 20th ICLS.[16]

3.6 Demographic and Health Surveys

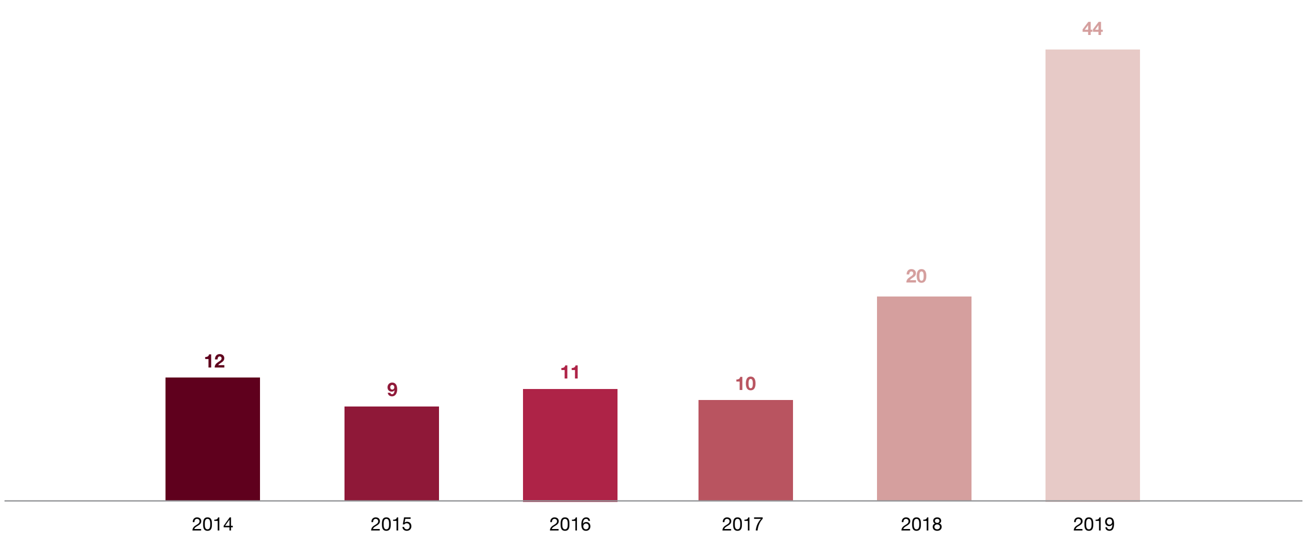
Demographic and Health Surveys (DHS) are nationally representative household surveys that provide data on a wide range of monitoring and impact evaluation indicators in the areas of population, health and nutrition.[17] Some of the surveys include a child labour section equivalent to that included in the MICS6 questionnaires.[18]

3.7 Surveys by year

As noted previously, the Global Estimates of Child Labour are derived from nationally representative household surveys. Although some countries have survey data for multiple years, some have no data at all. For each country, the UNICEF and ILO technical team selected the most recent data source and, where possible, the source used by countries to report their child labour data as part of the SDGs. Figure 3 depicts, at the country level, the distribution of household survey availability by year, for the indicator on children in employment.

Figure 3 shows that more than 80 per cent of surveys used were conducted between 2016 and 2020, the reference period of these global estimates. It was assumed that rates pertaining to indicators computed from the household surveys remain constant over the interval of time from when the survey was conducted until 2020. Surveys from 2014 and 2016 were also included, despite being outside the official reference period. This was done to increase coverage, thereby providing a more comprehensive representation of child labour global estimates.

Figure 3: Number of household surveys by year for the indicator on children in employment



3.8 Coverage of survey data

The available datasets cover more than 1.1 billion children aged 5 to 17 years, which represents about 66 per cent of the world population of children in that age group *(see Table 1)*. The coverage rate is slightly lower than the rate in the last global estimate of 2016 (70 per cent), but significantly higher than the rates of the two previous global estimates (44.4 per cent in 2008 and 53.1 per cent in 2012).

The highest regional coverage is for Southern Asia (96.4 per cent), Latin America and the Caribbean (91.7 per cent) and Northern America (91.3 per cent), followed by Northern, Southern and Western Europe (82.3 per cent), South-Eastern Asia and the Pacific (71.3 per cent), sub-Saharan Africa (68.2 per cent) and Northern Africa (64.6 per cent). The lowest coverage rates correspond to Eastern Europe (43 per cent), the Arab States (35.9 per cent), Central and Western Asia (11.1 per cent) and Eastern Asia (0.3 per cent).[19]

Table 1: Geographic coverage of child population aged 5–17 years represented by national datasets

ILO sub-region – broad	Code	Population of children 5-17 years (thousands)	Population of children 5-17 years in countries with national datasets (thousands)	Coverage rate (%)
World		**1,674,897**	**1,112,931**	**66.4**
Northern Africa	10	64,061	41,355	64.6
Sub-Saharan Africa	11	361,898	246,846	68.2
Latin America and the Caribbean	20	136,219	124,922	91.7
Northern America	21	58,943	53,816	91.3
Arab States	30	42,489	15,253	35.9
Eastern Asia	40	249,325	778	0.3
South-Eastern Asia and the Pacific	41	153,657	109,497	71.3
Southern Asia	42	463,663	446,894	96.4
Northern, Southern and Western Europe	50	62,074	51,113	82.3
Eastern Europe	51	41,742	17,928	43.0
Central and Western Asia	52	40,827	4,529	11.1

4. HARMONIZATION

The harmonization processes carried out in the framework of the global child labour estimates include the harmonization of datasets and the standardization of age groups. These harmonization steps are briefly described below. Harmonization of reference years is carried out implicitly as part of the calculation of the extrapolation weights.

4.1 Harmonization of datasets

The main means of harmonizing national datasets is processing national household survey data according to a pre-defined framework that facilitates comparability across countries and over time, following internationally agreed standards, concepts and definitions.

Data processing comprises four main steps: (1) preparation of the microdata in the needed format and review of the related documentation; (2) mapping of the national variables and classification items to international concepts and classifications based on the survey technical documentation; (3) generation of a separate dataset with standardized names and codes for all datasets; and (4) production of pre-coded indicator estimates and related quality measures for all datasets processed.[20]

4.2 Harmonization of age groups

The age groups available from EU-LFS are not in line with the standard age groupings of the Global Estimates of Child Labour. Instead of the required 15 to 17 years age band, only the 15 to 19 years band is available. To avoid the loss of data for EU-LFS countries, an interpolation procedure is conducted for the target indicators, to model the 15 to 17 years age group as a function of the 15 to 19 years group.

4.2.1 Harmonization procedure A: Age harmonization for rates of children in employment (CiE), child labour (CL), hazardous work (HW) and SDG indicator 8.7.1 – children engaged in economic activity[21]

First, the age harmonization procedure for CiE is carried out. Let $E(a)$ denote the levels of employment, E, at a given age, a. Similarly, let $P(a)$ denote the population at that same age. The employment rate, which refers to the number of persons in employment divided by population, available for EU-LFS countries, is:

1. $$\widetilde{ER} = \frac{\int_{15}^{20} E(a)\, da}{\int_{15}^{20} P(a)\ da}$$

It is important to note that this is the employment rate for persons aged between 15 and 20, $\widetilde{ER}$, that corresponds to the standard age band 15 to 19.[22] The target variable to derive via interpolation is:

2. $$ER = \frac{\int_{15}^{18} E(a)}{\int_{15}^{18} P(a)}$$

The countries covered by EU-LFS[23] are assumed to have zero employed children below the age of 15.[24] Furthermore, employment is assumed to be a linear function of age, starting from a zero rate at 15 and increasing at a fixed rate. Consequently, employment can be expressed as:

3. $$E(a) = \beta \cdot a \; if \; a \geq 15$$

Substituting and solving the integrals:

4.

$$\int_{15}^{18} E(a)\, da = \beta \cdot {3^2}/{2}\,; \int_{15}^{20} E(a)\, da = \beta \cdot {5^2}/{2}$$

A relationship between the target employment rate and the available employment rate can then be established.

5. $$ER = \frac{\int_{15}^{20} P(a)\, da}{\int_{15}^{18} P(a)\, da}\ \widetilde{ER} \cdot {3^2}/{5^2}$$

This relationship between the employment rates can be further simplified if it is assumed that at the relevant range of ages, between 15 and 20 years of age, EU-LFS countries have a constant population structure. This implies that $P(a) = P \; \forall \; a \in [15{,}20]$[25] and so:

$$6. \quad ER = \widetilde{ER} \cdot {}^{3}/_{5}$$

Thus, the target employment rate can be derived by correcting proportionally the available rate. The same set of assumptions are applied to the other indicators, CL, HW and SDG indicator 8.7.1 – children engaged in economic activity. The adjustment required for these indicators is illustrated below by an example focusing on the child labour indicator.

Let $CL(a)$ denote the number of children in CL as a function of age. As for CiE, it is assumed that for the countries covered by EU-LFS data, CL is zero below the age of 15. Furthermore, it is assumed to be a linear function of age starting from a zero rate at 15 and increasing linearly at a constant rate. Hence, CL can be expressed as:

$$7. \quad CL(a) = \gamma \cdot a \; if \; a \geq 15$$

The only difference with respect to CiE is the parameter γ, a different rate of increase. As discussed in section 5 of this document, CL is modelled as a share of CiE. The aim here is to establish which adjustment to the share of CL as a subset of CiE is necessary to produce the 15 to 17 standard age band from the wider 15 to 19 band, given this assumption. The EU-LFS provides the CL rate of:

$$8. \quad \widetilde{CL} = \frac{\int_{15}^{20} CL(a)\, da}{\int_{15}^{20} E(a)\, da}$$

Whereas the target indicator is:

$$9. \quad CL = \frac{\int_{15}^{18} CL(a)\, da}{\int_{15}^{18} E(a)\, da}$$

Solving the integral for $\widetilde{CL}$.

$$10. \quad \widetilde{CL} = \frac{\gamma \cdot {}^{5^2}/_{2}}{\beta \cdot {}^{5^2}/_{2}} = \frac{\gamma}{\beta}$$

Which is equivalent to the expression for CL:

$$11. \quad CL = \frac{\gamma \cdot {}^{3^2}/_{2}}{\beta \cdot {}^{3^2}/_{2}} = \frac{\gamma}{\beta}$$

This equivalence is a consequence of the constant rate of increase along with the same zero starting point. As both CL and CiE increase at a fixed rate, the ratio between the two remains constant. It is therefore shown that no adjustment is necessary for CL. The same reasoning can be applied to HW and SDG indicator 8.7.1 – children engaged in economic activity.

4.2.2 Harmonization procedure B: Age harmonization for breakdowns of economic sector, status in employment (STE) and school attendance (STU)

A different approach of interpolation is required for the breakdown of CiE, CL, and HW and SDG indicator 8.7.1 – children engaged in economic activity, by several classifications of interest (economic sector, STE and STU). The key modelling assumption behind the calculations in 4.2.1 is that the variable of interest starts at zero in the lower age of the interval and then increases at a fixed rate. In the current context, this is not a satisfactory assumption for a distribution by a further breakdown of a variable of interest, for which we have assumed an increasing linear rate. This is because, in a distribution, the target variable, for which we wish to measure the distribution, say CiE, is in the denominator. In the numerator, the magnitude to compute the distribution would be the adequate subset of CiE following the breakdown of interest, for instance, CiE attending school. Whether this distribution increases or decreases as a function of age depends on which magnitude the denominator or the numerator presents a greater rate of change and, of course, the sign of the change. Notice that this holds even if the assumption of linearity in CiE from the previous section is valid. For instance, the share of CiE attending school might well be decreasing in age, even if CiE actually increases by age. Hence, another set of assumptions and harmonization procedure is used.

Without loss of generality, this example focuses on the adjustment of the share of CiE that are attending school. Using the same notation as above, let $S(a)$ denote the number of children who are both in employment and attending school as a function of age. Similarly, $NS(a)$ denotes the number of CiE that are not attending school. The magnitude of interest is the distribution of CiE by schooling status:

12. $$\frac{S(a)}{NS(a)+S(a)}$$

and its natural complement (one minus the expression). Notice that, ex ante, it is not satisfactory to assume that this share does follow a linear path to zero as age declines, even if the overall level of CiE follows this path. It might very well be that it increases as age decreases (and a similar argument can be made about other distributions of interest). Given this, a new set of assumptions are needed to model the target age band 15 to 17 years on the basis of available EU-LFS data. For both $S(a)$ and $NS(a)$, age groups 15 to 19 years and age groups 20 to 24 years are available. The assumption concerning the behaviour of both variables is simply that they are a linear function of age. Below 15 years of age, the assumption is that both magnitudes are zero. Note that this assumption might imply a different value for CiE when adding both $S(a)$ and $NS(a)$ than in the section above. This is of no importance, as in this section we only target the distribution, whereas the CiE used for the modelling is the one derived from the previous section.

For this exercise, the notation is greatly simplified if a transformation of the age variable is done. Instead of focusing on age, given that below 15 all variables of interest are assumed to be zero, we can focus on the variable 'excess age', $\dot{a}$, which is defined as:

13. $$\dot{a} = a - 15 \; if \; a \geq 15; \dot{a} = 0 \; if \;\; a < 15$$

This can be interpreted simply as the number of years above 15. For instance, the age 18 corresponds to an 'excess age' of 3. With this new variable, the linearity assumption can be used to define the variables of interest as a function of excess age:

14. $$S(\dot{a}) = c_1 + \delta_1 \cdot \dot{a} \; if \; \dot{a} \geq 0$$

15. $$NS(\dot{a}) = c_2 + \delta_2 \cdot \dot{a} \; if \; \dot{a} \geq 0$$

The discussion focuses first on the $S(\dot{a})$ function. EU-LFS data are available for the total number of children in school for the age bands 15–19 and 20–24, denoted $S(15-19)$ and $S(20-24)$. This can be expressed, following $S(\dot{a})$, respectively, as:[26]

16. $$S(15-19) = \int_0^5 (c_1 + \delta_1 \cdot \dot{a}) \, d\dot{a}$$

17. $$S(15-19) = \int_0^5 (c_1 + \delta_1 \cdot \dot{a}) \, d\dot{a}$$

Solving the expressions, we get:

18. $$S(15-19) = c_1 \cdot 5 + \frac{\delta_1}{2} \cdot 25$$

19. $$S(20-24) = c_1 \cdot 5 + \frac{\delta_1}{2} \cdot 3 \cdot 25$$

Recall that both these magnitudes are available from the data, hence we can isolate the parameters, c_1, δ_1 as a function of the observed magnitudes.

20. $$\delta_1 = \frac{S(20-24) - S(15-19)}{25}$$

And,

21. $c_1 = \frac{3}{10}S(15-19) - \frac{1}{10}S(20-24)$

The target variable is:

22.

$$S(15-17) = \int_0^3 (c_1 + \delta_1 \cdot e)\, de = c_1 \cdot 3 + \frac{\delta_1}{2} \cdot 9$$

Which can be computed using the isolated parameters.

23.

$$S(15-17) = \frac{36}{50}S(15-19) - \frac{6}{50}S(20-24)$$

Notice that the same results will hold for the variable NS, as the expression above does not depend on any specific parameter. Hence, using the expression for both variables we can compute the distribution of interest:

24. $\frac{S(15-17)}{NS(15-17)+S(15-17)}$

The linearity assumption behind this deduction produces reasonable estimates for most cases. However, in certain cases the linear approximation of the distribution causes too strong of a decline, resulting in negative values for the levels. In that case, another functional form is used. Specifically, instead of assuming a linear function of age, an exponential function is used. In this case, the assumed functional form results in:

25. $S(\dot{a}) = A_1 e^{\omega_1 \dot{a}}\ if\ \dot{a} \geq 0$

26. $NS(\dot{a}) = A_1 e^{\omega_1 \dot{a}}\ if\ \dot{a} \geq 0$

Focusing on the $S(\dot{a})$ function, from EU-LFS data the total number of children in schooling for the age bands 15–19 and 20–24, denoted $S(15-19)$ and $S(20-24)$. Integrating over the relevant range and solving the integral, the observed data can be expressed as:

27.

$$S(15-19) = \int_0^5 A_1 e^{\omega_1 \dot{a}}\ d\dot{a} = \frac{A_1}{\omega_1}(e^{\omega_1 5} - e^0)$$

28.

$$S(20-24) = \int_5^{10} (c_1 + \delta_1 \cdot \dot{a})\, da = \frac{A_1}{\omega_1} e^{\omega_1 5}(e^{\omega_1 5} - e^0)$$

Using the same function to the target variable yields:

29.

$$S(15-17) = \int_0^3 A_1 e^{\omega_1 \dot{a}}\ d\dot{a} = \frac{A_1}{\omega_1}(e^{\omega_1 3} - e^0)$$

Using a procedure similar to the linear case, the result of the last expression can be found using the isolated parameters from the two expressions above. Additionally, the distribution of interest can be calculated in an identical manner as for the linear case.

The discussion has focused for ease of exposition only on the distribution by schooling status of CiE, but as mentioned at the beginning of this section, it can be applied without loss of generality to any of the other distributions of interest.

4.2.3 Results of the interpolation in high-income countries: A case study

Given the simplicity of the assumptions discussed in this section, which apply an identical function for any country, it is convenient to check in actual data how the approximations perform in practice. Of course, the data to test these assumptions are extremely limited; in fact, this is the reason behind adopting an approximation procedure in the first place. Nonetheless, some evidence data are available. In particular, the United Kingdom microdata from the LFS[27] includes the desired age target.

For the first harmonization procedure, the results of the approximation can be cross-checked against data for CiE. For the second approximation, data for the distribution by schooling status of CiE are compared against the approximated value. Table 2 summarizes the results.

5. MODELLING STRATEGY

In this section, we describe the methodology used to impute missing values for countries where national household survey data are missing.

The term ‘child labour models’ is used to refer to the estimates produced and their accompanying statistical methodologies. ‘Household survey data’ is used to describe either the rates or distributions obtained directly from primary survey data. ‘Household survey data’ is to be distinguished from ‘modelled data’, which is generated.

Linear regression and cross-validation are used in each of the child labour models to impute data for missing observations. First, the relationship between a number of explanatory exogenous variables and child labour indicators is established for countries where both sources of information are available. These relationships are, in turn, used to impute child labour information for countries where data are missing. Once missing observations are imputed, several procedures are applied to ensure consistency. A detailed description of each is provided in the subsequent subsections.

5.1 Overview of econometric models for imputation

There are two broad classes of indicators that will be produced, namely, those pertaining to rates and those pertaining to distributions. The indicators that consist of rates include children in CiE, CL, HW, domestic work (DW)[29] and two SDG indicators.[30] The rates are named thus because they are computed based on underlying levels of the indicator as a proportion of a relevant population. For instance, the rate of CiE is calculated as a proportion of CiE in the total population of children. The indicators that consist of distributions are further breakdowns of CiE, CL and HW. These breakdowns are modelled as distributions, and these indicators include STE,[31] STU,[32] and economic activity (EA).[33]

Except for DW,[34] the indicators that consist of rates are each defined at the country level by sex, age

Table 2: Interpolation in high-income countries

Harmonization procedure	Variable of interest	Observed data (15–17 year olds, %)	Approximated data (15–17 year olds, %)
Type I	CiE as per cent of total population	17.0	17.7
Type II – linear (default option)[28]	Percentage share of CiE attending school	79.7	79.0

and geography. A complete list of the breakdowns by sex, age and geographic categories is as follows:

- Age bands:
  - 5 to 11
  - 12 to 14
  - 15 to 17
  - 5 to 17
- Sex:
  - Male
  - Female
  - Total
- Geography:
  - Rural
  - Urban
  - National

This amounts to 36 observations per country, per year. However, these are not all independent observations. For instance, the 'Total' category by sex must be equal to the sum of males and females, in each age and geographic category.

The indicators modelled as distributions (i.e., STE, STU and EA) are further breakdowns of CiE, CL and HW. Specifically, for each of CiE, CL and HW, there is an additional level of disaggregation, corresponding to the categories of STE, STU and EA. For instance, for the STU model, in addition to the age, sex and geography levels, there is a 'school attendance status', which is either 'attending' or 'not attending'. Consequently, for the STU model, there are 72 possible observations per country, per year.

It is worth noting that countries generally have data for all breakdowns, or none at all. There is, however, a minority of countries for which only partial data are available.

