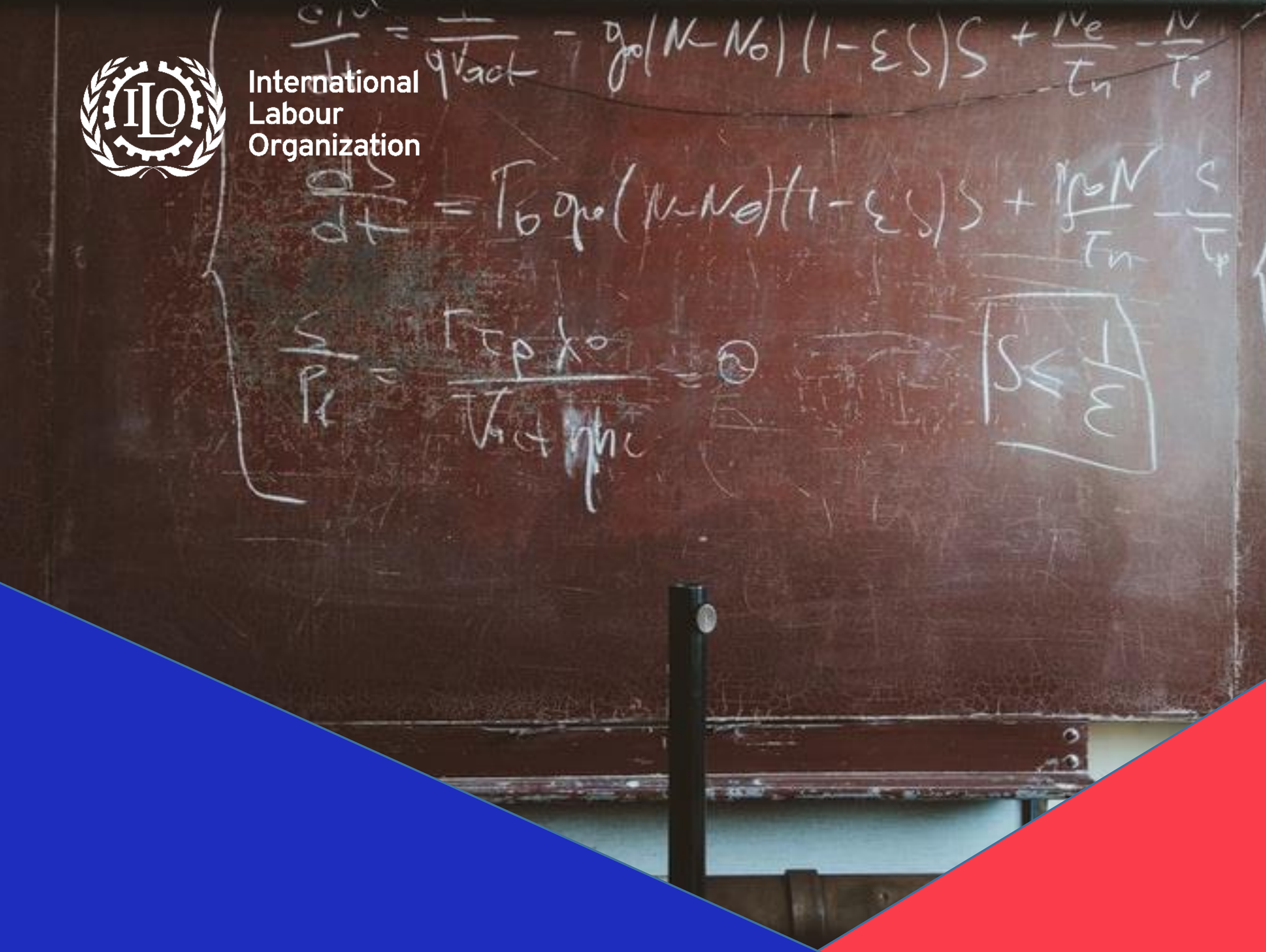

International Labour Organization

ILO modelled estimates Methodological overview

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Department of Statistics

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The ILO has designed and actively maintains a series of econometric models that are used to produce estimates of labour market indicators in the countries and years for which country-reported data are unavailable. The purpose of estimating labour market indicators for countries with missing data is to obtain a balanced panel data set so that, every year, regional and global aggregates with consistent country coverage can be computed. These allow the ILO to analyse global and regional estimates of key labour market indicators and related trends. Moreover, the resulting country-level data, combining both reported and imputed observations, constitute a unique, internationally comparable data set of labour market indicators.