Indicators are modelled as proportions of an underlying target population. This target population is referred to as a 'benchmark'. The 'benchmark data' are used to recover levels from all the rates and distributions pertaining to the different indicators. For instance, CiE is modelled as a rate of total population. For a given sex-age-geographic cell, if the rate of CiE is 50 per cent, and total population is 100, then the level of CiE is 50 per cent*100=50. The benchmarks are used to ensure that the rates and distributions are internally consistent with the levels that these rates imply.

Modelling the indicators as proportions affords a variety of advantages, the most salient of which is that the indicators are always within their respective bounds, according to their own definitions. In this example, as CiE would always be lesser than the total population of children, we can ensure that the CiE rate is less than or equal to one. In relation to this, the child labour models are produced sequentially. Indicators are modelled as proportions of their own respective benchmarks, with consideration given to the various interrelationships between them. Specifically, once consistent estimates for CiE are produced, they are used as benchmarks for the child labour model. The rates produced by the child labour model are then made consistent using the CiE benchmark. This is explained in more detail in the subsequent sections.

Succinctly, the aim of the production of the Global Estimates of Child Labour is four-fold. The first and main objective is to produce child labour estimates at the global and regional levels, which are based on a complete set of estimates at the national level. One constraint is missing survey data at the national level for several countries. To address this issue, imputation techniques are used to produce estimates for countries where data are missing. Secondly, the estimates must be internally consistent. Thirdly, the child labour indicators should also be consistent and valid across indicators.[35] Finally, the estimates must correspond to the year 2020, i.e., the latest year for which population data from the *United Nations World Population Prospects* (UN-WPP) are available.

The structure of this section is as follows: we first describe the explanatory variables used to generate modelled estimates. Then the data for total population are described, which forms the basis for each of the subsequent models, either directly or indirectly. Finally, the child labour models corresponding to rates are described and, finally, those corresponding to distributions.

5.2 Explanatory variables used in the modelling process

Modelled estimates are produced by applying econometric techniques to establish relationships between observed data and a set of explanatory variables considered to be good predictors of CL according to the literature.

The selection of explanatory variables has thus been driven by the existing economic theory and empirical studies on the determinants of child labour. Data availability has played a crucial role in the consideration of variables for their inclusion in the model, to balance the appropriateness of information and coverage of as many countries as possible. These explanatory variables are listed below:

- Gross domestic product (GDP) per capita, purchasing power parity (PPP) (constant 2011, international $)
- Share of population, 15–24 years of age
- Share of population, 0–14 years of age, total
- Old-age population covered by social protection
- Percentage of population age 25+ with no schooling
- UNESCO UIS: Percentage of population age 25+ with completed primary education
- Fertility rate, total (births per woman)
- Rural population /Total United Nations estimates and projections, July 2019 (thousands)
- Agricultural employment percentage
- SDG indicator 8.5.2 – Unemployment rate (per cent) (ages 15–24)
- SDG indicator 8.5.2 – Unemployment rate (per cent) (ages 15–64)
- Labour income distribution (ILO modelled estimates) 7–10 decile inclusive
- Youth not in employment, education or training (NEET)

The common assumption in the literature, led by the theoretical work of Basu and Van,[36] is that child labour is mainly driven by poverty. The luxury axiom asserts that the decision by households to send their children to work is mainly driven by poverty. In other words, child schooling and leisure represent a luxury good for poor households. Implicit in this assumption is an altruistic view of the household: Parents do not want to send their children to work unless compelled by circumstances.[37] The evidence seems largely to confirm this axiom.[38]

However, as well established in the literature, household decisions on whether to send a child to work or to school are rarely the consequence of one single factor. Child labour is a complex phenomenon, resulting from household decisions influenced by many factors, including income, uncertainty, fertility, local labour markets and relative returns of work and education. There is extensive literature on the determinants of child labour.[39]

Dammert and colleagues, by reviewing a set of impact evaluation studies, provide a comprehensive look at pathways through which social protection and labour programmes affect child labour.[40] The authors show that unconditional old-age pensions affect the labour supply and school participation of children living in beneficiary households.[41] Social pension programmes, even though explicitly designed to protect the elderly poor, also have an important impact on increasing the human capital of both children and the elderly in households.[42]

The correlation between child labour and local labour markets is straightforward. If children and adults are substitutes in production (substitution axiom), child labour depresses adult wages, which in turn makes it more likely that a child will work.[43] The more child workers in the economy, the lower the wages of jobs that children engage in (unskilled work), leading to an increase of demand for child labour.[44] The literature has widely shown that compromised education leaves young people more vulnerable to low-paid, insecure work and at high risk of being neither in employment, education nor training.

Workers who are more educated are increasingly likely to be in wage employment. On the other hand, less educated young persons appear much more likely to be found in the informal economy in low-paid, insecure jobs offering limited opportunity for upward advancement, perpetrating the vicious circle of poverty.[45]

There is also solid evidence that improvements in living standards are responsible for the observed declining levels of child labour typically associated with economic development.[46] Economic progress, associated with the increase in the demand for skills, as shown above, is also likely to reduce the incentives to engage in work at an early age, as the opportunity cost of dropping out of school increases. It is argued that changes in the industry mix are able to account for a sizable and significant share of the differential trends in child employment across Brazilian states.[47] For example, as child-intensive industries decline, such as agriculture, child labour falls.

These variables vary at the country level, and as much as possible, the ILOSTAT database is used to obtain them. Finally, two models[48] are defined comprising these variables:

Model 1 (short model): Simply uses GDP per capita, the share of population between 0 to 14 years, and the share of population between 15 to 24 years.

Model 2 (full model): This is the long model, which contains all the listed explanatory variables from above.

To identify which of these two models performs the best, cross-validation procedures are used to assess the explanatory power of each of these models. In short, this procedure involves selecting, for each model, random subsets of the data comprising 70 per cent of the total number of observations. For each draw, and for each model, linear regression techniques are used to estimate the coefficients corresponding to each explanatory variable. These coefficients are then used to predict values for the 30 per cent of the dataset aside, for a given CL indicator. The true value for the given CL indicator (where available) is then compared with the predicted value for each model. The model, which on average produces a 'closer' estimate to the true value, is then selected. Specifically, the model with the lower root mean square error (RMSE) is chosen (*See section 5.4* for more details on the cross-validation procedure).

5.3 Population data

The first step in the model development process is the method of obtaining and preparing the population data. It should be noted that each of the indicators in levels is based either directly or indirectly on total population data. The population data used are primarily obtained from the *United Nations World Population Prospects* data. These data contain annual population indicators by broad age groups and sex and for different countries (and years, with the latest 2020 data). The relevant age bands, as outlined above, are 5 to 11, 12 to 14 and 15 to 17 years. The UN-WPP data, however, do not contain data on the geographic (rural-urban) breakdown, which is one of the central target variables for disaggregation as mentioned in section 5.1. For that, data from ILOSTAT are used. The ILOSTAT data, in turn, do not have age bands defined in the same manner. Specifically, ILOSTAT only has data in 5- or 10-year age bands. Consequently, linear interpolation is used to compute counterfactual age bands with ILOSTAT data, which are compatible with the UN-WPP data.[49] The rural-urban breakdown rates are then calculated from ILOSTAT data at the national level and applied to the most recent UN-WPP data to construct the total population data by rural-urban division. At the end of this procedure, a complete set of total population data at the country-sex-age-geographic level for 2020 is generated. The total population data are then used to construct each econometric model. Specifically, total population is the first benchmark, to which every other indicator is anchored, either directly or indirectly.

In the next section, we turn to an analysis of the different models of child labour. First, the general modelling framework for the indicators in rates is discussed, after which each of the specificities pertaining to these indicators is described. Thereafter, we will move on to the indicators defined as distributions, which are explained in an analogous manner.

5.4 General procedure for modelling rates

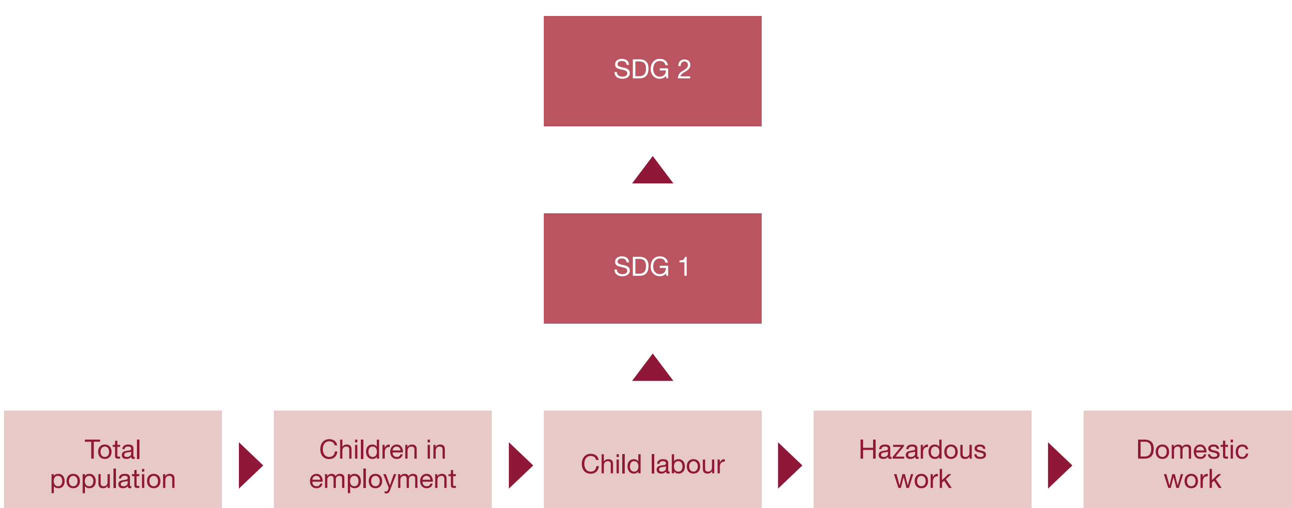
The child labour models described as rates correspond to six indicators, namely CiE, CL, HW, DW and two SDG indicators. National household survey datasets present data in levels, i.e., the total number of children in each of the child labour indicators. As mentioned, estimates are produced in a sequential manner. Intuitively, this is because some indicators are used as benchmarks for others; given that consistency of indicators is established in levels using benchmarks, it makes sense to produce the relevant benchmarks first.

Child labour estimates are modelled in the order shown in Figure 4 (with the indicator prior to the arrow functioning as the benchmark for the indicator after it).

As an example, total population estimates are produced first and are then used as a benchmark for CiE. Then, after obtaining consistent and complete estimates for CiE, they are used as a benchmark for CL, and so on.

Modelling rates for each of the indicators takes place in two steps. The first step in the production of each of these indicators, starting with CiE, is to use household survey data in levels of the indicator, and its benchmark, to calculate the values of the indicators expressed as proportions of the underlying benchmark. Note that for some countries, survey data for multiple years are available. For each indicator (except for total population), the most recent available data are selected. This year can be different from 2020. As an example, for Thailand, the latest data for CiE available are from 2018, obtained from the child labour survey, the National Working Children Survey. We take these data on CiE in levels and match them with the total

Figure 4: Dependencies in child labour estimates



population of children in 2018 in the given sex-age-geographic cell. This allows us to compute the 'real rate' of CiE for Thailand at the sex-age-geographic level. A crucial assumption we make here is that, over reduced time intervals, the rates remain stable. This allows us to use rates derived from survey data in past years to apply to total population data from 2020, and get new, recent levels of CiE. In this example, we would use the rate for Thailand computed for 2018 and apply it to the 2020 total population benchmark to obtain the counterfactual levels of CiE in 2020 for Thailand, with the assumption being that the rate of CiE has stayed constant from 2018 to 2020.

In the second step, we use data on real rates we have from step one, as well as the exogenous variable dataset as described above *(see section 5.2)*, to discern relationships between rates and these variables. We then use these relationships to infer what CiE rates would be for missing observations. Intuitively, imagine that, for instance, we find that CiE rates are negatively related with income across countries. Using the estimated relationship between household survey data on rates for CiE and income, we can work out CiE rates for countries with missing CiE data, but with income data present. This is essentially the goal of the imputation procedure for each of the indicators.

How do we select which variables to include to predict missing rates of the various CL indicators? We make use of a cross-validation procedure to select the 'best' model to impute missing data. Cross-validation refers to a procedure that involves setting aside a pseudo-test sample from the household data, while retaining a larger subset of data on which to train a given model. For the CL models, the sample to train the model in each case refers to a random subset of 70 per cent of countries.[50,51] We then use the estimated coefficients from the training sample to predict the pseudo out-of-sample data (the test sample), which allows us to compute a measure of model performance, such as RMSE.

Crucially, the regression models that we estimate for prediction purposes include all demographic, sex and geographic breakdowns simultaneously. This allows for several positive effects. First, it makes the code simpler. Second, and more importantly, it greatly increases the degrees of freedom.

We estimate different versions of the following regression equation.[52]

30.

$$\left(\frac{\text{Indicator}}{\text{Benchmark}}\right)_{\text{ijklr}} = \text{X}_\text{i}^{'}\beta + \rho\text{Sex}_\text{j} + \kappa\text{Age}_\text{k}$$

$$+ \gamma\text{Geographic}_\text{l} + \mu\text{Region}_\text{r} \times \text{Sex}_\text{j} + \varphi\text{Region}_\text{r}$$

$$\times \text{Age}_\text{k} + \psi\text{Region}_\text{r} \times \text{Geographic}_\text{l} + \varepsilon_{\text{ijklr}}$$

In the above, the subscript *i* refers to country, *j* refers to sex, *k* refers to age group, *l* refers to the geographic breakdown and *r* refers to a broad geographic region. The left-hand side expresses, for a given indicator, its level as a proportion of its benchmark. For instance, for the CiE model, the left-hand side boils down to CiE/total population. The vector of covariates *X* contains variables from either **Model 1** or **Model 2**. Notice first the *i* subscript on *X*. This is because *X* consists solely of variables at the country level, i.e., it captures cross-country variation in the macro indicators above. In addition to capturing differences across countries in the broad CiE rate, we include regional, sex, age and geographic fixed effects, along with region*sex, region*age and region*geographic effects. Intuitively, this allows for separate intercept terms for sex by region, age by region, and geographic breakdown by region, which capture systematic differences within breakdowns and across regions. For instance, one could postulate that the CiE rates are quite different for females in the 5 to 11 years age range in urban Latin America compared to males in the 15 to 17 age range in rural areas in Caribbean countries. This model is flexible enough to capture systematic differences in CiE/total population across breakdowns, as well as parsimonious enough to not be too computationally intensive or perform poorly out of sample.

For the cross-validation procedure, we fix a model and perform 50 regressions on different training datasets, each consisting of a randomly selected set of countries. The predicted values from each regression are then compared with actual values of the rates in the test dataset, and the squared error is saved. Briefly, we compute, for each model, the RMSE across observations and draws in the following manner:

31. $$RMSE_{\text{Model}} =$$

$$\sqrt{\frac{1}{N}\sum_{n=1}^{50}\frac{1}{I(n)}\sum_{i(n)jkl=1}^{I(n)}\left(\left(\widehat{\frac{\text{Indicator}}{\text{Benchmark}}}\right)_{i(n)jkl}-\left(\frac{\text{Indicator}}{\text{Benchmark}}\right)_{i(n)jkl}\right)^2}$$

Note in the above, the subscripts are the same as before, with the addition of a new set, *N*, representing draws. Each set potentially contains different sets of countries, which is why the dependence of the *ijkl* has been made explicit on the realization of a particular draw. As is customary, predicted values are denoted by a 'hat'. We then compare the *RMSE* across the two models, to select the one that minimizes it.[53]

After selection of the models, we carefully ensure the predicted values respect certain definitional and feasible limits. For instance, the rate of CiE can never exceed 1 (there cannot be more CiE than children in total). Moreover, and importantly, we retain real observations, i.e., for countries where data on rates are present, we use these data rather than modelled data. At this step, we have a complete set of rates (36 rates), per country. As mentioned above, however, these rates are not independent. For instance, for a given sex-geography group, the number of CiE in age group 5 to 17 years must be equal to the sum of those in the 5 to 11, 12 to 14 and 15 to 17 age groups. As such, the rate of CiE for age group 5 to 17 years is pinned down by this implied level, and the given level of total population of children in the 5 to 17 years age group for 2020. A similar argument can be made for the category 'total' in the sex breakdown and 'national' in the rural breakdown.

Essentially, we use the complete set of estimated rates for each country (could be either real or modelled), and then, using the latest benchmark data on levels, compute the implied levels of the indicator. We then construct internally consistent levels for each breakdown by computing aggregate categories as the sum of their smaller components. Finally, we re-compute rates for each category for 2020, given that the underlying total population structure could have changed.

As an example, for a given country, age group and geographic breakdown, assume that household survey data for CiE in levels and total population are available from 2018.

In the hypothetical example in Table 3, notice that from 2018 data, 60 per cent of males are CiE, 40 per cent of females are CiE, and the population structure is evenly distributed (i.e., males and females are equal in number), such that the aggregate CiE rate is 50 per cent. In 2020, however, the population structure changes dramatically. Males now comprise 75 per cent of the population. Under the assumption of the constancy of rates from 2018, there are now 90 males, and 20 females. This implies that the total (aggregate) sex category now has a higher rate of 0.55, as it skews more towards the male rate, given the increased composition of males as part of the total population in 2020. Importantly, using the 2018 rate for sex totals would be inconsistent with the new population structure. We reconstruct levels for each sex-age-geography cell, all the while ensuring that the aggregate categories (age totals [5–17], geography totals [national] and sex totals) are consistent in levels with the levels of their respective constituent parts.

Finally, there is a small subset of countries that has data only at the national level, and not with a rural-urban breakdown. Given that it is preferable to retain as much household survey data as possible, we ensure that, for these countries, we adjust upward or downward the modelled rural and urban levels, so that their sum equals the given national level in 2020, implied by the household survey data in rates (assuming again, constancy of this rate from when the latest data were available to 2020). There are multiple ways that this can be done. However, a method is chosen that preserves the relative importance of rural and urban breakdown in national levels, while adding up to the given national level. Specifically, imagine that the national level in 2020 implied by the CL rate in the household survey data is 100 for an arbitrary country (for a given age and sex category). The modelled rates for the rural and urban, along with their respective CiE data, imply levels of 75 and 50, respectively. The sum is therefore 125. Notice that we have to re-scale 125 by a factor of 0.8 for it to equal 100. As such, we scale 75 and 50 by 0.8 each. This implies that their new values are 60 and 40, respectively. Notice that these i) add up to 100, and ii) are related by the same factor of proportionality, i.e., 1.5 (75/50=60/40=1.5).

Regarding the sequence of models that are produced, each indicator is directly or indirectly tied to the UN-WPP data. For instance, imagine a country that has data on CiE, CL and total population from 2018. We compute the CiE rates as a fraction of total population from 2018, and under the assumption of constancy over small intervals, we compute the counterfactual levels of CiE for 2020. These values of CiE are directly related to the underlying values of total population in 2020. We then model the CL rate as a fraction of CiE from 2018. To obtain CL levels in 2020, we use the levels of CiE from 2020 that we have produced in the first step as a benchmark. As such, although CL is directly related to CiE, it is still indirectly related to total population. One reason why each indicator is not modelled as a fraction of total population is because it is much easier to establish logical bounds implied by the definitions of the various indicators when they are modelled as fractions of each other.

5.5 Imputation of specific rates

We now describe the imputation procedure for each of the specific child labour indicators corresponding to rates. They each follow the general structure outlined previously, with specific modelling features and constraints described below.

5.5.1 Imputation of children in employment

Children in employment (CiE) refers to children in System of National Accounts (SNA) work. This definition represents the broadest possible category of the child labour models (apart from SDG 2) and, as such, is not constrained by any other indicators. Due to the availability of household survey CiE data at the country-sex-geography-age level, it is modelled at this level. Importantly, CiE is modelled as a fraction of total population (hence, the rate of CiE). To reiterate, for the CiE model, total population

Table 3: Example showing how 2018 data are used to calculate the rate of children in employment for 2020

Sex	Rate of CiE (from 2018 data)	Total population in 2020 (UN-WPP estimates)	Levels for 2020	Rate of CiE for 2020
Male	0.6	150	90	0.6
Female	0.4	50	20	0.4
Total	0.5	200	90+20=110	110/200=0.55

serves as the benchmark. In other words, although the rates of CiE are computed with respect to total population for the latest year data are available, these rates are assumed to be constant; therefore, the CiE level for 2020 is obtained by multiplying rates with the total population in 2020.

After the imputation procedure (which involves an unconstrained regression), we bound the rate below by zero (this rate can never be negative as both CiE and total population are positive) and above by one (CiE can never exceed total population).[54] Moreover, as discussed, we only impute rates for those observations where household survey data are not available. We then make use of institutional knowledge and set the CiE rate to exactly zero for age groups 5 to 11 and 12 to 14 years for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea; Taiwan Province of China; and the United States of America. Finally, we follow the rebalancing outlined above to establish a complete and internally consistent set of CiE rates (and their corresponding levels in accordance with total population data) for each of the 189 countries, and the 36 observations per country, for 2020. These levels of CiE can now be used as benchmarks for the subsequent indicator, child labour.

5.5.2 Imputation of child labour

Child labour (CL) comprises employment that children are too young to perform and/or work that, by its nature or circumstances, is likely to harm children's health, safety or morals. The exact definition can be found in Figure 1, which outlines age-specific conditions that should be met for a child to be considered a child labourer. The definition of CL implies that its level is at most equal in value to CiE. At this point, CL can be modelled as a proportion of total population or of CiE. CiE was used here, as it is convenient to set the logical bounds imposed by the definition directly in the modelling step.

The CL data are also available at the country-sex-geography-age level, and we first merge household survey CL data in levels with household survey CiE data as well (again, for the latest year that data are available for both indicators). However, one issue with the CL indicator is that there are limited data. Specifically, even though there are national household survey data for 106 countries (out of 189), for 40 of these countries, they do not include all the variables required to classify the work as CL (for instance, branch of EA, occupation at the three- or four-digit level, and weekly hours in employment). This leaves 67 countries with CL data.

To augment the set of countries for which there are household survey data, an SDG indicator is used, which considers the SNA production boundary. This indicator, which is referred to as SDG 1, is very closely related to CL and is a subset of CL data. Given that there is substantially more information for SDG 1, an auxiliary regression is run to exploit the relationship between CL and SDG 1 to predict CL for those observations where SDG 1 is present, but CL is missing. This allows us to augment the CL data prior to subsequent model selection. Specifically, the following regression is estimated:

32. $$\left(\frac{\mathrm{CL}}{\mathrm{CiE}}\right)_{\mathrm{ijkl}} = \alpha + \beta_1 \theta_{\mathrm{ijkl}} + \beta_2 \mathrm{Income}_{\mathrm{i}} + \epsilon_{\mathrm{ijkl}}$$

where

$$\theta_{\mathrm{ijkl}} = \left(\frac{\mathrm{SDG1}}{\mathrm{CiE}}\right)_{\mathrm{ijkl}}$$

In the above, *i* denotes country, *j* denotes sex, *k* denotes age group and *l* denotes geographic breakdown. The estimated coefficients are then used to generate predicted values for the CL rate and augment the dataset. Given the very high correlation between SDG1 and CL, we have ample confidence in our prediction for the CL rates. This auxiliary step then gives us an augmented set of CL rates as household survey data, which are then used in the model selection and imputation process.

After the imputation procedure, as it again involves an unconstrained regression of equation 30, we ensure that the CL rates are between zero and one. CL can never be negative, nor can it ever be greater than CiE, by definition. For the age group 15 to 17 years, the lower bound is set at 0.01, as it is not plausible for a lesser proportion of children to be considered in CL for this age group. In the case of CL, we impute rates only for those observations with fully missing data, i.e., missing CL rates from both household survey data and the auxiliary regression. Importantly, we set the CL rate to exactly one for all observations corresponding to the age group 5 to 11 years, as everyone in CiE for this age group is in CL by definition *(see Figure 4)*. CL rate is then set to exactly zero for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea: Taiwan Province of China; and the United States of America, for age groups 5 to 11 and 12 to 14 years. The set of CL rates that we have, although complete, still correspond to potentially inconsistent levels. We make use of the 2020 CiE levels obtained from the CiE imputation procedure as a benchmark for these rates and rebalance the CL levels to produce a set of consistent and complete CL rates and levels. The latter is used as a benchmark for the subsequent indicator, hazardous work.

5.5.3 Imputation of hazardous work

Children in hazardous work (HW) is a subset of CL. It refers to work that, by its nature or circumstances, is likely to harm children's health, safety or morals. The statistical definition can be found in Figure 1, which outlines age-specific conditions upon meeting of which a child is considered in HW. The statistical definition of HW implies that it is, at most, equal in value to CL. HW is also available at the country-sex-geography-age level, and HW is modelled as a rate of CL. Consequently, the estimates of CL for 2020 that are produced function as a benchmark for HW. The same steps are followed in CL and CiE, with the latest year of HW household survey data merged in levels with CL to produce (real) HW rates.

We then proceed with the unconstrained regression of the HW rate as outlined in equation 30. Again, we only impute HW rates for observations that do not have household survey data and bind the HW rates between zero and one (HW can never be negative, nor can it exceed CL in levels). Importantly, we set this rate equal to one for age group 15 to 17, as this follows from the definition of HW (only children in HW for this age group are in CL). Finally, HW is hardcoded as zero for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea; Taiwan Province of China; and the United States of America for age groups 5 to 11 and 12 to 14 years. We then proceed with rebalancing to obtain an internally consistent set of levels of HW, and their associated rates, making use of the CL benchmark.

5.5.4 Imputation of domestic work

Domestic work (DW) corresponds to the distribution of children in DW by work status, which can be either CiE, CL or HW (and sex and age). It is therefore essential to ensure in the modelling methodology that the estimates preserve the logical bounds between these three indicators simultaneously. Only national-level data are used, as the household survey data do not vary at the geographic level.

The first step is to convert the data on DW in levels to rates, for each of CIE, CL and HW. Essentially, the fraction of children in each of CiE, CL or HW who are in the services sector is modelled, as per the ISIC classification. The DW model is intimately connected to the EA model. Essentially, the EA model produces for each of the CiE, CL and HW indicators a breakdown of children by EA, of which services is one. DW is a subset of services and is modelled as a proportion (rate) of it (and consequently, for each of CiE, CL and HW). Unfortunately, due to a lack of data, it is not possible to merge levels of DW with levels of services for CiE, CL and HW on the same, most recent year. Instead, they are merged on the latest year data are available for each. By construction, given that DW is always a subset of services of either CiE, CL or HW, it is always less than or equal to 1.

In the modelling step, we jointly model children in DW with CiE, CL and HW. Specifically, for each country-region-sex-age observation, there are three separate DW observations, corresponding to each work status, which are included in the regression simultaneously. Given this joint modelling component, as well as the lack of geographic variation, we estimate instead the following regression:

33.

$$\left(\frac{\text{Domestic Work}}{\text{Benchmark Services}}\right)_{\text{ijklr}} = \text{X}_\text{i}^{'}\beta + \rho\text{Sex}_\text{j} + \kappa\text{Age}_\text{k} + \gamma\text{Benchmark}_\text{b} + \mu\text{Region}_\text{r} \times \text{Sex}_\text{j} + \varphi\text{Region}_\text{r} \times \text{Age}_\text{k} + \psi\text{Region}_\text{r} \times \text{Benchmark}_\text{b} + \varepsilon_{\text{ijklr}}$$

The distinction here is the presence of the indicator *b*, denoting benchmark, which refers to either CiE, CL or HW, depending on which observation is in question. The regression model includes an interaction term between regions and benchmark.

Post cross-validation, we retain, as usual, real rates of DW and ensure that these rates are below zero and one. Thereafter, we again set DW rates to zero for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea; Taiwan Province of China; and the United States of America, for age groups 5 to 11 and 12 to 14 years. The rebalancing, conceptually, is identical to the other rates discussed above. However, DW is modelled for each of the CiE, CL and HW indicators sequentially. Internal consistency is ensured by computing updated levels for 2020 using the appropriate benchmarks derived from the previous models. Importantly, given that CiE, CL and HW are related in terms of definitions (for instance, CiE=CL for age group 5 to 11), we need to ensure that this is true for DW as well. Given that the regression in equation 33 was again an unconstrained regression, it is possible for instance, that (ignoring subscripts):

34.

$$DW_{CL,2020} = \frac{\widehat{DW}}{CL} \times CL_{2020} > DW_{CiE,2020} = \left(\frac{\widehat{DW}}{CiE}\right) \times CiE_{2020}$$

where the ^ denotes estimated values. In principle, therefore, the estimated rate of DW/CL can be so high, relative to the rate of DW/CiE, that it ends up being higher in levels. This is not legitimate, even though the levels of CL and CiE for 2020 are themselves consistent. The same can be true of CL and HW as well. To address both potential types of pitfalls, an additional step is implemented to make sure that DW measures for each of the different indicators are consistent. Specifically, we make certain that DW in CL is exactly equal to that in CiE for the age group 5 to 11 years, and that DW in HW is exactly equal to that in CL for the age group 15 to 17 years. Further, we bound the DW in CL from above by DW in CiE first, and then bound DW in HW above by DW in CL. The end of this procedure then results in 6,804 observations (2,268 corresponding to each work status), which are levels of DW (and their associated rates) that are internally consistent with their respective benchmarks.

The next section discusses indicators related to SDG 1 and SDG 2.

5.5.5 Imputation of Sustainable Development Goal 1

SDG 1 aims to capture child labour by considering the System of National Accounts production boundary (also referred to as SDG SNA PB). Critically, SDG 1 measures a concept similar to CL, but is different in important aspects. Specifically, SDG 1 does not consider work in hazardous occupations or industries. This renders SDG 1 a subset of CL, as CL is a more expansive indicator for age groups 12 to 14 and 15 to 17 years. Table 4 illustrates this distinction.

The SDG 1 model is linked to the school attendance model described in detail in section 5.6.3 (as there is a further breakdown of SDG 1 by school attendance). As such, SDG 1 is present at the country-sex-geography-school attendance-age level. Specifically, for each country-sex-geography-age breakdown, there are three further observations of the number of children in SDG 1: those attending school, those not attending school and the total number in SDG 1. Given that SDG 1 is a subset of, and is closely related to CL, it would be preferable to model it as a rate of CL itself. However, the limitations in terms of data coverage for CL would result in a loss of a significant number of observations. Consequently, model SDG 1 is modelled as a fraction of CiE, which then functions as a benchmark. Specifically, we model:

35. $$\tau_{\mathrm{ijkls}} = \left(\frac{\mathrm{SDG\ 1}}{\mathrm{CiE}}\right)_{\mathrm{ijkls}}$$

where *i* represents country, *j* represents sex, *k* represents age group, *l* represents geographic breakdown and *s* represents school attendance (attending or not attending school). Essentially, the household survey data in rates represent the number of children in SDG 1 as a fraction of CiE who are attending school, not attending school and the total in SDG 1, by country-sex-geography-age.

We then proceed with model selection and ensuing unconstrained regression of the SDG 1 rate as outlined above, while retaining those observations for which household survey data are present. We ensure that the rate of SDG 1 is zero for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea; Taiwan Province of China; and the United States of America, for age groups 5 to 11 and 12 to 14 years. The rebalancing exercise is performed as usual, using CiE by school attendance as the benchmark. It is worth mentioning that although the benchmark used is CiE, we ensure the levels of SDG 1 for 2020 are always less than or equal to those of CL, except for the age group 5 to 11 years, where they are equal. Secondly, an additional rebalancing step is required for the breakdown of SDG 1 for total school attendance. Within a country-sex-age breakdown, the total number of children in SDG 1 would equal the sum of those attending school and those not attending school. Consequently, the levels of children attending school and not attending school are rescaled by a factor of proportionality, such that their sum equals the total.

Table 4: Comparison of child labour and Sustainable Development Goal 1 definitions of age subgroups

Age group	CL definitions, by age subgroup	SDG definitions (based on the SNA production boundary), by age subgroup
5–11	Works for one hour or more per week in employment	Works for one hour or more per week in employment
12–14	Works for 14 hours or more per week in employment, or works in hazardous industries or occupations	Works for 14 hours or more per week in employment
15–17	Works for 43 hours or more per week in employment, or works in hazardous industries or occupations	Works for 43 hours or more per week in employment

At the end of this procedure, an internally consistent set of SDG 1 levels is obtained, consisting of 20,412 observations.

5.5.6 Imputation of Sustainable Development Goal 2

SDG 2 (also referred to as SDG general production boundary, or SDG GPB) is an expansion of SDG SNA PB. This expansion is based on hours of work in unpaid household services. Specifically, for age group 15 to 17 years, the definition of both SDGs is identical, but for children below 15 years of age, the SDG GPB adds children that work in unpaid household services for 21 hours or more per week. This makes SDG 1 a subset of SDG 2. Table 5 summarizes the differences according to age group definitions.

Like SDG 1, SDG 2 is also tied to the school attendance model *(see section 5.6.3)* and is thus present at the country-sex-geography-school attendance-age level. SDG 2 is modelled directly as a ratio of SDG 1. Given that its definition is more expansive than that of SDG 1, this ratio can be greater than one for age groups 5 to 11 and 12 to 14 years.

We then run the cross-validation procedure to select the best model and impute the predicted values of this ratio for missing observations. Next, these rates are converted to levels for 2020, using SDG 1 levels in 2020 as the benchmark. Importantly, there are no constraints on the levels of SDG 2 with respect to CiE (and consequently, with respect to CL and HW); however, SDG 2 has total population as an upper bound. As a first step, we ensure that for the 'total' cell within the school-attendance category at the country-sex-geography-age level, the level of SDG 2 is, at most, that of the total population. However, given that the regression is an unconstrained one, despite having constrained SDG 2 to being less than or equal to total population, the levels of children in SDG 2 (at the country-sex-geography-age level) attending school or not may still exceed that of total population. To address this, we ensure that the levels of children attending school or not are adjusted by a factor of proportionality, so that their sum always equals the total category. We further ensure that for age group 15 to 17 years, the levels of SDG 2 for 2020 equal those for SDG 1, given the definition.

We then proceed with rebalancing to achieve internal consistency across age groups, sex and

Table 5: Comparison of Sustainable Development Goal 1 and Sustainable Development Goal 2 definitions of age subgroups

Age group	SDG 1 definitions (based on the SNA production boundary), by age subgroup	SDG 2 definitions (based on the SNA general production boundary), by age subgroup
5–11	Works for one hour or more per week in employment	Works for one hour or more per week in employment, or 21 hours or more per week in unpaid household services
12–14	Works for 14 hours or more per week in employment	Works for 14 hours or more per week in employment, or 21 hours or more per week in unpaid household services
15–17	Works for 43 hours or more per week in employment	Works for 43 hours or more per week in employment

geography. The end of this procedure yields 20,412 observations for levels of SDG 2, which are internally consistent.

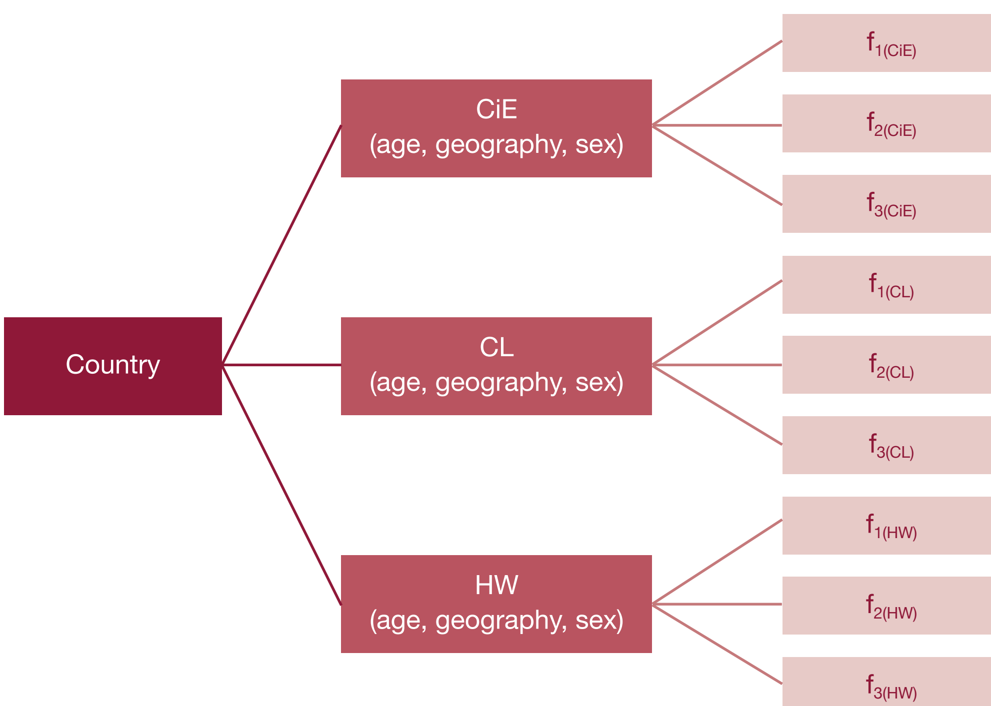
5.6 Missing distributions

This section explains how indicators, which are best thought of as 'distributions', are modelled. The distributions are best thought of as breakdowns of CiE, CL and HW models that have been produced in previous sections. This affects the model in an important way and, consequently, it is important to make sure that the estimates will preserve the logical bounds between these three variables. For this reason, an additional correction step after the imputation regression is needed. In a manner similar to the one above, the data preparation step will be explained, followed by the modelling step. The tree diagram in Figure 5 illustrates the conceptual nature of the distributions.

In Figure 5, for a particular country, and an age-geography-sex cell for each of the three main indicators (namely CiE, CL and HW), the aim is to produce estimates of various breakdowns of these indicators. The breakdowns that are discussed are as follows: school attendance (STU), status in employment (STE) and economic activity (EA).

We will refer to f as a generic distribution of a particular indicator, which is either CiE, CL or HW. A particular value of f, $f_{d\ (b)}$, refers to the fraction of population of the cell in that breakdown. For instance, $f_{attending\ school\ (CiE)}$, would refer to the fraction of CiE attending school. This value, naturally,

Figure 5: Conceptual framework showing indicators, which are modelled as distributions: Status in employment,[55] school attendance[56] and economic activity[57]



would be between 0 and 1 and the notion of a benchmark would still hold. The benchmark corresponding to 2020 is denoted as y_{2020}, such that $f_{d\ (b)}\ {}^*y_{2020}=Level_{2020}$. The breakdowns/distributions must be logically consistent both within and across indicators.

The steps taken to produce the models for the breakdowns are conceptually similar to those used to produce the indicators. The breakdowns of each indicator are modelled simultaneously to make the implementation of logical consistencies easier. This is similar to what we did in the DW model in the preceding section on rates.

The household survey data correspond to the levels of the breakdown for each country-sex-(geography)-age by indicator.[58] As an example, for the STE model, we have household survey data for Armenia on females aged 12–14 years, who are either contributing family workers, employees or own-account workers, for each of CiE, CL and HW. Importantly, within an indicator, once we have information on the level of breakdowns, the sum of the levels is a sufficient statistic for $f_{d\ (j)}$ in the household survey data. This is because the sum of the levels of the breakdowns corresponds to the level of the indicator itself, which allows us to compute $f_{d\ (j)}$. Consider the computation of $f_{Own\ Account\ (CiE)}$ as an example:

36.

$$f_{\text{Own Account}}(CiE) = \frac{\text{Own Account (CiE)}}{\text{Own Account (CiE)+Employees (CiE)+Family Workers(CiE)}}$$

In equation 36, we have, for a given country-sex-(geography)-age cell, the fraction/distribution of own-account workers in CiE. This is different from the model in rates, where we had to merge data with the benchmark from the same (latest) year the data were available, to calculate rates. The important modelling assumption here is that we assume the distribution is constant from the latest year survey data were available, to 2020. This then allows us to use the benchmarks for the main indicators (i.e., CiE, CL and HW for 2020) constructed above to calculate levels for 2020, i.e., $f_{d\ (b)}\ {}^*y_{2020}$.