Relevant references

- International Conference of Labour Statisticians (ICLS). The ILO modelled estimates use and promote the use of the recommendations of the ICLS[1]. For instance, the labour underutilisation model estimates the indicators introduced by the 19th ICLS.
- Detailed documentation is available for the ILO modelled estimates of working-hours (annexes of ILO Monitor: COVID-19 and the world of work), employment by economic class (working poverty), and the labour income share and distribution.
- For a better understanding of the underlying data used in the ILO modelled estimates, please refer to the quick guides on sources and uses of labour statistics, ILOSTAT microdata processing, and interpretation of the unemployment rate.
- The ILO modelled estimates use as input data third-party databases including: the World Economic Outlook from the International Monetary Fund, the World Development Indicators and PovcalNet from the World Bank, UIS.Stat from UNESCO, and the World Population Prospects and National Accounts Data from the United Nations.

Data collection and evaluation

The ILO modelled estimates are generally derived for 189 countries and territories, disaggregated by sex and age as appropriate. For selected indicators an additional disaggregation by geographical area (urban and rural) is presented. Before running the models to obtain the estimates, labour market information specialists from the ILO Department of Statistics, in cooperation with the Research Department, evaluate existing country-reported data and select only those observations deemed sufficiently comparable across countries. The recent efforts by the ILO to produce harmonized indicators from country-reported microdata

[1] The employment definition following 19th ICLS is not yet implemented in the ILO modelled estimates for countries in which it would generate a methodological break, as there are not enough data points based on the new standard to produce reliable global and regional estimates.

have greatly increased the comparability of the observations. Nonetheless, it is still necessary to select the data on the basis of the following four criteria: (a) type of data source; (b) geographical coverage; (c) age-group coverage; and (d) presence of methodological breaks or outliers.

With regard to the first criterion, in order for labour market data to be included in a particular model, they must be derived from a labour force survey, a household survey or, more rarely, a population census. National labour force surveys are generally similar across countries and present the highest data quality. Hence, the data derived from such surveys are more readily comparable than data obtained from other sources. Strict preference is therefore given to labour force survey-based data in the selection process. However, many developing countries, which lack the resources to carry out a labour force survey, do report labour market information on the basis of other types of household surveys or population censuses. Consequently, to balance the competing goals of data comparability and data coverage, some (non-labour force survey) household survey data and, more rarely, population census-based data are included in the models.

The second criterion is that only nationally representative (i.e. not prohibitively geographically limited) labour market indicators are included. Observations corresponding to only urban or only rural areas are not included, because large differences typically exist between rural and urban labour markets, and using only rural or urban data would not be consistent with benchmark data such as gross domestic product (GDP). Nonetheless, when the data are broken down by urban versus rural location, geographically limited data covering the area of interest are included.

The third criterion is that the age groups covered by the observed data must be sufficiently comparable across countries. Countries report labour market information for a variety of age groups, and the age group selected can influence the observed value of a given labour market indicator.

The last criterion for excluding data from a given model is whether a methodological break is present or if a particular data point is clearly an outlier. In both cases, a balance has to be struck between using as much data as possible and including observations likely to distort the results. During this process, particular attention is paid to the existing metadata and the underlying methodology for obtaining the data point under consideration.

Historical estimates can be revised in cases where previously used input data are discarded because a source that is more accurate according to the above-mentioned criteria has become available.

Methodology used to estimate labour market indicators

Labour market indicators are estimated using a series of models, which establish statistical relationships between observed labour market indicators and explanatory variables. These relationships are used to impute missing observations and to make projections for the indicators.

There are many potential statistical relationships, also called “model specifications” that could be used to predict labour market indicators. The key to obtaining accurate and unbiased estimates is to select the best model specification in each case. The ILO modelled estimates generally rely on a procedure called cross-validation, which is used to identify those models that minimize the expected error and variance of the estimation. This procedure involves repeatedly computing a number of candidate model specifications using random subsets of the data: the missing observations are predicted and the prediction error is calculated for each iteration. Each candidate model is assessed on the basis of the pseudo-out-of-sample root mean squared error, although other metrics such as result stability are also assessed depending on the model. This makes it possible to identify the statistical relationship that provides the best estimate of a given labour market indicator. It is worth noting that the most appropriate statistical relationship for this purpose could differ depending on the country.

The benchmark for the ILO modelled estimates is the 2019 Revision of the United Nations World Population Prospects, which provides estimates and projections of the total population broken down into five-year age groups. The working-age population comprises everyone who is at least 15 years of age.

Although the same basic approach is followed in the models used to estimate all the indicators, there are differences between the various models because of specific features of the underlying data. Further details are provided below for each model.

Labour force estimates

The basic data used as input for the labour force participation rate (LFPR) model are single-year LFPRs disaggregated by sex and age groups, the latter comprising two intervals (15–24 and 25+). The underlying methodology has been extensively assessed in terms of pseudo-out-of-sample performance. However, for certain types of missing data patterns, the LFPR uses judgemental model selection.

Linear interpolation is used to fill in the missing data for countries for which such a procedure is possible. The performance of this procedure has been found to be reasonable, which is not surprising, given that the LFPR is a very persistent variable. In all other cases, weighted

multivariate estimation is carried out. Countries are divided into nine estimation groups, which were chosen on the combined basis of broad economic similarity and geographical proximity. On the basis of the data structure and the heterogeneity among the countries covered by the input data, the model was specified using country fixed effects. The regressions are weighted by the inverse of the likelihood of a labour force survey's availability. The explanatory variables used include economic and demographic variables. To produce estimates for 2020, a cross-validation approach is used to select the model that minimizes prediction error in that specific year. The tested models include annual averages of high-frequency indicators related to the evolution of the COVID-19 pandemic. The global figures are calculated using the benchmark population from the United Nations World Population Prospects and the reported or model-derived labour force participation rates.

Rebalancing the estimates ensures that the implied total rate obtained from summing the demographic breakdowns matches the total rate as derived from the labour force surveys or as estimated.

In previous editions of the ILO modelled estimates detailed age information for the labour force were available.[2] Currently, the model has been discontinued and the associated dataset (except for the indicator of the median age of the labour force) is no longer published to avoid inconsistencies with the LFPR model described above.

Unemployment estimates

This model estimates a complete panel data set of unemployment rates disaggregated by sex and age (15–24, 25+). For countries for which at least one observation is reported,[3] regressions involving country fixed effects are used. Three models are combined with equal weighting in order to impute missing values. The models have been chosen based on pseudo-out-of-sample root mean squared error and stability of results (judgemental assessment of the two components). For countries with no reported observations, models are selected on the basis of cross-validation. The evolution of the average unemployment rate of a particular demographic group in a given region is highly predictive of the evolution of the unemployment rate of that particular group in a country in that region, and this variable is used for countries with no available data over the entire period. A separate cross-validation approach is used to select the model that minimizes the prediction error in the year 2020. The candidate models include annual averages of high-frequency indicators related to the evolution of the COVID-19 pandemic. Indicative confidence intervals based on the pseudo out-of-sample estimation error are produced for imputed observations. Rebalancing the estimates ensures that the implied

[2] Five-year age intervals (15–19, 20–24, and so on until 60–64) and a last age group of 65 years and above.
[3] For ease of exposition, we abstract here from the case in which reported observations exist for some demographic groups but not for others in a given country and year.

total rate obtained from summing the demographic breakdowns matches the total rate as derived from the labour force surveys or as estimated.

Hours worked

The ratio of weekly hours worked to the population aged 15–64 is the target variable that is estimated for countries with missing data. Total weekly working hours are derived by multiplying this ratio by the population aged 15–64.

For estimates up to and including 2019, the regression approach uses the share of the population aged 15–64 in the total population, the employment-to-population ratio and the rate of time-related underemployment to predict missing values. For countries without any observations of this indicator, the country intercept is estimated as a combination of a regional and an income group mean.