For ease of exposition, let us focus on a given breakdown. Our first step is to compute $f_{d\ (CiE)}$ for a given country-sex-(geography)-age cell, for each i. In a similar fashion, we compute $f_{d\ (CL)}$ and $f_{d\ (HW)}$. Next, we include all the indicators together for a given breakdown in a single regression, and estimate versions of the following equation:

37.

$$\begin{aligned} \mathrm{f_{ijklrbd}} &= \mathrm{X_i'}\beta + \psi\mathrm{Region_r} + \rho\mathrm{Sex_j} + \kappa\mathrm{Age_k} + \lambda\mathrm{Geographic_l} \\ &+ \gamma\mathrm{Benchmark_b} + \mu\mathrm{Region_r} \times \mathrm{Sex_j} + \varphi\mathrm{Region_r} \times \mathrm{Age_k} \\ &+ \chi\mathrm{Region_r} \times \mathrm{Geographic_l} + \theta\mathrm{Region_r} \times \mathrm{Benchmark_b} \\ &+ \delta\mathrm{Breakdown_d} + \zeta\mathrm{Breakdown_d} \times \mathrm{Region_r} + \varepsilon_{\mathrm{ijklrbd}} \end{aligned}$$

The equation above is conceptually the same as equation 30, but accounts for the fact that we are allowing for different effects for benchmark*region as well as breakdown*region. Intuitively, benchmark*region dummies capture the idea that there are systematic (average) differences in the fraction of individuals in breakdown by region (for instance, East Asia and Pacific may have a higher fraction of children attending school than another sub-region).

We repeat the cross-validation and model selection steps, and obtain predicted values for $f_{d\ (j)}$ (ignoring subscripts) for missing observations, while retaining real values whenever available. Importantly, each of the $f_{d\ (j)}$ within country-sex-(geography)-age has a separate benchmark, b across the breakdowns d. For instance, we model the fraction of children attending school or not for CiE and CL, as well as HW. We ensure that we merge the distribution with the appropriate benchmark, to recover appropriate levels of the breakdown.

The rebalancing procedure is like that in rates, with two additional elements. First, we ensure that the distribution adds up to 100 per cent with respect to the benchmark. Consider, for a particular country, predicted rates, which we then convert to levels using the benchmark:

$$38.\quad \widehat{f_{NA}}(\text{CiE}) \times \text{CiE}_{2020} = \widehat{\text{NA}_{2020}}$$

$$\widehat{f_{A}}(\text{CiE}) \times \text{CiE}_{2020} = \widehat{\text{A}_{2020}}$$

In equation 38, we recover the levels of children not attending school and attending school, using the CiE benchmark for 2020. Notice, however, that the levels of children attending school, and not in 2020, are not guaranteed to equal total CiE in 2020. To resolve this issue, we calculate first the level of CiE in 2020 implied by the unadjusted number of children not attending school and attending school:

$$39.\quad \widehat{\text{NA}_{2020}} + \widehat{\text{A}_{2020}} = \widehat{\text{CiE}_{2020}}$$

The factor of proportionality is then calculated

$$40.\quad \frac{\text{CiE}_{2020}}{\widehat{\text{CiE}_{2020}}} \equiv \varphi$$

such that

$$41.\quad \underbrace{\phi\widehat{\text{NA}_{2020}}}_{\text{Adjusted NA}} + \underbrace{\phi\widehat{\text{A}_{2020}}}_{\text{Adjusted A}} = \text{CiE}_{2020}$$

This adjustment by the factor of proportionality ϕ ensures that the estimates of the numbers of children not attending school and attending school for 2020 are in accordance with those computed for the benchmark in question, i.e., CiE in this case.

To reiterate, the data structure is at the country-sex-(geography)-age breakdown-benchmark level. The rebalancing of the levels to add up to the totals (i.e., for the sex totals, age totals and possible geography totals) is done in an analogous manner to that done for the indicators involving rates. Given our choice of modelling, i.e., by modelling the breakdowns jointly, and not sequentially, we need to make sure that the logical bounds across the breakdowns are respected as well. This implies, first, that levels of children at the level of the breakdown are identical for CL and CiE for ages 5 to 11 years, and those for HW and CL for ages 15 to 17 years. In other words, the number of children attending school for ages 5 to 11 years are identical for CL and CiE, as well as those not attending school. For other cases, we need to ensure that the levels of CiE are at least as high as CL, and the levels of CL at least as high as those of HW. Notice that the estimated values we calculate $f_{d\,(j)}$, are distributions of the breakdown d for a particular benchmark j. As such, even though $CiE(2020) \geq CiE(2020)$, there is no guarantee that:

$$42.\quad \widehat{f_d}(CiE_{2020}) \times CiE_{2020} \geq \widehat{f_d}(CL_{2020}) \times CL_{2020}$$

because the f are estimated in an unconstrained manner across indicators. Essentially, our strategy is to ensure that the implied values of the breakdowns of CiE, CL and HW respect logical bounds. This is done in a sequential manner. Table 6 shows how we ensure consistency between CiE and CL for the breakdown of school attendance.

In Table 6, the hypothetical example corresponds to an underlying estimation of $f_{d\,(j)}$, which allows us to compute the estimated levels of children attending school or not in 2020, in CiE as well as CL (using the fact that $f_{d\,(j)} * y_{2020}$=Level$_{2020}$). Notice that the unconstrained estimation procedure yields values of children not attending school in CL that are higher than CiE (which is an impossibility). The values of children attending school, however, are possible, across CL and CiE (in that they are lower for CL than those for CiE). To obtain valid results, we need to ensure that the levels of children not attending school for CL must be at most 100 (alternatively, we could ensure that the levels in CiE are at least 110 as well). Given that the excess number of children not attending school in levels is 10, but the deficit amount attending school is 20 (100–80), we categorize the 10 excess children not attending school as attending school. This results in an adjusted level of CL, which is legitimate across the distribution, as it is always less than or equal to the level of CiE. Given that the re-allocation is exact, the sum of children not attending school and attending school in CL still equals the original CL benchmark. Two points are worth mentioning:

1. For each of the three indicators classified as distributions, we first adjust the estimated levels of CL to be, at most, equal to those of CiE, and then adjust the estimated levels of HW to be, at most, equal to those of the adjusted values of CL. This ensures that the levels of HW are, at most, equal to those of CiE as well.

2. In the case where the number of categories across the breakdown are more (such as for EA and STE), we re-allocate from the excess category(ies) to the deficient category(ies) based on the proportion of total adjustment available in the deficient category(ies). Table 7 describes this using a detailed example for STE.

Given that the adjustment required is +100 (excess/greater number of own-account workers in CL relative to CiE), we reallocate this number to both contributing family workers and employees, based on the relative proportion of the total deficit they have available between them. In particular, because the total requirement of adjustment is 100, and because contributing family workers have 100 out of the 150 total deficit, they are allocated 66.67 per cent (100/150) of the total excess.

Table 6: Adjustments to ensure consistency between children in employment and child labour for the breakdown of school attendance

	Estimated levels of CiE (2020)	Estimated levels of CL (2020)	Adjustment required	Adjusted levels of CL (2020)
Not attending school	100	110	-10	100
Attending school	100	80	+10	90

Table 7: Adjustments to ensure consistency between children in employment and child labour for the breakdown of status in employment

	Estimated levels of CiE (2020)	Estimated levels of CL (2020)	Adjustment available	Adjustment required	Adjusted levels of CL (2020)
Contributing family workers	100	0	+100	100*(100/150) ≈67	67
Employees	100	50	+50	100*(50/150) ≈33	83
Own-account workers	100	200	-100	-100	100

In the following sections, specific indicators corresponding to distributions are explained.

5.6.1 Imputation of status in employment

The status in employment (STE) model corresponds to status in employment (employee, own-account worker or contributing family worker) in which children fall under the following work statuses: CiE, CL or HW. For the STE model, as it is best thought of as a distribution, the household survey data correspond, for a particular work status (i.e., CiE, CL or HW), to the breakdown into STE.

For the STE model, there is no geographic variation present (data are only present at the national level), and we model this indicator at the country level by sex and age breakdown. We merge real data with the appropriate status in employment (benchmark) as a first step. We then stack all observations (across breakdowns and benchmarks) on top of each other and perform the cross-validation procedure to obtain estimates of $f_{d\,(j)}$.

We retain values of $f_{d\,(j)}$ wherever household survey data are present, and then hardcode $f_{d\,(j)}$ as 0 for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea; Taiwan Province of China; and the United States of America, for age groups 5 to 11 and 12 to 14 years. We then calculate the levels of the STE for each of CiE, CL or HW. We then make these levels internally consistent, as outlined in section 5.5. We take particular care to ensure that the distribution of $f_{d\,(j)}$ sums to 1 for a particular country-sex-age-benchmark, and that the dependencies and logical bounds across benchmarks are respected. These include, for instance, ensuring the levels of children corresponding to various statuses in employment are identical for CiE and CL in age group 5 to 11 years.

The final dataset corresponding to the STE model consists of 20,412 observations: 6,804 for each of CiE, CL and HW.

5.6.2 Imputation of economic activity

The economic activity (EA) model corresponds to branch of economic activity (agriculture, industry or services) in which children fall under the following work statuses: CiE, CL or HW. As noted above, the household survey data obtained correspond, for a particular work status (i.e., CiE, CL or HW), to the breakdown into branch of EA.

For the EA model as well, there is no geographic variation present, and the indicator is modelled at the country level by sex and age breakdown as well. As described above, for each benchmark, we first merge the breakdowns with their respective benchmarks for real data. We then stack the observations for each of the breakdowns on top of each other, and then perform the cross-validation procedure to obtain estimates of $f_{d\,(j)}$.

As customary, we retain real values of $f_{d\,(j)}$, wherever possible, following which we hardcode values of $f_{d\,(j)}$ to 0 for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea; Taiwan Province of China; and the United States of America, for age groups 5 to 11 and 12 to 14. We calculate then the levels of the branch of EA for each of the work statuses implied by the estimated $f_{d\,(j)}$ and the respective benchmarks for CiE, CL and HW. We then proceed to adjust these levels to make them internally consistent as per the steps outlined above. In particular, in addition to our usual rebalancing steps, we ensure that the sum of the distribution of the $f_{d\,(j)}$ equals 1, as well as the fact that dependencies across benchmarks are respected.

The final dataset consists of 20,412 observations at the country-sex-age-economic activity benchmark level. Importantly, as noted above, the DW model uses the EA model as a benchmark, as DW is modelled as a rate of services.

5.6.3 Imputation of school attendance

The school attendance (STU) model corresponds to the distribution of children by school attendance (attending or not attending) in which children fall under the following work statuses: CiE, CL or HW. As noted above, the household survey data obtained correspond, for a particular work status (i.e., CiE, CL or HW), to the breakdown into STU.

The STU model represents the most comprehensive model, in terms of preponderance of data. In particular, the household survey data consist of observations at the country level by sex, age and school attendance. As in the EA and STE models, we stack all observations (across breakdowns and benchmarks) on top of each other, and perform the cross-validation procedure to obtain estimates of $f_{d\,(j)}$.

In a procedure similar to that implemented in the EA and STE models, we retain real values of $f_{d\,(j)}$ wherever possible. We then hardcode values of $f_{d\,(j)}$ to 0 for countries for which the data source is EU-LFS, as well as for Australia; Canada; Channel Islands; China, Hong Kong Special Administrative Region; Israel; Japan; New Zealand; Republic of Korea; Taiwan Province of China; and the United States of America, for age groups 5 to 11 and 12 to 14 years. We then calculate the levels of the branch of EA for each of the work statuses implied by the estimated $f_{d\,(j)}$ and the respective benchmarks for CiE, CL and HW. Our re-adjustment procedure to make these levels internally consistent is identical to that used for the EA and STE models. One important distinction, however, is that we must make sure that the sum of the rural and urban levels equals that of the national level, given that we have geographic variation present as well.

The final dataset corresponding to the STU model consists of 40,824 observations: 13,608 for each of CiE, CL and HW.

The next section describes how we construct data at the aggregate level for each of these models.

6. GOING FROM COUNTRY-LEVEL DATA TO REGIONAL AGGREGATES

The imputation procedure for missing rates and distributions provides a complete set of modelled estimates for each indicator. However, the level at which data are available depends on the indicator in question. For instance, for the CiE model, data were available at the country level by sex, area of residence and age, whereas for the STU model, data were available at the country level by sex, age and area of residence. For each model, it was necessary to aggregate upwards, from country to region, while retaining the original breakdowns. This aggregation is done in levels, and then converted into rates. A full list of ILO regions can be found in Annex 1, Table A3.

The example below shows how to obtain aggregate data for the Asia and the Pacific region, for the CiE model.

For each breakdown in terms of sex, age and area of residence, the total number of CiE in the Asia and the Pacific region is obtained by summing the levels for each country in the region. This is the numerator for the CiE rate. For the denominator, the total populations for each country in the region are added together within the same sex, age and area of residence classification. The resulting CiE rate would then correspond to the CiE rate in the Asia and the Pacific region. The CiE rate in the region can also be expressed as a weighted average of each individual country's CiE rates, weighted by their respective share in the regional population. Specifically, 43.

$$\widetilde{\mathrm{CiE}}_{\text{Asia and Pacific},jkl} = \frac{\sum_{i\in\text{Asia and Pacific}} CiE\ Level_{ijkl}}{\sum_{i\in\text{Asia and Pacific}} Total\ Population_{ijkl}}$$

$$= \frac{\sum_{i\in\text{Asia and Pacific}} \widehat{CiE}_{ijkl} * Total\ Population_{ijkl}}{\sum_{i\in\text{Asia and Pacific}} Total\ Population_{ijkl}}$$

$$= \sum_{\mathrm{i}\in\text{Asia and Pacific}} \omega_{\mathrm{i}}\ \widehat{CiE}_{ijkl}$$

where $\widetilde{\mathrm{CiE}}_{\text{Asia and Pacific},jkl}$ and $\widehat{CiE}_{ijkl}$ denote the aggregate rate of CiE in the Asia and the Pacific region and the rate of CiE in country I for sex *j*, age group *k* and geographic breakdown *l,* respectively. Moreover,

44. $$\omega_i \equiv \frac{Total\ Population_{ijkl}}{\sum_{i\in\text{Asia and Pacific}} Total\ Population_{ijkl}}$$

Regional values of all indicators are calculated in the same manner, aggregating the results for all countries in a specific region, while carefully preserving the structure of the data with respect to the other breakdowns.[59]

7. COMPARABILITY OF TRENDS 2016–2020

The methodology of the 2016–2020 Global Estimates of Child Labour was designed to be as similar as possible to the previous edition, 2012–2016.[60] The 2016 Global Estimates of Child Labour aimed to provide a clear picture of child labour in 2012–2016, by producing estimates anchored to the 2016 population, and using datasets available from 2008 to 2016. In the current edition, the same procedure was applied, with the estimates aiming to represent the 2016–2020 period, using the latest available data ranging from 2014 to 2019, and anchored to the 2020 population.

However, some methodological changes were introduced, in line with other global estimates undertaken by the ILO Department of Statistics. First, explicit country-level imputation, rather than implicit country-level imputation, was carried out. This implies that, for every country, there are either household survey data or imputed data. Secondly, the imputation process used a series of econometric models, as explained in section 5.4. Third, the aggregation of country-level data to produce global and regional estimates is performed using the population-weighted average, as opposed to the arithmetic (unweighted) mean.

In order to assess the effect of these methodological changes and to be able to determine the feasibility of a trend analysis, the following procedure was followed:

1. A sub-sample of 71 datasets included in the 2012–2016 global estimates was selected, based on current microdata availability.
2. Global and regional estimates were calculated following exactly the same methodology applied in 2012–2016 for this set of 71 countries.
3. Global and regional estimates were calculated for this subset of 71 countries using the new methodology.
4. The results were cross-checked.

Results comparison:

The 2020 model vintage produces an EA rate for children aged 5 to 17 years of 12.6 per cent, slightly below the 13.2 per cent produced by the old model, corresponding to a deviation of 0.6 percentage points. This amounts to a difference of approximate 10 million children. This difference in the estimates at the global level is within any reasonable estimate of uncertainty. The corresponding regional variations include: 0.2 p.p. for sub-Saharan Africa (the lowest of all observed regions); 1.5 p.p. for Latin America and the Caribbean, and 1.6 p.p. for Asia and the Pacific. These are the three regions for which trend data are presented in the statistical analysis. The observed change between 2016 and 2020 for Latin America and the Caribbean and Asia and the Pacific exceeds these p.p. differences between the 2020 model vintage and the old model. This leads to the conclusion that there is indeed a clear downward trend in the EA data for children aged

5 to 17 years in these regions. It should be noted that it is expected that the differences would be reduced if the full set of countries was used for the comparison, since the dependence on imputation decreases.

8. MODELLING THE IMPACT OF COVID-19 ON CHILD LABOUR

Analysis of the data available at the time of production of this report suggests that the effect of COVID-19 on children in employment (CiE), and child labour (CL) is likely to change very substantially according to the horizon considered.

- In the short term, we can expect a temporary effect that lowers the level of employment among children. Driven by restrictions such as lockdowns that temporarily affect work activity, work among all ages is expected to decline. This includes work activities carried out by children.
- In the medium term, we can expect that the socioeconomic conditions created by the pandemic, such as poverty increases, can affect employment among children and child labour. Once public health restrictions are lifted, or relaxed, this effect is expected to lead to higher counts of both children in employment and child labour.

Using existing evidence for analysis, a decline in CiE and CL can be observed during the initial stages of the pandemic, due to lockdowns and related public health restrictions. This validates, with only partial data, the temporary effect hypothesis. Conversely, in the longer term, modelling exercises using the latest poverty projections suggest that there is likely to be a substantial rise in child labour – this would be consistent with the persistent effect hypothesis.[61] Therefore CiE during the COVID-19 crisis can be written as:

45.

$$CiE_{i,t} = CiE_{i,2019} + Temporary\ effect_{i,t} + Persistent\ effect_{i,t}\ ,$$

where i=country, t=time period of interest

The evolution of child labour can be written in an analogous manner. The critical assumption behind the estimation procedure is to assume that at a sufficiently long horizon, t=2022 in particular, the temporary effect can be assumed to be zero. Hence, by that year the persistent effect will be the only driver of children in employment.

8.1 Existing evidence on the temporary effect

Despite limited data sources, existing evidence from short-term indicators suggests that there was a decline in CiE and CL in the early stages of the pandemic, due to reasons such as lockdowns and other public health restrictions. While some insight can be gained, data-quality limitations, such as small sample sizes and changes to survey collection methodologies due to pandemic restrictions, must be considered.

8.1.1 Data on children in employment

An analysis of employment in 2019 and 2020 in five countries (Brazil, Ecuador, Paraguay, Peru and Viet Nam) was conducted, comparing quarterly employment figures for various age groups between the two years. Aside from single-year age groups, comparisons were made for ages 14–17; 15–17; 16–17; 5–17; total population (15+); and youth (15–24) subsets.

From 2019 to 2020, an inter-annual decline in quarterly employment was observed for all age subgroups and countries for Q2 and Q3, and the majority of Q4. Percentage decline ranged considerably between countries, with the highest percentages seen in Ecuador. For Brazil and Ecuador specifically, greater declines in employment between years were seen for children than the total population and youth age groups. For example, in Q3 in Ecuador, the decline in CiE for all the age subsets between 5 and 7 years old ranged between 17 and 69 per cent, as opposed to the decline of 8 and 11 per cent for the total population and youth subsets. Similarly, in Viet Nam, the largest decline in employment was observed for 15-year-old children, with declines also observed for children of other ages. Only a minimal decline was seen in the total population age group, suggesting that the employment status of older workers was less impacted by COVID-19 than child workers. Mixed results were seen, for example in Paraguay, but this is not unexpected given the complexity of the situation.

CiE in agriculture has experienced smaller declines or even, in a few cases, increases, in contrast to the rest of the sectors. For example, in Paraguay, CiE in agriculture increased by 71 per cent in Q2, while CiE in non-agricultural sectors dropped by 38 per cent. A similar trend, although to a lesser degree, was observed in Q3. This supports the idea that when employment opportunities in many industries declined, child workers instead became involved in subsistence family agriculture.

Graphs showing results for the different countries and age groups can be found in Annex 4.

8.1.2 Data on child labour, SDG 8.7.1 – proportion of children engaged in economic activity and SDG 8.7.1 – proportion of children engaged in economic activity and household chores

Data for CL and SDG 8.71 – proportion of children engaged in EA – show similar declines in the early stages of the pandemic. However, limited data are available for these indicators, as well as SDG 8.7.1 – proportion of children engaged in EA and household chores (for which no data at all are available). It therefore difficult to draw specific conclusions regarding global trends and it is not possible to generalize results to a wider population.