Working hours up to and including the third quarter of 2021 are estimated using the ILO nowcasting model, which means drawing on the values of high-frequency indicators in real time or with a very short publication lag in order to predict the current value of the target variable. This is a data-driven statistical prediction model that provides a real-time measure of the state of the labour market, drawing on real-time economic and labour market data. The specific target variable of the ILO nowcasting model is change in hours worked adjusted for population aged 15-64 relative to a pre-COVID-19 benchmark. To estimate this change, a fixed reference period is set as the baseline, namely, the fourth quarter of 2019 (seasonally adjusted). The model produces an estimate of the change in hours worked adjusted for population aged 15-64 relative to this baseline. The figures reported should therefore not be interpreted as quarterly or inter-annual growth rates. In addition, to compute the full-time equivalent jobs of the changes in working hours adjusted for population aged 15-64, a benchmark of weekly hours worked in the fourth quarter of 2019, before the COVID-19 pandemic, is used. This benchmark is also used to compute the time series of average hours worked adjusted for population aged 15 to 64.

The ILO nowcasting model draws from multiple sources: labour force survey data up to the third quarter of 2021 and up-to-date high-frequency economic data such as retail sales, administrative labour market data or confidence survey data. Additionally, up-to-date mobile phone data from Google Community Mobility Reports and the most recent values of the COVID-19 Government Response Stringency Index (hereafter “Oxford Stringency Index”), are used in the estimates.

Drawing on available real-time data, the model estimates the historical statistical relationship between these indicators and hours worked per person aged 15-64, and uses the resulting coefficients to predict how hours worked adjusted for population aged 15-64 change in response to the most recent observed values of the nowcasting indicators. Multiple candidate

relationships were evaluated on the basis of their prediction accuracy and performance around turning points to construct a weighted average nowcast. For countries for which high-frequency data on economic activity were available, but either data on the target variable itself were not available or the above methodology did not work well, the estimated coefficients and data from the panel of countries were used to produce an estimate. The resulting estimates are referred to as "direct nowcasts".

An indirect approach is applied for the remaining countries: this involves extrapolating the change in hours adjusted for population aged 15-64 from countries with direct nowcasts. The basis for this extrapolation is the observed mobility decline from the Google Community Mobility Reports and the Oxford Stringency Index, since countries with comparable drops in mobility and similar stringent restrictions are likely to experience a similar decline in hours worked adjusted for population aged 15-64. From the Google Community Mobility Reports, an average of the workplace and "retail and recreation" indices is used. The stringency and mobility indices are combined into a single variable using principal component analysis.[4] Additionally, for countries without data on restrictions, mobility data, if available, and up-to-date data on the incidence of COVID-19 were used to extrapolate the impact on hours worked adjusted for population aged 15-64. Because of countries' different practices in counting cases of COVID-19 infection, the more homogenous concept of deceased patients is used as a proxy of the extent of the pandemic. The variable was computed at an equivalent monthly frequency, but the data were updated daily based on the Our World in Data online repository.[5] Finally, for a small number of countries with no readily available data at the time of estimation, the regional average was used to impute the target variable.

Estimates of labour underutilization (LU2, LU3 and LU4 rates)

The target variables of the model are the measures of labour underutilization defined in the resolution concerning statistics of work, employment and labour underutilization adopted by the 19th International Conference of Labour Statisticians (ICLS) in October 2013. These measures include the combined rate of time-related underemployment and unemployment

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[4] Additionally, for the first three quarters of 2021, a dummy variable is used dividing countries into two clusters to account for differential impacts of those variables on working-hours. The clusters are based on a k-means split by geographical region, demographic characteristics and national income per capita. In addition, a de-trending procedure for Google Mobility Reports data is used.