8.2 Estimation of the impact of COVID-19 on child labour

COVID-19 and Child Labour: A time of crisis, a time to act[62] describes the potential effect of the pandemic in the medium-term in a stark yet clear manner: "With poverty comes child labour as households use every available means to survive." In the same study, the causal link between poverty and child labour is described. This is used in the present analysis as the basic assumption: Poverty is a strong predictor of child labour. The focus on poverty allows us to draw on existing medium-run projections from the World Bank. Figure 6 from the World Bank depicts the global trend of extreme poverty due to the impact of COVID-19.[63]

World Bank country-level poverty rates until 2022 were used for the modelling exercise. In order to make predictions for all 189 countries, missing values were imputed using the methodology in section 8.2.5.

CiE and CL are estimated using the following regression by i-country (cross-section):

46.

$$CiE\ Rate_{i,pre-COVID} = a + \beta x'_{i,pre-COVID} + \gamma Poverty\ Rate_{i,pre-COVID} + \varepsilon_i$$

The persistent effect can be via the fitted effect of poverty:

47.

$$Persistent\ effect_{i,post-COVID} = \hat{\gamma}(Poverty\ Rate_{i,post-COVID} - Poverty\ Rate_{i,pre-COVID})$$

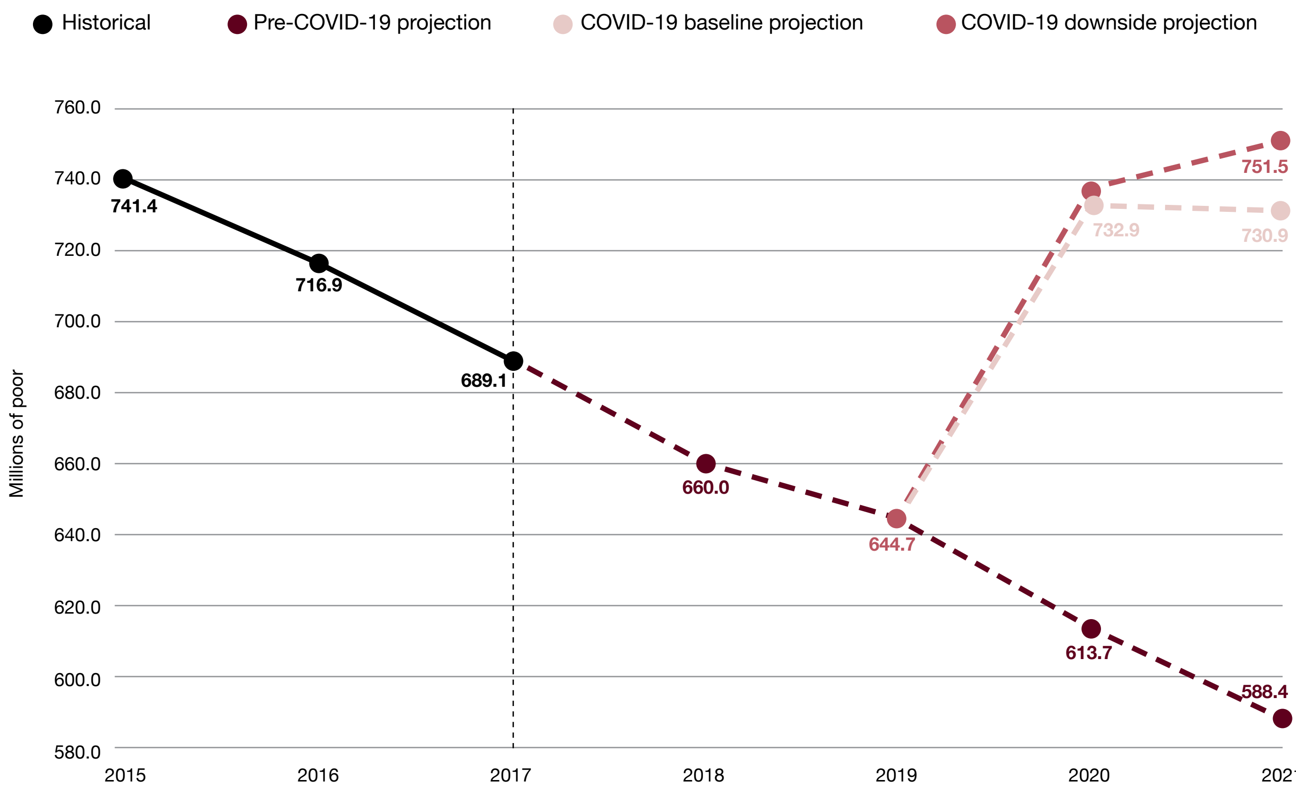
The selection of control variables (x in the equation) was done after considering multiple alternatives; the model selected to give the baseline prediction is:

48.

$$CiE\ Rate_{i,pre-COVID} = a + \beta_{age} AGE\ GROUP_i + \beta_{region} REGION_i + \gamma Poverty\ Rate^{\$3.20}_{i,pre-COVID} + \beta_{SOCPRO} SOCPRO_{i,pre-COVID} + \varepsilon_i$$

The above equation includes a constant, a single poverty line (US$3.20 a day), two fixed-effects variables (i.e., age group and region), and a social protection indicator: the proportion of the population protected in at least one area of social protection (SDG 1.3.1).

Figure 6: Nowcast of extreme poverty, 2015–2021 (global), by the World Bank[64]



Sources: Lakner, Christoph, et al., 'How Much Does Reducing Inequality Matter to to Global Poverty?' World Bank Group, Washington, D.C., 2020; World Bank, 'PovcalNet', 2020.[65]

The estimated poverty coefficients are: $\hat{\gamma}$=0.151 for CiE and $\hat{\gamma}$=0.087 for CL, and the estimated coefficient for the social protection indicator is: $\widehat{\beta_{SOCPRO}}$ =-0.401 for CiE and $\widehat{\beta_{SOCPRO}}$ =-0.223 for CL.[66]

The above specification was selected because of its simplicity in explaining its results and its satisfactory sample size. The results from using other alternative specifications were very similar to the ones obtained using the above. Results had expected coefficient signs and the specification was not an outlier in the range of all the models that were considered.

8.2.1 Expected changes to CiE and CL by 2022 as a result of changes in poverty due to COVID-19

Consider the main assumption for this simulation exercise, that when poverty increases, then CiE and CL also rise. For the aggregated age group (i.e., 5-17 year olds), in 2022, the estimated COVID-19 induced CiE via the poverty channel is set to rise to 11.8 million *(see Table 8)*. About three quarters of these children working will be classified as CL (i.e., 8.9 million is 75.4 per cent of 11.8 million).

8.2.2 Checking the sensitivity of the coefficients to the specific sample

To check whether the above coefficients are robust, the regressions were run 100 times, each time dropping 25 per cent of the sample. The average values of those iterations are close to the values of the coefficients using the full sample. For example, the average coefficient of poverty for CiE after randomly dropping 25 per cent of the sample is 0.155, as opposed to 0.151 when using the full sample *(see Table 9)*. This gives us more confidence that our coefficients are not sample-specific.

Table 8: Children in employment and child labour changes because of increases in poverty due to COVID-19 (global, 189 countries)

Age group (years)	CiE in 2019 (millions)	Added CiE by 2022 (millions)
5–11	88.0	4.9
12–14	54.3	3.3
15–17	76.5	3.6
5–17	218.7	11.8

Age group (years)	CL in 2019 (millions)	Added CL by 2022 (millions)
12–14	35.0	2.2
15–17	34.6	1.7
5–17	157.5	8.9

Table 9: Sensitivity analysis results for children in employment and child labour

Children in employment		
Poverty rate coefficient using the full sample (N=142)	Poverty rate coefficient using 75% of the sample (N≈107)	
	Mean among 100 iterations	Standard deviation among 100 iterations
0.151	0.155	0.0615

Child labour		
Poverty rate coefficient using the full sample (N=100)	Poverty rate coefficient using 75% of the sample (N=75)	
	Mean among 100 iterations	Standard deviation among 100 iterations
0.087	0.093	0.0747

8.2.3 A comparison of the implied poverty elasticity to the reported one

COVID-19 and Child Labour: A time of crisis, a time to act (ILO and UNICEF, 2020) states that "… causal estimates of elasticity are mostly above 0.7. In other words, a 1 percentage-point rise in poverty leads to at least a 0.7 percentage-point increase in child labour." The elasticity calculated based on the results here is very close to the one reported *(see Table 10)*.

8.2.4 Children in employment and child labour changes under three scenarios: baseline, mitigated and downside

Aside from increases in poverty, CiE and CL are likely to be negatively influenced by pandemic-induced changes to other socioeconomic conditions. Nonetheless, no projections of relevant indicators were readily available. To communicate the uncertainty around these global predictions as a result of the use of poverty as the only driver of children in employment and child labour in the medium run, two scenarios were created: a mitigated one and a downside one. For both scenarios, regional standard deviation is used as an assumption on how much the social protection indicator (SDG 1.3.1) can change. Regional standard deviation is used as the per cent increase/decrease for each scenario. Table 11 shows the proportion of the population protected in at least one area of social protection, percentage (latest available year), by income group.

Table 12 presents the simulation at a global level, only for countries with social protection data available (i.e., 161 countries in total). The results show that actions towards enhancing the social protection floor could potentially reverse the upward projected trends in CiE and CL that are induced by the pandemic.

8.2.5 Poverty rates imputation

The poverty rates used in this simulation exercise were shared by the World Bank. The file shared is referred to as 'nowcast' data or 'nowcast' file.

There are three types of missing data:

1. A poverty line is missing (e.g., US$1.90 and US$3.20 exist, but US$5.50 is missing[67]),
2. A year is missing, or
3. A country is missing.

Table 10: 'Robustness check' at the global level (189 countries)

	Lower-middle-income poverty (US$3.20 in 2011, PPP), millions – *imputed values included*	CiE (5-17), millions	CL (5-17), millions
2019	1,805.1	218.7	157.5
2022	1,935.5	230.6	166.4
Percentage-point change between 2019 and 2022	7.2	5.4	5.6
Implied elasticity		0.7	0.8

Table 11: Summary statistics of the proportion of the population protected in at least one area of social protection, percentage (latest available year), by income group

Income group	Mean	Standard deviation	Median
High income	78.1	25.4	87.5
Low income	11.0	6.7	8.9
Lower middle income	29.8	22.0	26.6
Upper middle income	49.0	22.7	41.2

Table 12: Children in employment and child labour changes under three scenarios: baseline, mitigated and downside (global, 161 countries)

Year	Age group (years)	Population (millions)	CiE (millions)			CL (millions)		
			Baseline	Mitigation scenario	Downside	Baseline	Mitigation scenario	Downside
2019	[5–11]	873.2	79.8			79.8		
2022	[5–11]	883.6	84.2	72.2	108.1	84.2	72.2	108.1
2019	[12–14]	360.1	48.9			31.6		
2022	[12–14]	368.5	51.8	43.9	61.8	33.6	28.2	40.9
2019	[15–17]	350.6	70.5			31.9		
2022	[15–17]	359.1	73.7	62.8	86.8	33.4	27.8	40.5
2019	Total [5–17]	1,583.9	199.2			143.2		
2022	Total [5–17]	1,611.2	209.8	178.9	256.7	151.2	128.2	189.5

The primary source for filling the gaps in the poverty data is the PovcalNet estimates, for 2017–2018.[68]

For the countries and lines with no data available at all, the detailed sub-regional or the broad sub-regional or the regional or the income group average based on countries with a complete time series is borrowed, if at least 50 per cent of the group's countries have a complete time series.

9. EVALUATION OF THE RESULTS

The 106 countries used to generate the estimates are a sample of all the countries in the world. If another sample had been selected, the results would have differed to a degree. It is important to determine this difference in order to understand the robustness of the estimated results. This can be achieved through the calculation of standard deviations associated with different global and regional estimates.

Accordingly, the standard deviations of the 2020 global and regional estimates were calculated to assess the change in estimates caused by sampling variability. This indicator of uncertainty does not account for the uncertainty associated with actual observations. Furthermore, the exercise cannot account for unknown bias in the modelling procedure. These limitations notwithstanding, the results indicate the margin of error resulting from the imputation of countries that have been excluded in a pseudo out-of-sample exercise.

The variation in the indicator of CiE was estimated by running the econometric model 150 times. In each run, countries with a probability of 15 per cent were removed from the sample, which resulted, on average, in 15 countries dropped per run. This yielded the standard deviation of the global and regional estimates *(see Table 13)*. Whereas this exercise did not compute a confidence interval (as we were not accounting for all sources of uncertainty, including input data uncertainty), it quantified the robustness of the modelled estimates.

Table 13: Standard deviation of the global and regional estimates for children in employment

	Estimated number of children engaged in economic activity (thousands)	Estimate of economic activity rate of children (%)	Standard deviation (% points)
World	222,088	13.3	1.0
Africa	124,122	29.1	0.8
Sub-Saharan Africa	115,766	32.0	0.8
Americas	14,672	7.5	0.6
Latin America and the Caribbean	12,422	9.1	0.7
Arab States	3,447	8.1	-
Asia and the Pacific	67,960	7.8	1.8
Europe and Central Asia	11,886	8.2	0.7

Notes: The table shows regional groupings used for ILO reporting. The dash for the Arab States indicates that the standard deviation could not be calculated due to the small number of available datasets for this region.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18. Since the inception of the DHS programme, at least 85 surveys have included a child labour section. For an exhaustive list of countries, see ‘Child labor’ at: <https://dhsprogram.com/methodology/survey-search.cfm?pgtype=char#>
19. It is important to note that the coverage in Eastern Asia is 0, due to the lack of actual data for China.
20. More information on the processing of anonymized household survey microdata is available at: <https://www.ilo.org/wcmsp5/groups/public/---dgreports/---stat/documents/publication/wcms_651746.pdf>
21. The complementary SDG indicator 8.7.1 – children engaged in economic activity and household chores – is not available from EU-LFS and hence no adjustment is applicable. Domestic work is not available either and, hence, no adjustment applies.
22. The integral above models the employment rate as a function of continuous age. The integral between the continuous interval of 15–20 will produce an equivalent employment rate to the standard age band 15–19. An intuitive way to think about this would be that the standard age band 15–19 in discrete terms includes a person that in continuous terms has an age of, say, 19.99 – close to 20.

23. Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

24. This assumption reflects a judgemental approach, given the institutional and economic situation of the countries.

25. To keep in line with the notation of the definite integral, the closed interval is chosen; note that choosing a half-open interval would not have any effect on the analysis.

26. Notice that the value of e=5 is included both as the upper limit of the first expression and the lower limit of the second expression and is of no consequence, given the functions involved; including or excluding one finite point does not alter the value of the integral.

27. The fourth quarter of 2019 is selected as the dataset to validate the approximation. This is the last dataset available before COVID-19 had any impact on the economy of the United Kingdom.

28. Using the exponential approach, which is only applied to cases in which the linear approach would result in a negative value, the inferred rate is 62.7 per cent.

29. Although DW is tied to the EA model, it is characterized by different data availability and is thus treated as a separate indicator.

30. Each of these is modelled separately.

31. The key categories for STE are i) employees, ii) own-account workers and iii) contributing family workers.

32. The key categories for STU are either i) attending school or ii) not attending school.

33. The key categories for EA are i) agriculture, ii) industry and iii) services.

34. DW does not have breakdowns for the geography category, i.e., data are only present at the ‘national’ level.

35. For instance, CL is a subset of CiE and is exactly equivalent to CiE for the age group 5 to 11 years. This relationship should hold in the estimates.

36. Basu, Kaushik, and Pham Hoang Van, ‘The Economics of Child Labor’, *The American Economic Review*, vol. 88, no. 3, 1998, pp. 412–27.

37. Rosati, Furio Camillo, and Zafiris Tzannatos, ‘Child Work: An expository framework of altruistic and non-altruistic models’, Social Protection Discussion Papers and Notes, 25984, World Bank, Washington, D.C., 2003, <https://ideas.repec.org/p/wbk/hdnspu/25984.html>

38. Edmonds, Eric, ‘Will Child Labour Decline with Improvements in Living Standards’, Dartmouth College Mimeo, 2001; Admassie, Assefa, ‘Explaining the High Incidence of Child Labour in Sub–Saharan Africa’, *African Development Review*, vol.14, no. 2, 16 December 2002, pp. 251–75, <https://doi.org/10.1111/1467-8268.00054>; Wahba, Jackline, ‘The Influence of Market Wages and Parental History on Child Labour and Schooling in Egypt’, IZA Discussion Papers, 1771, Institute of Labor Economics, Bonn, 2005, <https://ideas.repec.org/p/iza/izadps/dp1771.html>; Grootaert, Christiaan, and Harry Anthony Patrinos, *The Policy Analysis of Child Labor: A comparative study*, St. Martin’s Press, New York, 1999; Patrinos, Harry Anthony, and Christiaan Grootaert, ‘Child Labor in Bolivia and Colombia’, vol. 09, World Bank, Washington, DC, 2002, <https://openknowledge.worldbank.org/handle/10986/10404>

39. Rosati and Tzannatos, ‘Child Work: An expository framework of altruistic and non-altruistic models’; Cigno, Alessandro, and Furio Rosati, ‘The Economics of Child Labour’, OUP Catalogue, Oxford University Press, 2005, <https://econpapers.repec.org/bookchap/oxpobooks/9780199264452.htm>; Edmonds, Eric, ‘Does Child Labor Decline with Improving Economic Status?’ *Journal of Human Resources*, vol. XL, no. 1, 2005, pp. 77–99, <https://doi.org/10.3368/jhr.XL.1.77>; International Labour Organization, ‘Joining Forces against Child Labour: Inter-Agency Report for The Hague Global Child Labour Conference of 2010/Understanding Children’s Work (UCW) Programme’, ILO, Geneva, 2010; Basu, Kaushik, and Zafiris Tzannatos, ‘The Global Child Labor Problem: What do we know and what can we do?’, *The World Bank Economic Review 17*, no. 2, 2003, pp. 147-173; Fors, Heather Congdon, ‘Child Labour: A review of recent theory and evidence with policy implications’, *Journal of Economic Surveys*, vol. 26, no. 4, 2012, pp. 570–93, <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-6419.2010.00663.x>

40. Dammert, Ana C., et al., ‘Effects of Public Policy on Child Labor: Current knowledge, gaps, and implications for program design’, *World Development*, vol. 110, 2018, pp. 104–23, <https://doi.org/10.1016/j.worlddev.2018.05.001>

41. For details on the studies included in the review, see Edmonds, Eric, ‘Child Labor and Schooling Responses to Anticipated Income in South Africa’, *Journal of Development Economics*, vol. 81, no. 2, 2006, pp. 386–414; de Carvalho Filho, Irineu Evangelista, ‘Household Income as a Determinant of Child Labor and School Enrollment in Brazil: Evidence from a social security reform’, *Economic Development and Cultural Change*, vol. 60, no. 2, 2012, pp. 399–435, <https://doi.org/10.1086/662576>; de Hoop, Jacobus, and Furio C. Rosati, ‘Cash Transfers and Child Labor’, *World Bank Research Observer*, vol. 29, no. 2, 2014, pp. 202–34, <https://doi.org/10.1093/wbro/lku003>

42. Case, Anne, ‘Does Money Protect Health Status? Evidence from South African pensions’, NBER Working Paper 8,495, National Bureau of Economic Research, Cambridge, MA, 2001; Case, Anne, and Angus Deaton, ‘Large Scale Transfers to the Elderly in South Africa’, *Economic Journal,* vol. 018, no. 450, 1998, pp. 1,330–1,261; Duflo, Esther, ‘Grandmothers and Granddaughters: Old-age pensions and intrahousehold allocation in South Africa’, *World Bank Economic Review*, vol. 17, no.1, 2003, pp. 1–25, <https://doi.org/10.1093/wber/lhg013>

43. Basu and Van, 'The Economics of Child Labor.'

44. See also Levison, Deborah, et al., 'Is Child Labour Really Necessary in India's Carpet Industry?', Labour Market Papers No. 15, ILO, Geneva, 1996, <www.ilo.org/empelm/pubs/WCMS_126308/lang--en/index.htm>; Edmonds, 'Does Child Labor Decline with Improving Economic Status?'; Manacorda, Marco, and Furio Camillo Rosati, 'Local Labor Demand and Child Work', *Research in Labor Economics*, edited by Randall K.Q. Akee, Eric V. Edmonds and Konstantinos Tatsiramos, vol. 31, 2010, pp. 321–54, Emerald Group Publishing Limited, <https://doi.org/10.1108/S0147-9121(2010)0000031014>

45. Guarcello, Lorenzo, Lyon Scott and Furio C. Rosati, 'Child Labour and Education for All: An issue paper', SSRN Electonic Journal, 2008, <https://doi.org/10.2139/ssrn.1780257>; ILO, 'Joining Forces against Child Labour.'