[5] Hannah Ritchie, Edouard Mathieu, Lucas Rodés-Guirao, Cameron Appel, Charlie Giattino, Esteban Ortiz-Ospina, Joe Hasell, Bobbie Macdonald, Diana Beltekian and Max Roser (2020) - "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. Retrieved from: 'https://ourworldindata.org/coronavirus' [Online Resource]

(LU2), the combined rate of unemployment and the potential labour force (LU3), and the composite measure of labour underutilization (LU4). The measures are defined as:

$$\text{LU2} = \frac{\text{Unemployed} + \text{Time related underemployed}}{\text{Labour force}}$$

$$\text{LU3} = \frac{\text{Unemployed} + \text{Potential labour force}}{\text{Labour force} + \text{Potential labour force}}$$

$$\text{LU4} = \frac{\text{Unemployed} + \text{Potential labour force} + \text{Time related underemployed}}{\text{Labour force} + \text{Potential labour force}}$$

Persons in time-related underemployment are defined as all persons in employment who, during a short reference period, wanted to work additional hours, whose working time in all their jobs was below a specified threshold of hours, and who were available to work additional hours if they had been given the opportunity to do so. The potential labour force consists of people of working-age who were actively seeking employment, were not available to start work in the reference week but would become available within a short subsequent period (unavailable jobseekers), or who were not actively seeking employment but wanted to work and were available in the reference week (available potential jobseekers).

The model uses the principles of cross-validation and uncertainty estimation to select the regression models with the best pseudo-out-of-sample performance, not unlike the unemployment rate model. The labour underutilization model, however, has three very specific features. First, all demographic groups are jointly estimated, using the appropriate categorical variable as a control in the regression, because the groups are interdependent and data availability is roughly uniform across breakdowns. Second, the model incorporates the information on unemployment and labour force into the regressions (used alongside other variables to reflect economic and demographic factors). Finally, the LU4 rate is uniquely pinned down by the LU2 and LU3 rates, since it is a composite measure based on the two indicators.

The resulting estimates include the LU2, LU3 and LU4 rates and the level of time-related underemployment and of the potential labour force.

Estimates of the distribution of employment by status, occupation and economic activity

The distribution of employment by status, occupation and economic activity (sector) is estimated for total employment and also disaggregated by sex. In the first step, a cross-country regression is performed to identify the share of each of the employment-related categories in countries for which no data are available. This step uses information on demography, per capita income, economic structure and a model-specific indicator with high predictive power for the estimated distribution. The indicators for each category are as follows:

- for status, the index called "work for an employer" from the Gallup World Poll;
- for occupation, the share of value added of a sector in which people with a given occupation are most likely to work;
- for sector, the share of value added of the sector.

The next step estimates the evolution of the shares of each category, using information on the economic cycle and also on economic structure and demographics. The third step estimates the change in the shares of each category in the years 2020 and 2021. Lastly, the estimates are rebalanced to ensure that the individual shares add up to 100 per cent.

The estimated sectors are based on an ILO-specific classification that ensures maximum consistency between the third and fourth revisions of the United Nations International Standard Industrial Classification of All Economic Activities (ISIC). The sectors A, B, C, F, G, I, K, O, P and Q correspond to the ISIC Rev.4 classification. Furthermore, the following composite sectors are defined:

- "Utilities" is composed of sectors D and E.
- "Transport, storage and communication" is composed of sectors H and J.
- "Real estate, business and administrative activities" is composed of sectors L, M and N.
- "Other services" is composed of sectors R, S, T and U.

The estimated occupations correspond in principle to the major categories of the 1988 and 2008 iterations of the ILO International Standard Classification of Occupations (ISCO-88 and ISCO-08). However, subsistence farming occupations are classified inconsistently across countries, and sometimes even within one country across years. According to ISCO-08, subsistence farmers should be classified in ISCO category 6, namely as skilled agricultural workers. However, a number of countries with a high incidence of subsistence farming reported a low share of workers in category 6, but a high share in category 9 (elementary occupations). This means that the shares of occupational categories 6 and 9 can differ widely between countries that have a very similar economic structure. It is not feasible to determine the extent of misclassification between categories 6 and 9. Consequently, in order to obtain a consistent

and internationally comparable classification, categories 6 and 9 are merged and estimated jointly.

Estimates of employment by economic class

The estimates of employment by economic class are produced for a subset of 138 countries. The model uses the data derived from the unemployment, status and economic activity models as inputs in addition to other demographic, social and economic variables.