46. Edmonds, Eric, 'Child Labour', *Handbook of Development Economics*, vol. 4, 2008, pp. 3,607–3,709, Elsevier, <https://econpapers.repec.org/bookchap/eeedevchp/5-57.htm>

47. Manacorda, Marco, and Furio Camillo Rosati, 'Industrial Structure and Child Labor Evidence from the Brazilian Population Census', *Economic Development and Cultural Change*, vol. 59, no. 4, 2011, pp. 753–76, <https://doi.org/10.1086/660002>

48. The model search space is restricted on purpose to mitigate the risk of over-fit.

49. In particular, the ILOSTAT database contains the age bands of 5–9, 10–14 and so on. We use linear interpolation by modelling the evolution of the demographic structure across different age bands, and then computing the age bands that are needed. This procedure is like that outlined in section 4.1 for the EU-LFS data.

50. The structure of missing data, for the most part, is such that if countries have data, they have data for each breakdown. In other words, countries (with a few notable exceptions) either have data for each sex-age-geographic cell or no data at all. For the sake of simplicity, the selection of the training sample is done at the country level, instead of at the country-sex-age-geographic level.

51. The determination of the size of the training set vs. the test set falls under a branch of the machine learning literature called training/test partitioning. For a recent example, which uses 70 per cent as the training set, please see Liu, Han, and Mihaela Cocea, 'Semi-random Partitioning of Data into Training and Test Sets in Granular Computing Context', *Granular Computing*, 2017, <https://doi.org/10.1007/s41066-017-0049-2>

52. Categorical variables are introduced as fixed effects in the regression model; the notation used in the equation is chosen for simplicity.

53. It is worth pointing out that the sample size is approximately 70 per cent of 6,804.

54. More specifically, we bound CiE rates for all age groups below 15 years by 0, and 15 to 17 years by 0.01. This is because it is extremely unlikely that any country would have precisely 0 CiE for this age group.

55. The key categories for STE are i) employees, ii) own-account workers and iii) contributing family workers.

56. The key categories for STU are either i) attending school or ii) not attending school.

57. The key categories for EA are i) agriculture, ii) industry and iii) services.

58. The reason we put geography in brackets is because STE and EA are not present at the geographic level, although STU is.

59. In the example above, this would correspond to conditioning on particular values of *j, k* and *l*.

60. International Labour Organization, 'Methodology of the Global Estimates of Child Labour, 2012–2016', ILO, Geneva, 2017, <www.ilo.org/ipec/Informationresources/WCMS_586125/lang--en/index.htm>

61. Notice that whereas we have partial data to test the temporary-effect hypothesis, the required data to validate the persistent-effect hypothesis will not be available for a considerable time period.

62. International Labour Organization and United Nations Children's Fund, *COVID-19 and Child Labour: A time of crisis, a time to act*, ILO and UNICEF, New York, 2020, <https://data.unicef.org/resources/covid-19-and-child-labour-a-time-of-crisis-a-time-to-act/>

63. World Bank, 'Updated Estimates of the Impact of COVID-19 on Global Poverty: Looking back at 2020 and the outlook for 2021', World Bank, Washington, D.C., <https://blogs.worldbank.org/opendata/updated-estimates-impact-covid-19-global-poverty-looking-back-2020-and-outlook-2021>

64. Figure 6 was copied without permission from: World Bank, 'Updated Estimates of the Impact of COVID-19 on Global Poverty: Looking back at 2020 and the outlook for 2021'. Extreme poverty is measured as the number of people living on less than US$1.90 per day. 2017 is the last year with official global poverty estimates. Regions are categorized using PovcalNet definition.

65. Lakner, Christoph, et al., 'How Much Does Reducing Inequality Matter to Global Poverty?', World Bank Group, Washington, D.C., 2020; World Bank, 'PovcalNet', 2020, <http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx>

66. The sample size for the regressions were: 142 observations for CiE and 100 observations for CL.The R-squared for the regressions were: 0.534 for CiE and 0.279 for CL.

67. All $ in this section refer to constant PPP US$, 2017.

68. World Bank, 'PovcalNet.'

ANNEXES

Annex 1. ISCO-88 and ISCO-08 minor groups (three-digit categories) used to minimize disruption to existing time series

Table A1: ISCO-88 and ISCO-08 minor groups (three-digit categories)

ISCO-88 code	ISCO-88 minor group title	ISCO-08 code	ISCO-08 minor group title
313	Optical and electrical equipment operators	223	Traditional and complementary medicine professionals
322	Health associate professionals	224	Paramedical practitioners
323	Nursing midwife	226	Other health professionals
516	Protective services	312	Mining, manufacturing and construction supervisors
614	Forestry and related workers	312	Process control technicians
615	Fishery, hunters and trappers	321	Medical and pharmaceutical technicians
711	Miners, shot fires, stone cutters and carvers	322	Nursing and midwifery associate professionals
712	Building frame and related workers	324	Veterinary technicians and assistants
713	Building finishers	325	Other health associate professionals
721	Metal moulders, welders and related workers	352	Telecommunications and broadcasting technicians
722	Blacksmith, toolmakers and related workers	541	Protective services workers
723	Machinery mechanics and fitters	621	Forestry and related workers
724	Electrical, electronic equipment mechanics and fitters	622	Fishery workers, hunters and trappers
731	Precision workers in metal	711	Building frame and related trades workers
732	Potters, glass makers and related workers	712	Building finishers and related trades workers
811	Mining, mineral processing plant operators	721	Sheet and structural metal workers, moulders and welders, and related workers
812	Metal processing plant operators	722	Blacksmiths, toolmakers and related trades workers
813	Glass, ceramics and related plant operators	723	Machinery mechanics and repairers
814	Wood processing and papermaking plant operators	731	Handicraft workers
815	Chemical processing plant operators	741	Electrical equipment installers and repairers
816	Power production, related plant operators	742	Electronics and telecommunications installers and repairers
821	Metal and mineral machine operators	754	Other craft and related workers
822	Chemical machine operators	811	Mining and mineral processing plant operators
823	Rubber machine operators	812	Metal processing and finishing plant operators
825	Wood products machine operators	813	Chemical and photographic products plant and machine operators
826	Textile, fur, leather machine operators	814	Rubber, plastic and paper products machine operators
827	Food machine operators	815	Textile, fur and leather products machine operators
828	Assemblers	816	Food and related products machine operators
829	Other machine operators	817	Wood processing and papermaking plant operators

ISCO-88 code	ISCO-88 minor group title	ISCO-08 code	ISCO-08 minor group title
832	Motor vehicle drivers	818	Other stationary plant and machine operators
833	Agriculture, other mobile plant operators	821	Assemblers
834	Ships' deck crew, related workers	832	Car, van and motorcycle drivers
911	Street vendors and related workers	833	Heavy truck and bus drivers
912	Shoe cleaning, other street services	834	Mobile plant operators
915	Messengers, porters, doorkeepers	835	Ships' deck crews and related workers
916	Garbage collectors, related workers	921	Agricultural, forestry and fishery labourers
921	Agriculture fishery, related workers	931	Mining and construction labourers
931	Mining and construction labourers	933	Transport and storage labourers
933	Transport and freight handlers	951	Street and related services workers
		961	Refuse workers
		962	Other elementary workers

Annex 2. Hazardous occupations at ISCO-08 four-digit level to minimize time series breaks (based on initial ILO analysis using ISCO-88/08 correspondence table)

Table A2: ISCO-08 (four-digit categories)

ISCO-88 code	ISCO-08 unit group title
2240	Paramedical practitioners
2230	Traditional and complementary medicine professionals
2264	Physiotherapists
2265	Dieticians and nutritionists
2266	Audiologists and speech therapists
2267	Optometrists and ophthalmic opticians
2269	Health professionals not elsewhere classified
3121	Mining supervisors
3122	Manufacturing supervisors
3123	Construction supervisors
3131	Power production plant operators
3132	Incinerator and water treatment plant operators
3133	Chemical processing plant controllers
3134	Petroleum and natural gas refining plant operators
3135	Metal production process controllers
3211	Medical imaging and therapeutic equipment technicians

ISCO-88 code	ISCO-08 unit group title
3213	Pharmaceutical technicians and assistants
3214	Medical and dental prosthetic technicians
3221	Nursing associate professionals
3222	Midwifery associate professionals
3240	Veterinary technicians and assistants
3251	Dental assistants and therapists
3253	Community health workers
3254	Dispensing opticians
3255	Physiotherapy technicians and assistants
3256	Medical assistants
3257	Environmental and occupational health inspectors and associates
3259	Health associate professionals not elsewhere classified
3431	Photographers
3521	Broadcasting and audio-visual technicians
5212	Street food salespersons
5243	Door-to-door salespersons
5244	Contact centre salespersons
5411	Fire fighters
5412	Police officers
5413	Prison guards
5414	Security guards
5419	Protective services workers not elsewhere classified
6210	Forestry and related workers
6221	Aquaculture workers
6222	Inland and coastal waters fishery workers
6223	Deep-sea fishery workers
6224	Hunters and trappers
7111	House builders
7112	Bricklayers and related workers
7113	Stonemasons, stone cutters, splitters and carvers
7114	Concrete placers, concrete finishers and related workers
7115	Carpenters and joiners
7119	Building frame and related trades workers not elsewhere classified
7121	Roofers
7122	Floor layers and tile setters
7123	Plasterers
7124	Insulation workers
7125	Glaziers

ISCO-88 code	ISCO-08 unit group title
7126	Plumbers and pipe fitters
7127	Air conditioning and refrigeration mechanics
7211	Metal moulders and coremakers
7212	Welders and flamecutters
7213	Sheet-metal workers
7214	Structural-metal preparers and erectors
7215	Riggers and cable splicers
7221	Blacksmiths, hammersmiths and forging press workers
7222	Toolmakers and related workers
7223	Metal working machine tool setters and operators
7224	Metal polishers, wheel grinders and tool sharpeners
7231	Motor vehicle mechanics and repairers
7232	Aircraft engine mechanics and repairers
7233	Agricultural and industrial machinery mechanics and repairers
7234	Bicycle and related repairers
7311	Precision-instrument makers and repairers
7312	Musical instrument makers and tuners
7313	Jewellery and precious-metal workers
7314	Potters and related workers
7315	Glass makers, cutters, grinders and finishers
7316	Sign writers, decorative painters, engravers and etchers
7411	Building and related electricians
7412	Electrical mechanics and fitters
7413	Electrical line installers and repairers
7421	Electronics mechanics and servicers
7422	Information and communications technology installers and servicers
7541	Underwater divers
7542	Shotfirers and blasters
7549	Craft and related workers not elsewhere classified
8111	Miners and quarriers
8112	Mineral and stone processing plant operators
8113	Well drillers and borers and related workers
8114	Cement, stone and other mineral products machine operators
8121	Metal processing plant operators
8122	Metal finishing, plating and coating machine operators
8131	Chemical products plant and machine operators
8141	Rubber products machine operators
8142	Plastic products machine operators

ISCO-88 code	ISCO-08 unit group title
8143	Paper products machine operators
8151	Fibre preparing, spinning and winding machine operators
8153	Sewing machine operators
8154	Bleaching, dyeing and fabric cleaning machine operators
8155	Fur and leather preparing machine operators
8156	Shoemaking and related machine operators
8157	Laundry machine operators
8159	Textile, fur and leather products machine operators not elsewhere classified
8160	Food and related products machine operators
8171	Pulp and papermaking plant operators
8172	Wood processing plant operators
8181	Glass and ceramics plant operators
8182	Steam engine and boiler operators
8183	Packing, bottling and labelling machine operators
8189	Stationary plant and machine operators not elsewhere classified
8211	Mechanical machinery assemblers
8212	Electrical and electronic equipment assemblers
8219	Assemblers not elsewhere classified
8321	Motorcycle drivers
8322	Car, taxi and van drivers
8331	Bus and tram drivers
8332	Heavy truck and lorry drivers
8341	Mobile farm and forestry plant operators
8342	Earthmoving and related plant operators
8343	Crane, hoist and related plant operators
8344	Lifting truck operators
8350	Ships' deck crews and related workers
9211	Crop farm labourers
9212	Livestock farm labourers
9213	Mixed crop and livestock farm labourers
9214	Garden and horticultural labourers
9215	Forestry labourers
9216	Fishery and aquaculture labourers
9311	Mining and quarrying labourers
9312	Civil engineering labourers
9313	Building construction labourers
9331	Hand and pedal vehicle drivers
9332	Drivers of animal-drawn vehicles and machinery

ISCO-88 code	ISCO-08 unit group title
9333	Freight handlers
9334	Shelf fillers
9510	Street and related service workers
9520	Street vendors (excluding food)
9611	Garbage and recycling collectors
9612	Refuse sorters
9613	Sweepers and related labourers
9621	Messengers, package deliverers and luggage porters
9622	Odd job persons
9623	Meter readers and vending-machine collectors
9624	Water and firewood collectors
9629	Elementary workers not elsewhere classified
9312	Civil engineering labourers

Annex 3. Information on household surveys used for the global estimates

The following contains a list of national household surveys for the children in employment model. As CiE is the most expansive indicator, this list can be thought of as being comprehensive, given that if household survey data are present for any other indicator, it would have to be present for CiE as well.

Table A3: National datasets for children in employment

ISO country abbreviation	Country name	Survey year	Survey	ILO region	SDG region	UNICEF region
AGO	Angola	2016	DHS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
BEN	Benin	2018	DHS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
BFA	Burkina Faso	2014	EMC	Africa	Sub-Saharan Africa	Sub-Saharan Africa
BDI	Burundi	2017	DHS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
CMR	Cameroon	2014	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
TCD	Chad	2015	DHS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
COG	Congo	2015	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
CIV	Côte d'Ivoire	2016	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
COD	Democratic Republic of the Congo	2018	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
EGY	Egypt	2014	DHS	Africa	Northern Africa and Western Asia	Middle East and North Africa
ETH	Ethiopia	2015	NCLS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
GMB	Gambia	2018	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
GHA	Ghana	2018	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa

ISO country abbreviation	Country name	Survey year	Survey	ILO region	SDG region	UNICEF region
GIN	Guinea	2016	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
GNB	Guinea-Bissau	2019	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
LSO	Lesotho	2018	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
MDG	Madagascar	2018	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
MWI	Malawi	2015	NCLS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
MLI	Mali	2018	EMOP	Africa	Sub-Saharan Africa	Sub-Saharan Africa
MRT	Mauritania	2015	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
NER	Niger	2014	ECVM	Africa	Sub-Saharan Africa	Sub-Saharan Africa
RWA	Rwanda	2017	EICV	Africa	Sub-Saharan Africa	Sub-Saharan Africa
STP	Sao Tome and Principe	2014	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
SEN	Senegal	2016	DHS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
SLE	Sierra Leone	2017	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
ZAF	South Africa	2015	SAYP	Africa	Sub-Saharan Africa	Sub-Saharan Africa
SDN	Sudan	2014	MICS	Africa	Northern Africa and Western Asia	Sub-Saharan Africa
TGO	Togo	2017	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
UGA	Uganda	2017	LFS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
TZA	United Republic of Tanzania	2014	LFS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
ZMB	Zambia	2018	LFS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
ZWE	Zimbabwe	2019	MICS	Africa	Sub-Saharan Africa	Sub-Saharan Africa
ARG	Argentina	2017	EANNA	Americas	Latin America and the Caribbean	Latin America and the Caribbean
BOL	Bolivia (Plurinational State of)	2019	EH	Americas	Latin America and the Caribbean	Latin America and the Caribbean
BRA	Brazil	2016	PNADCCL	Americas	Latin America and the Caribbean	Latin America and the Caribbean
COL	Colombia	2019	ENTI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
CRI	Costa Rica	2018	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
DOM	Dominican Republic	2014	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
ECU	Ecuador	2019	ENEMDU	Americas	Latin America and the Caribbean	Latin America and the Caribbean
SLV	El Salvador	2018	EHPM	Americas	Latin America and the Caribbean	Latin America and the Caribbean
GTM	Guatemala	2017	ENEI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
GUY	Guyana	2014	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
HND	Honduras	2019	EPHPM	Americas	Latin America and the Caribbean	Latin America and the Caribbean
JAM	Jamaica	2016	NCLS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
MEX	Mexico	2019	ENOETI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
PAN	Panama	2014	ETI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
PRY	Paraguay	2016	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
PER	Peru	2019	ENAHO	Americas	Latin America and the Caribbean	Latin America and the Caribbean

ISO country abbreviation	Country name	Survey year	Survey	ILO region	SDG region	UNICEF region
SUR	Suriname	2018	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
USA	United States of America	2018	CPS	Americas	Europe and Northern America	North America
VEN	Venezuela (Bolivarian Republic of)	2017	EHM	Americas	Latin America and the Caribbean	Latin America and the Caribbean
IRQ	Iraq	2018	MICS	Arab States	Northern Africa and Western Asia	Middle East and North Africa
JOR	Jordan	2016	NCLS	Arab States	Northern Africa and Western Asia	Middle East and North Africa
AFG	Afghanistan	2014	LCS	Asia and the Pacific	Central and Southern Asia	South Asia
BGD	Bangladesh	2019	MICS	Asia and the Pacific	Central and Southern Asia	South Asia
KHM	Cambodia	2017	HSES	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
IND	India	2018	P-LFS	Asia and the Pacific	Central and Southern Asia	South Asia
IDN	Indonesia	2019	LFS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
LAO	Lao People's Democratic Republic	2017	MICS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
MNG	Mongolia	2018	MICS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
MMR	Myanmar	2019	LFS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
NPL	Nepal	2014	MICS	Asia and the Pacific	Central and Southern Asia	South Asia
PAK	Pakistan	2018	LFS	Asia and the Pacific	Central and Southern Asia	South Asia
LKA	Sri Lanka	2016	CAS	Asia and the Pacific	Central and Southern Asia	South Asia
THA	Thailand	2018	NWCS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
TLS	Timor-Leste	2016	LFS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
TON	Tonga	2019	MICS	Asia and the Pacific	Oceania	East Asia and the Pacific
VNM	Viet Nam	2018	NCLS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
ARM	Armenia	2015	NCLS	Europe and Central Asia	Northern Africa and Western Asia	Europe and Central Asia
AUT	Austria	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
BEL	Belgium	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
BGR	Bulgaria	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
HRV	Croatia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
CYP	Cyprus	2019	EU-LFS	Europe and Central Asia	Northern Africa and Western Asia	Europe and Central Asia
CZE	Czechia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
DNK	Denmark	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
EST	Estonia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
FIN	Finland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
FRA	France	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
GEO	Georgia	2015	NCLS	Europe and Central Asia	Northern Africa and Western Asia	Europe and Central Asia
GRC	Greece	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
HUN	Hungary	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ISL	Iceland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
IRL	Ireland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia

ISO country abbreviation	Country name	Survey year	Survey	ILO region	SDG region	UNICEF region
ITA	Italy	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
KGZ	Kyrgyzstan	2018	MICS	Europe and Central Asia	Central and Southern Asia	Europe and Central Asia
LVA	Latvia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
LTU	Lithuania	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
LUX	Luxembourg	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
MLT	Malta	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
MNE	Montenegro	2018	MICS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
NLD	Netherlands	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
MKD	North Macedonia	2019	MICS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
NOR	Norway	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
POL	Poland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
PRT	Portugal	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ROU	Romania	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SRB	Serbia	2019	MICS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SVK	Slovakia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SVN	Slovenia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ESP	Spain	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SWE	Sweden	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
CHE	Switzerland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
TKM	Turkmenistan	2016	MICS	Europe and Central Asia	Central and Southern Asia	Europe and Central Asia
UKR	Ukraine	2015	NCLS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
GBR	United Kingdom of Great Britain and Northern Ireland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ARG	Argentina	2017	EANNA	Americas	Latin America and the Caribbean	Latin America and the Caribbean
BOL	Bolivia (Plurinational State of)	2019	EH	Americas	Latin America and the Caribbean	Latin America and the Caribbean
BRA	Brazil	2016	PNADCCL	Americas	Latin America and the Caribbean	Latin America and the Caribbean
COL	Colombia	2019	ENTI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
CRI	Costa Rica	2018	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
DOM	Dominican Republic	2014	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
ECU	Ecuador	2019	ENEMDU	Americas	Latin America and the Caribbean	Latin America and the Caribbean
SLV	El Salvador	2018	EHPM	Americas	Latin America and the Caribbean	Latin America and the Caribbean
GTM	Guatemala	2017	ENEI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
GUY	Guyana	2014	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
HND	Honduras	2019	EPHPM	Americas	Latin America and the Caribbean	Latin America and the Caribbean
JAM	Jamaica	2016	NCLS	Americas	Latin America and the Caribbean	Latin America and the Caribbean