The methodology involves two steps. In the first step, the various economic classes of workers are estimated using the economic class of the overall population (among other explanatory variables). This procedure is based on the fact that the distribution of economic class in the overall population and the distribution in the working population are closely related. The economic class of the overall population is derived from the World Bank's PovcalNet database.[6] In general, the economic class is defined in terms of consumption, but in particular cases for which no other data exist, income data are used instead.

Once the estimates from this first step have been obtained, a second step estimates the data for those observations for which neither data on the economic class of the working population, nor estimates from step 1 are available. This second step relies on cross-validation and subsequent selection of the best-performing model to ensure a satisfactory performance.

In the present edition of the model, employment is subdivided into five different economic classes: workers living with their families on US$0–1.9 per day, US$1.9–3.2 per day, US$3.2–5.5 per day, US$5.5–13.0 per day, and above US$13.0 per day, in purchasing power parity terms.

Estimates of the labour income share and the labour income distribution

The model estimates a complete panel dataset of the labour income share and the labour income distribution. To this end, national accounts data from the United Nations Statistics Division and labour income data from the ILO Harmonized Microdata collection are combined. When national accounts data or microdata are not available, the estimates rely on a regression

[6] The 2020-2021 poverty data are from the World Bank, Macro and Poverty Outlook: Country-by-country analysis and projections for the developing world, World Bank, Washington, DC, 2021, combined with World Bank estimates (June 2021 edition) of the impact of COVID-19 on poverty. For a discussion of the methodology to estimate the impact, see Gerszon Mahler, Daniel, et al., 'Updated Estimates of the Impact of COVID-19 on Global Poverty: Turning the corner on the pandemic in 2021?',World Bank Blogs, 24 June 2021.

analysis to impute the necessary data. The imputation is based on countries that are similar in terms of key economic and labour market variables.

The methodology involves two steps. The first step is to compute the labour income share, adjusted for the labour income of the self-employed. Taking into account the labour income of the self-employed has been recognized in the economic literature as a crucial element for international comparability. In order to achieve this, detailed data on status in employment are used (from the model outlined in the preceding section), which subdivides self-employment into three different groups: own-account workers, contributing family workers and employers. Furthermore, the labour income of each group of the self-employed relative to the income of employees is estimated on the basis of a regression analysis of the microdata. The resulting estimate corresponds to the share of total income that accrues to labour:

$$\text{Labour income share} = \frac{\text{Labour income}}{\text{Gross domestic product}}$$

The second step, drawing on the level of labour income estimated in the first step and on the microdata, produces a detailed distribution, at the percentile level, of the labour income for each country and year. It is thus possible to determine the percentage of aggregate labour income that accrues to the bottom (first) percentile, to the second percentile, and so on. Importantly, given that the definition of employment follows the ICLS recommendations, the labour income is estimated on a per worker basis, not on a full-time equivalent basis. Additionally, the distribution of labour income at the global and regional level is computed, at the decile level. Because of the cross-country differences in prices, the distribution of global and regional labour income deciles is computed in purchasing power parity terms.

Estimates related to youth not in employment, education or training

The target variable of the model is the share of youth not in employment, education or training (NEET):

$$\text{NEET share} = \frac{\text{Youth not in employment, education or training}}{\text{Youth population}}$$

It is worth noting that, by definition, 1 minus the NEET share gives the share of young people who are either in employment or enrolled in some educational or training programme. The NEET share is included as one of the indicators used to measure progress towards the achievement of the Sustainable Development Goals, specifically of Goal 8 (“Promote sustained,

inclusive and sustainable economic growth, full and productive employment and decent work for all”).

The model uses the principles of cross-validation and uncertainty estimation to select the regression models with the best pseudo-out-of-sample performance, not unlike the unemployment rate model. The NEET model estimates all demographic groups jointly, using the appropriate categorical variable as a control in the regression, because the groups are interdependent and data availability is roughly uniform across breakdowns. The model incorporates the information on unemployment, labour force and enrolment rates into the regressions (used alongside other variables to reflect economic and demographic factors). The resulting estimates include the NEET share and the number of NEET youth.

Estimates of key indicators by geographical area: Urban and rural labour market indicators

Separate estimates for urban and rural areas are produced for the following indicators: labour force, unemployment, LU2, LU3, LU4, youth NEET share and the employment distribution by status, economic activity and occupation.

In order to produce the estimates, the models decompose the variable of interest into two components. The procedure described here is for the labour force model; an analogous procedure is used for the other models. The labour force participation rate (LFPR) by geographical area that the model estimates can be expressed as:

$$\text{Labour force participation rate}_{\text{ij}} = \frac{\text{Labour force}_{\text{ij}}}{\text{Population}_{\text{ij}}}$$

$$\text{i} = \{\text{urban}, \text{rural}\}\,;\ \text{j} = \{\text{gender} \times \text{age}\}$$

One relationship of particular importance between the urban and rural rates and the national rates is that the distance of the former rates to the latter rate determines the respective share of the urban and rural population (the denominator of the LFPR expression). The strategy of the modelling approach is to target, for the estimation, two variables that jointly determine the rural and urban LFPRs. The main variable used to produce the LFPR is the spread between urban and rural LFPR:

$$\text{Spread urban} = \frac{\text{Urban LFPR}}{\text{Rural LFPR}} = \frac{1}{\text{Spread rural}}$$

This variable alone does not pin down both the urban and rural LFPRs. Another variable is necessary to complete the system of equations that can be used to produce the two rates. The other variable is the share of the denominator of the LFPR expression by type of area, which is simply the population:

$$\text{Share urban} = \frac{\text{Urban labour force /Urban LFPR}}{\text{Rural labour force/Rural LFPR} + \text{Urban labour force/Urban LFPR}} = 1 - \text{Share rural}$$

Decomposing the two rates into the spread and share variables has two main advantages. First, it makes it possible to model explicitly the dependence between the distances of the two rates to the total rate and the share of the population in urban and rural areas. The second advantage is that this framework is easy to extrapolate to the other variables of interest. Once these two auxiliary variables have been estimated using regression methods, the results can easily be used to compute the urban and rural rates of interest:

$$\text{Urban LFPR} = \frac{\text{LFPR}}{\text{Share urban} + \frac{\text{Share rural}}{\text{Urban spread}}}$$

$$\text{Rural LFPR} = \frac{\text{LFPR} - \text{Share urban} * \text{Urban LFPR}}{\text{Share rural}}$$

As mentioned above, the unemployment, labour underutilization, NEET and employment distribution models follow the same procedure.

In order to estimate the spread and share for all the variables, the models of key indicators by geographical area use the principles of cross-validation and uncertainty estimation to select the regression models with the best pseudo-out-of-sample performance, not unlike the unemployment rate model. However, the targets of the estimation are the spread and share variables instead of the variable of interest directly. In the geographical models, all demographic groups are jointly estimated, using the appropriate categorical variable as a control in the regression, because the groups are interdependent and data availability is roughly uniform across breakdown. The models use various indicators to reflect economic and social factors as explanatory variables for the imputation. Finally, the modelling procedure ensures the consistency of interdependent variables. For this purpose, labour force estimates are used as a basis for the models of the distribution of unemployment and labour underutilization by geographical area. The population benchmark, derived from the labour force model, is used in the model of the NEET distribution by geographical area. Similarly, estimates of unemployment by rural and urban area are used as the basis for the estimates of labour underutilization by geographical area. Finally, the employment estimates derived jointly from the models of the distribution of the labour force and unemployment by geographical area are used as a basis for estimating the distributions of employment with respect to status, economic activity and occupation by geographical area.

The resulting estimates are of the shares or rates and the corresponding levels. The following estimates are available by rural and urban breakdown: LFPR, number of people in the labour force, unemployment rate, unemployment level, LU2 rate, time-related underemployment, LU3

rate, potential labour force, LU4 rate, composite labour underutilization measure, and the distribution of employment by employment status, economic activity and occupation.

Models used to project labour market indicators

The ILO has developed projection models to estimate and forecast hours worked[7], employment, unemployment, and the labour force for the years 2021 to 2023. In a first step, the hours worked are projected. In a second step, the projection of hours worked serves as a basis for the simultaneous projection of employment, unemployment and the labour force.