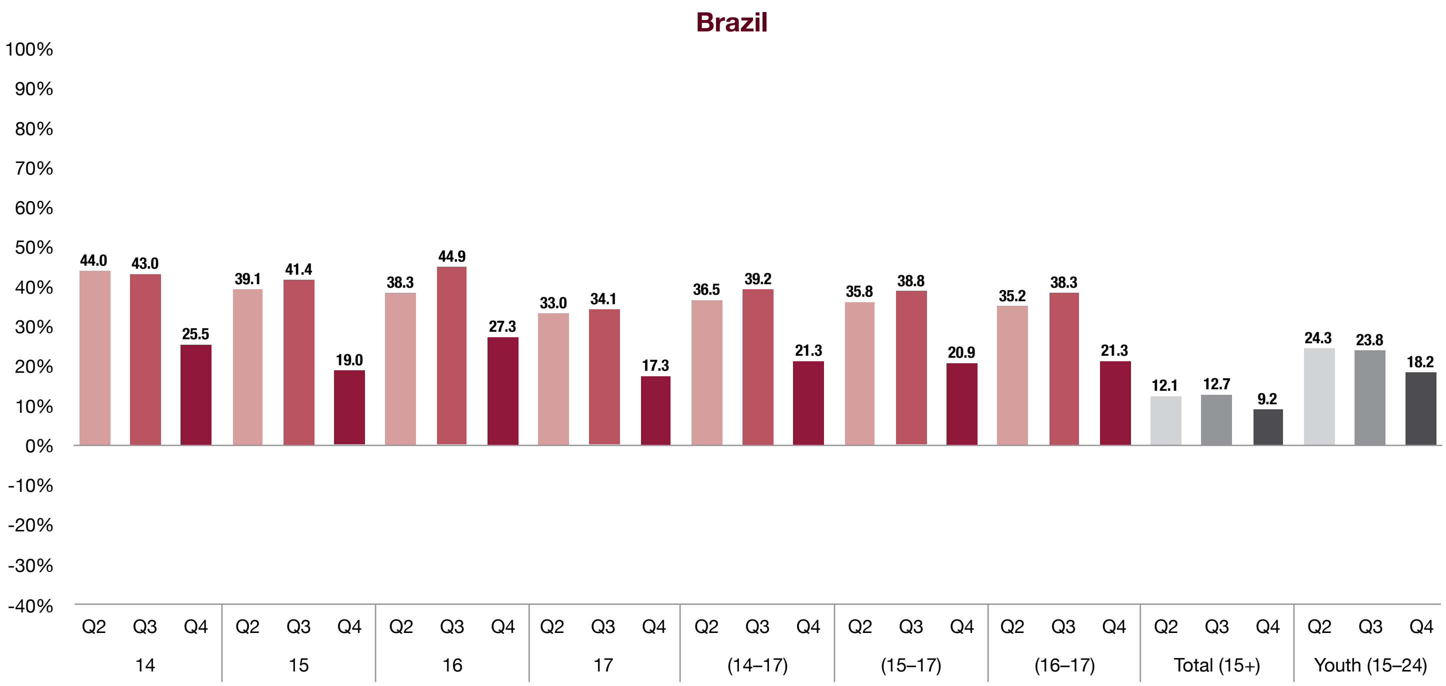
ISO country abbreviation	Country name	Survey year	Survey	ILO region	SDG region	UNICEF region
MEX	Mexico	2019	ENOETI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
PAN	Panama	2014	ETI	Americas	Latin America and the Caribbean	Latin America and the Caribbean
PRY	Paraguay	2016	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
PER	Peru	2019	ENAHO	Americas	Latin America and the Caribbean	Latin America and the Caribbean
SUR	Suriname	2018	MICS	Americas	Latin America and the Caribbean	Latin America and the Caribbean
USA	United States of America	2018	CPS	Americas	Europe and Northern America	North America
VEN	Venezuela (Bolivarian Republic of)	2017	EHM	Americas	Latin America and the Caribbean	Latin America and the Caribbean
IRQ	Iraq	2018	MICS	Arab States	Northern Africa and Western Asia	Middle East and North Africa
JOR	Jordan	2016	NCLS	Arab States	Northern Africa and Western Asia	Middle East and North Africa
AFG	Afghanistan	2014	LCS	Asia and the Pacific	Central and Southern Asia	South Asia
BGD	Bangladesh	2019	MICS	Asia and the Pacific	Central and Southern Asia	South Asia
KHM	Cambodia	2017	HSES	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
IND	India	2018	P-LFS	Asia and the Pacific	Central and Southern Asia	South Asia
IDN	Indonesia	2019	LFS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
LAO	Lao People's Democratic Republic	2017	MICS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
MNG	Mongolia	2018	MICS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
MMR	Myanmar	2019	LFS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
NPL	Nepal	2014	MICS	Asia and the Pacific	Central and Southern Asia	South Asia
PAK	Pakistan	2018	LFS	Asia and the Pacific	Central and Southern Asia	South Asia
LKA	Sri Lanka	2016	CAS	Asia and the Pacific	Central and Southern Asia	South Asia
THA	Thailand	2018	NWCS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
TLS	Timor-Leste	2016	LFS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
TON	Tonga	2019	MICS	Asia and the Pacific	Oceania	East Asia and the Pacific
VNM	Viet Nam	2018	NCLS	Asia and the Pacific	Eastern and South-Eastern Asia	East Asia and the Pacific
ARM	Armenia	2015	NCLS	Europe and Central Asia	Northern Africa and Western Asia	Europe and Central Asia
AUT	Austria	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
BEL	Belgium	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
BGR	Bulgaria	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
HRV	Croatia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
CYP	Cyprus	2019	EU-LFS	Europe and Central Asia	Northern Africa and Western Asia	Europe and Central Asia
CZE	Czechia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
DNK	Denmark	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
EST	Estonia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
FIN	Finland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
FRA	France	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia

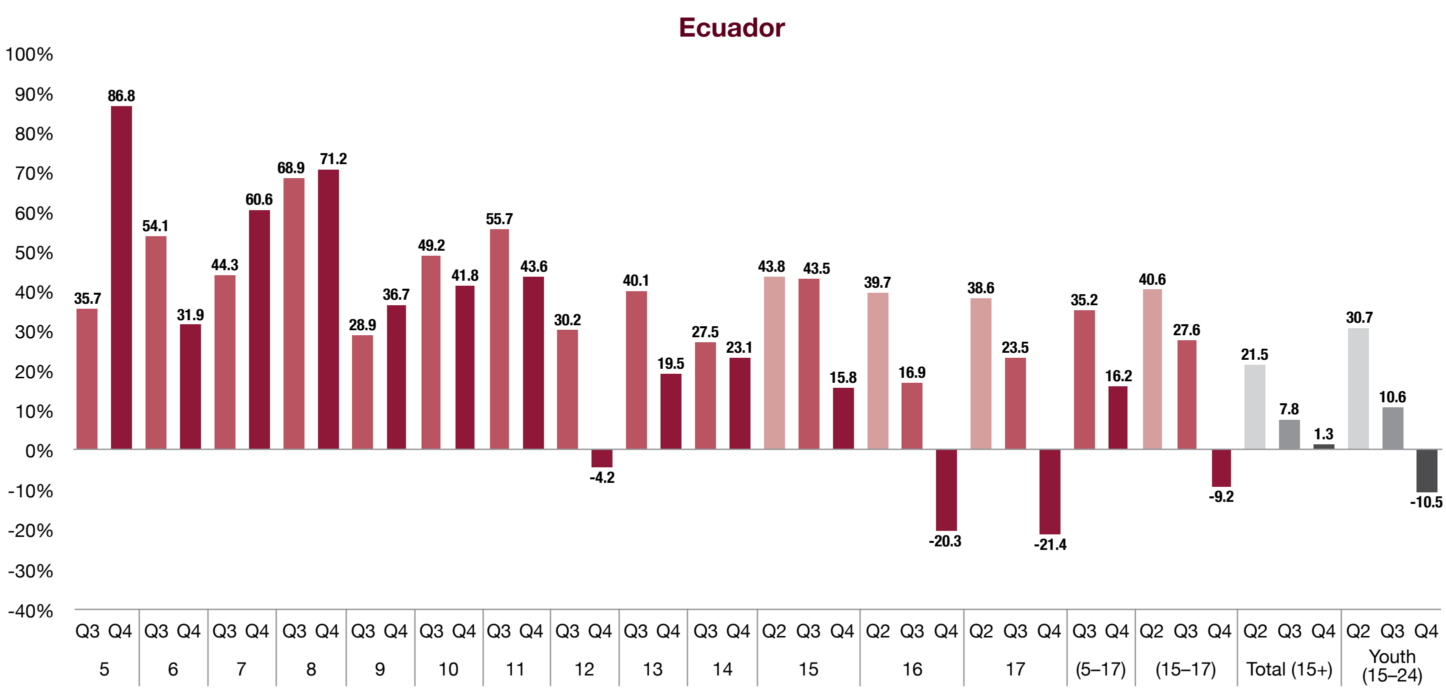
ISO country abbreviation	Country name	Survey year	Survey	ILO region	SDG region	UNICEF region
GEO	Georgia	2015	NCLS	Europe and Central Asia	Northern Africa and Western Asia	Europe and Central Asia
GRC	Greece	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
HUN	Hungary	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ISL	Iceland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
IRL	Ireland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ITA	Italy	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
KGZ	Kyrgyzstan	2018	MICS	Europe and Central Asia	Central and Southern Asia	Europe and Central Asia
LVA	Latvia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
LTU	Lithuania	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
LUX	Luxembourg	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
MLT	Malta	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
MNE	Montenegro	2018	MICS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
NLD	Netherlands	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
MKD	North Macedonia	2019	MICS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
NOR	Norway	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
POL	Poland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
PRT	Portugal	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ROU	Romania	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SRB	Serbia	2019	MICS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SVK	Slovakia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SVN	Slovenia	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
ESP	Spain	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
SWE	Sweden	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
CHE	Switzerland	2019	EU-LFS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
TKM	Turkmenistan	2016	MICS	Europe and Central Asia	Central and Southern Asia	Europe and Central Asia
UKR	Ukraine	2015	NCLS	Europe and Central Asia	Europe and Northern America	Europe and Central Asia
GBR	United Kingdom of Great Britain and Northern Ireland	2019	EU-LFS	Europe and Central Asia	Northern America and Europe	Europe and Central Asia

Annex 4: Inter-annual decline in children in employment, child labour and SDG 8.7.1 – proportion of children engaged in economic activity

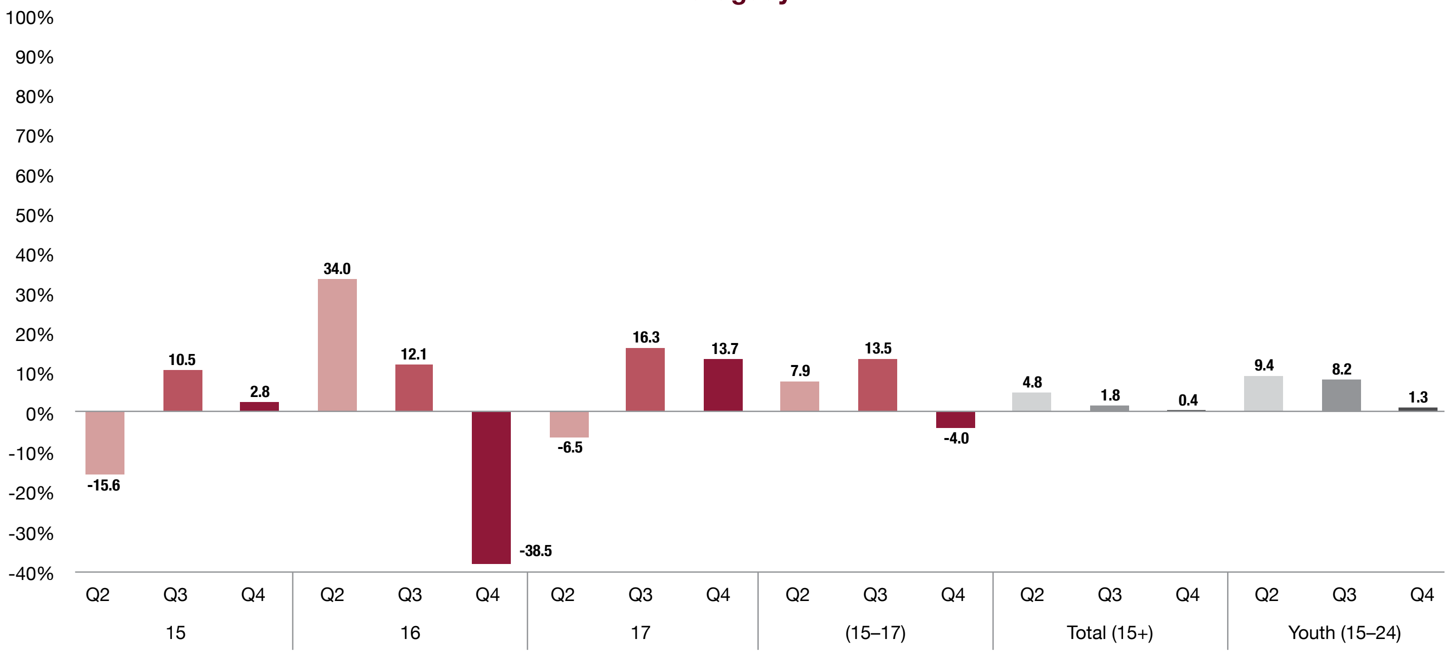
Figure A1: Inter-annual decline in children in quarterly employment

Inter-annual decline in quarterly employment (by age), Qx-2020 (compared to Qx-2019) in Brazil, Ecuador, Paraguay, Peru and Viet Nam[38]