Projecting hours worked

The estimate of working hours in the fourth quarter of 2021 is based on a crisis recovery model. This is specified as an error correction model of the form:

$$\Delta h_{i,t} = \beta_{0,i} + \beta_{1,i}\, gap_{i,t-1} + \beta_{2}\, gap^2_{i,t-1} + \beta_{3} h_{i,t-1} + \beta_{4}\, \Delta GDP_{i,t} \quad (1)$$

The gap is given by the difference of hours worked relative to a medium-term trend, $gap_{i,t} = h_{i,t} - trend_{i,t}$, where the evolution of the trend in working hours is determined by a geometric average between the long-run target and a function of current working hours.

The variable of interest $\Delta h_{i,t}$ is the change in working hours per population aged 15-64. The gap refers to the working hours relative to the long-run trend. The crisis recovery mechanism works through this gap, where the size of parameters $\beta_{1,i}$ and β_{2} determine the speed with which working hours increase to close the gap when such a gap exists. The model mechanics are such that larger gaps result in a larger change in hours worked. In order to capture scarring or hysteresis, the medium-term trend is modelled to react to the gap with a parameter γ_1, but it also has a component reverting to its long-term target with a parameter γ_2. The country-specific constant is calculated to imply zero change when the long-run target is achieved.

The parameters of the projection model are estimated empirically to the largest extent possible. Equation (1) is estimated at the quarterly frequency for 30 countries with suitable data up to 2019 using multilevel mixed-effects methods, meaning that the distribution of the slope parameters for the gap is also estimated. This provides baseline estimates of the parameters. In addition, the impact of vaccination on the recovery speed parameter $\beta_{1,i}$ is estimated. This parameter is then adjusted for each country according to the projected progress in vaccination.

[7] The projection in the case of hours worked starts at the fourth quarter of 2021, as the first three quarters of 2021 are produced by the nowcasting model.

The scarring parameters are set to $\gamma\_1=0.05$ and $\gamma\_2=0.9$ for upper-middle- and high-income countries, and to $\gamma\_1=0.02$ and $\gamma\_2=0.95$ for lower-middle- and low-income countries.

Projecting employment, unemployment and the labour force

The projection of employment, unemployment and the labour force occurs in two steps. The first step exploits the data from up to three quarters of the year 2021 that are available for 58 countries to increase the precision of the estimates for the year 2021. The second step utilizes a projection model at the annual frequency to estimate and project the labour market indicators for the remaining countries. Since the labour force equals the sum of unemployment and employment, one would only need to project two of the three indicators, and could obtain the third as a residual. However, due to the high uncertainty and the resulting large variance in the projections, all three indicators are projected and then rebalanced to match the identity.

The quarterly projections for the unemployment rate utilize high-frequency data such as confidence indices in addition to economic growth forecasts in order to test a series of models. These models are evaluated using the model search routines described above, specifically by splitting the data into training and evaluation samples. Because of the high serial correlation of quarterly unemployment rates, a block of observations around the evaluation sample needs to be excluded from the estimation to ensure the training sample's independence from the observation that is being evaluated. Models are combined using a "jackknife model-averaging" technique described in Hansen and Racine (2012), which essentially finds the linear combination of models that minimizes the variance of the prediction error.

The quarterly projection model for employment and the labour force focuses on the hours worked per employed, and the hours worked per person in the labour force. Those ratios have been strongly affected through the COVID-19 crisis, especially in countries where employment retention schemes and furloughs were widespread. The projection model is based on the assumption that this ratio will return to its long-term trend. The speed of recovery is estimated using a multi-level mixed model quite similar to the one used to project the hours worked.

The annual projection model utilizes vector error correction models. In fact, two different models are estimated, whose projections are then averaged. In the first model, the dependent variables are the change in the unemployment rate, the employment-to-population ratio and the labour force participation rate. The independent variables are the lag of the respective variable, GDP growth and the lagged value of the change in one of the other variables. The second model utilizes the hours worked per employed person, and the hours worked as a ratio of the labour force.