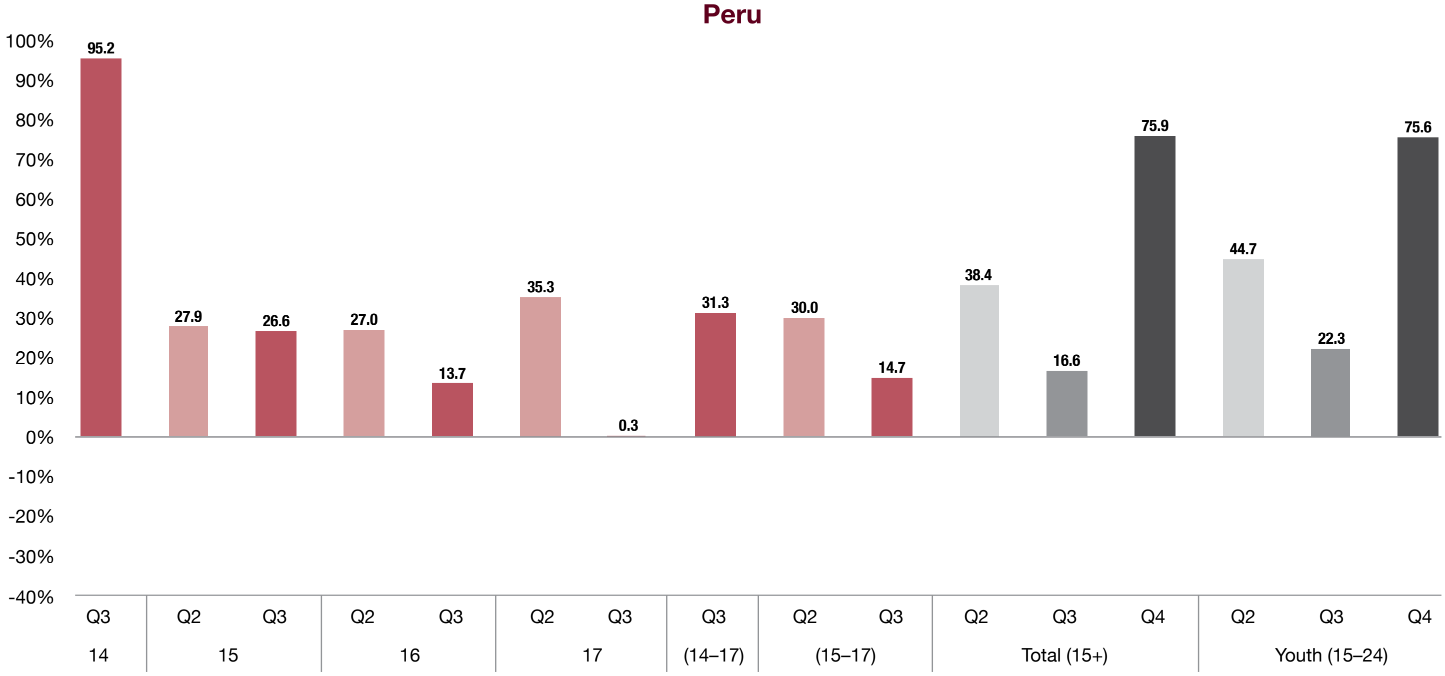




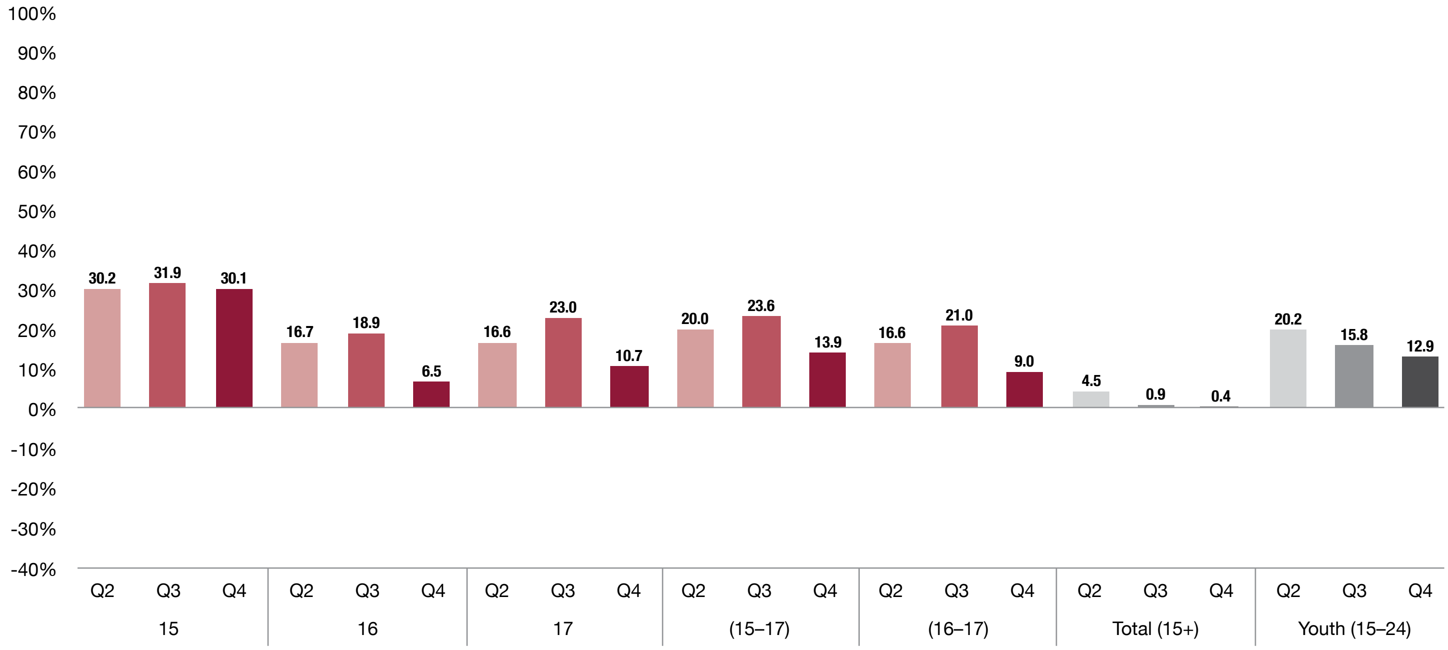
Paraguay



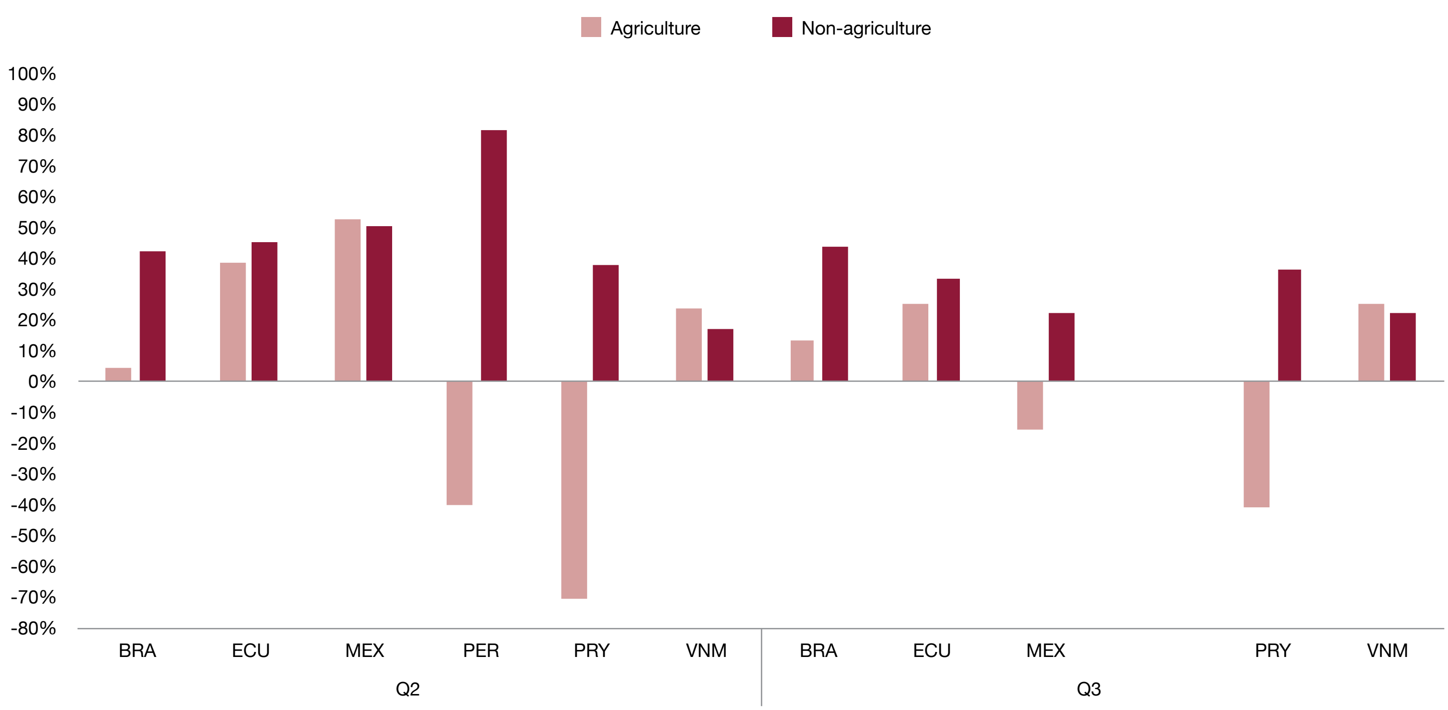
Peru



Viet Nam



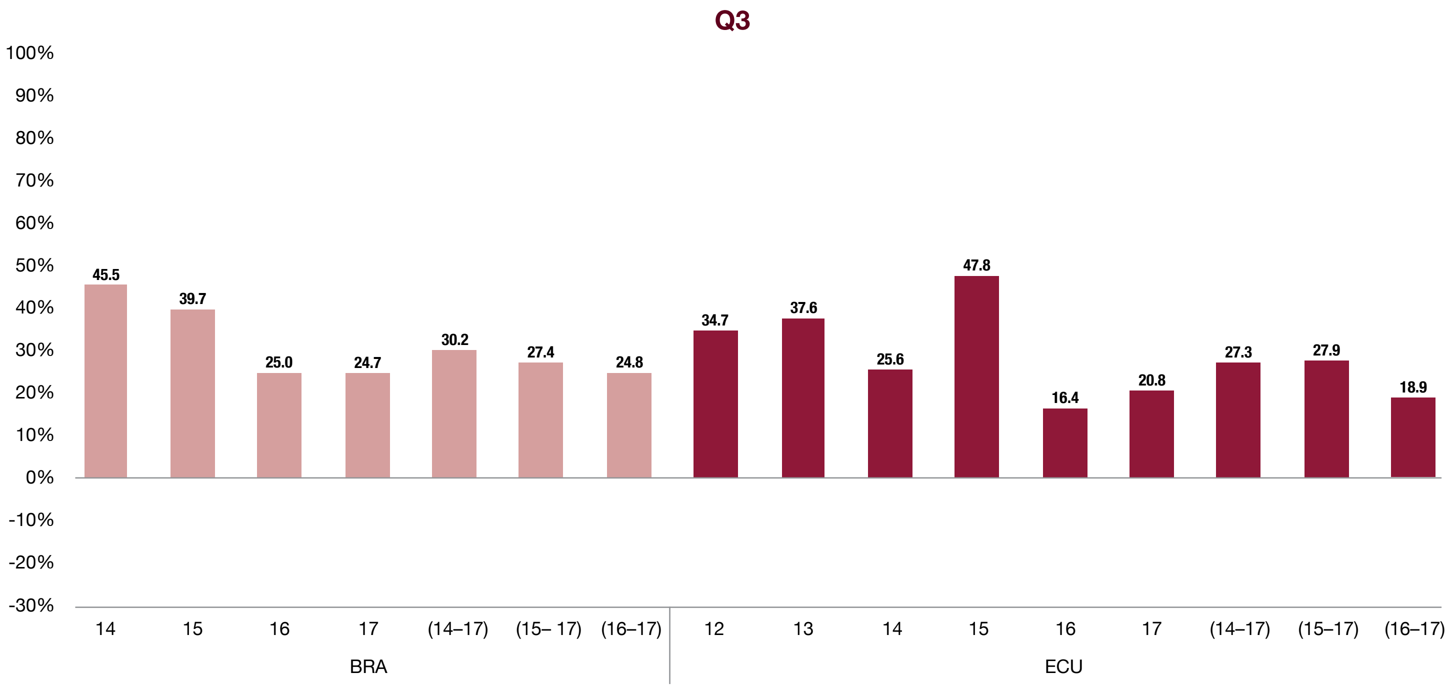
Inter-annual decline in employment by sector for 2020 by quarter and country, age group 15–17 years, selected countries[39]

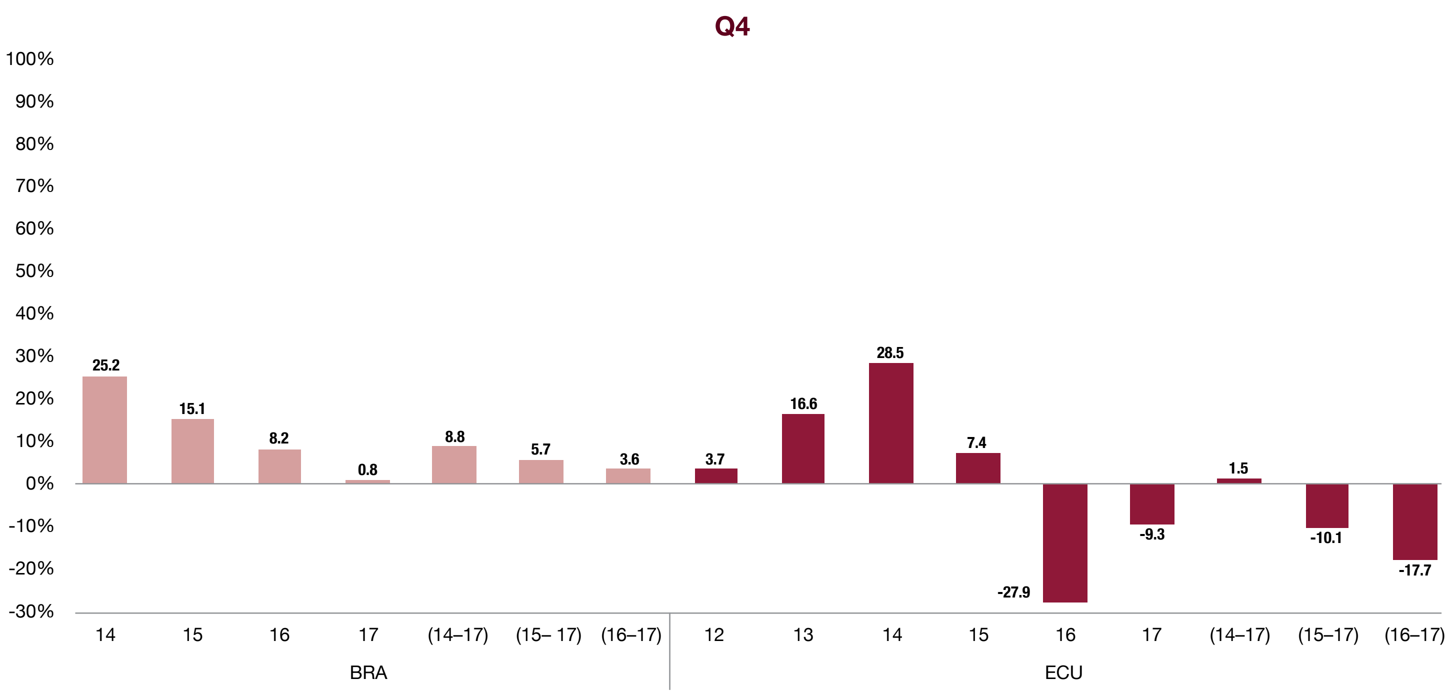


Source: ILO global databases.

Figure A2: Inter-annual decline in quarterly child labour

Inter-annual decline in quarterly child labour (by age), Qx-2020 (compared to Qx-2019), Brazil and Ecuador[40]

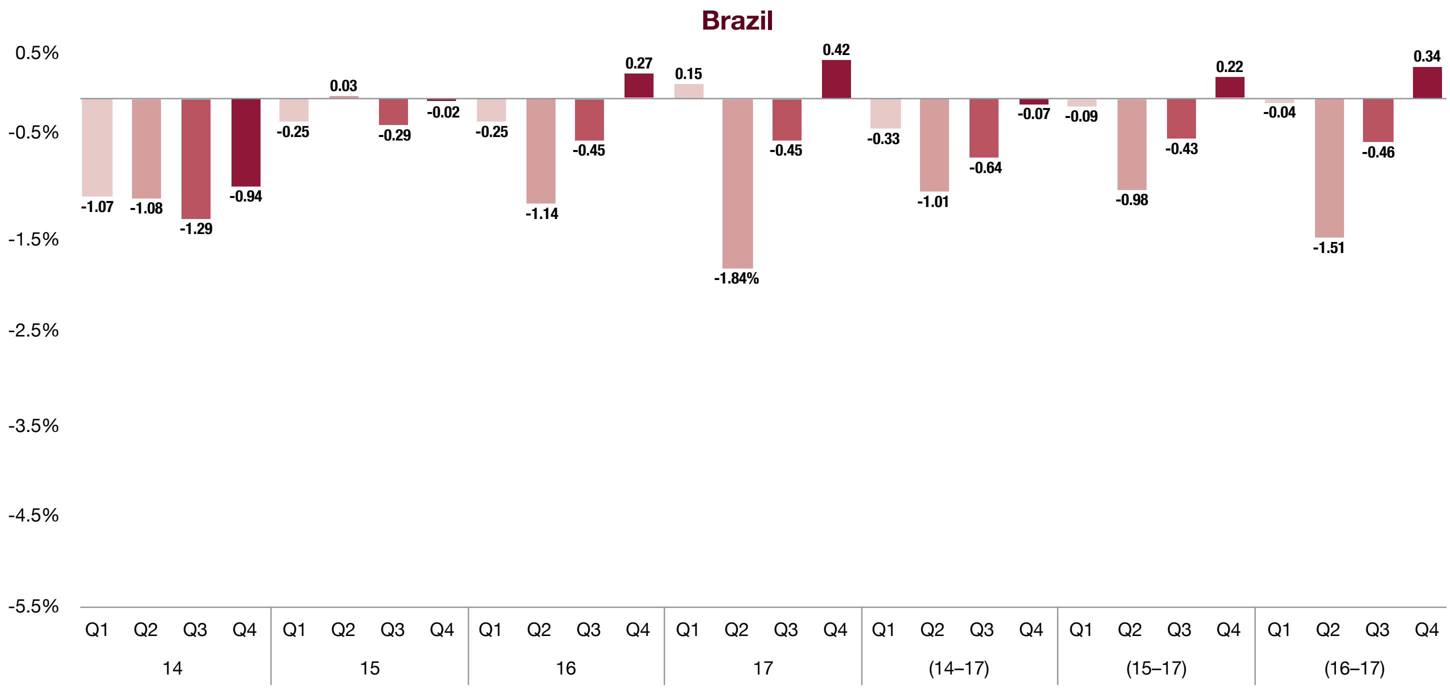


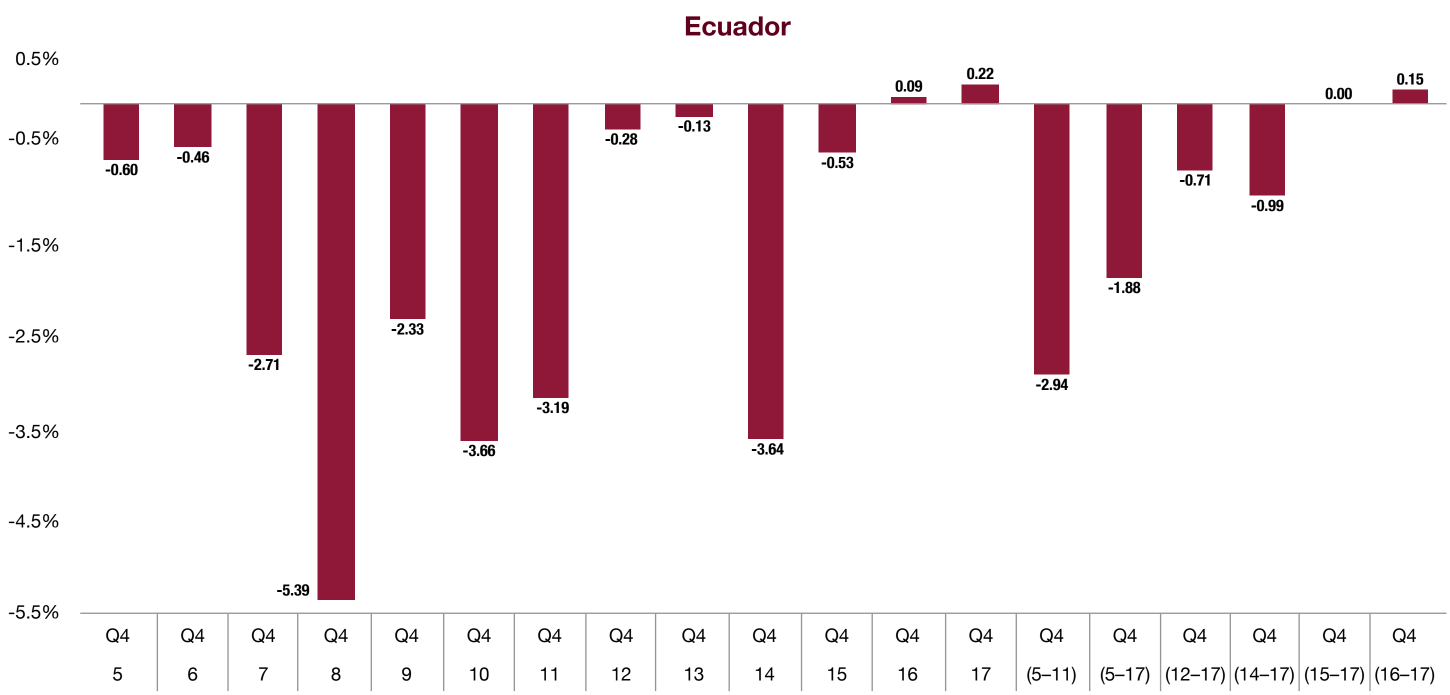


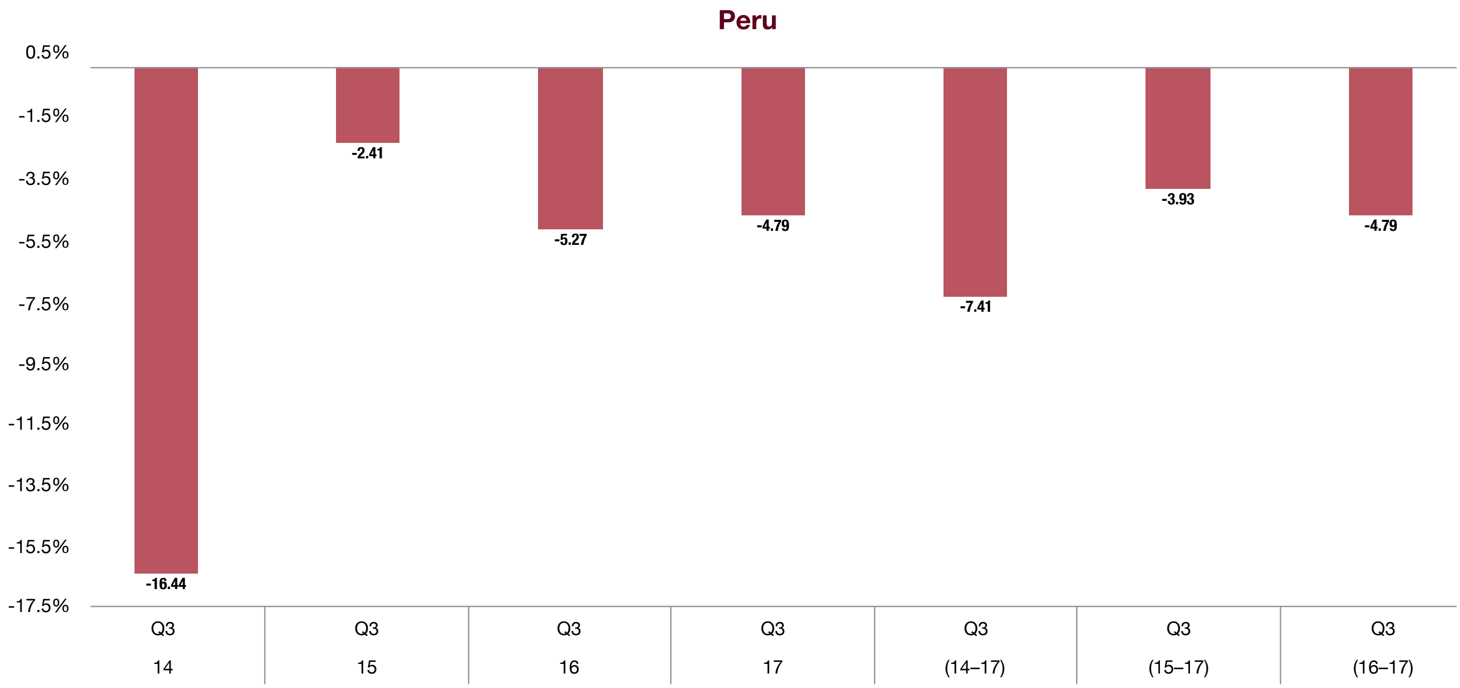
Source: ILO global databases.

Figure A3: Inter-annual percentage-point difference in quarterly SDG 8.7.1 – proportion of children engaged in economic activity

Inter-annual percentage-point difference in quarterly SDG 8.7.1 – proportion of children engaged in economic activity (by age), Qx-2020 (compared to Qx-2019), Brazil, Ecuador and Peru







Source: ILO global databases.

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