

► Technical annexes to the 9th edition of the ILO Monitor

Annex 1. Changes in hours worked: The ILO's nowcasting model

The ILO continues to monitor the labour market impacts of the COVID-19 pandemic using its “nowcasting” model. 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 target variable of the ILO nowcasting model is change in hours worked in the main job 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.

For this edition of the ILO Monitor the model incorporates: additional labour force survey data, 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”), have been 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.

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 was used. The stringency and mobility indices were combined into a single variable using principal component analysis. During 2021 additionally a dummy variable for developed countries to account for differential impacts of those variables on working-hours, as well as a de-trending procedure for Google Mobility Reports data, were used. In 2022 the model was further augmented to include GDP growth estimates and to take into account time-series properties of the recovery process. 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 was 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.¹ 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. Table AX summarizes the information and statistical approach used to estimate the target variable for each country.

Table A1. Approaches used to estimate changes in working-hours

Approach	Data used	Reference area
Nowcasting based on high frequency economic data	High-frequency economic data, including: labour force survey data; administrative register labour market data; Purchasing Managers Index ; national accounts data; consumer and business confidence surveys	Albania, Argentina, Australia, Austria, Belgium, Bolivia (Plurinational State of), Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Dominican Republic, Ecuador, Estonia, Finland, France, Germany, Greece, Hong Kong-China, Hungary, Iceland, India, Indonesia, Iran (Islamic Republic of), Ireland, Israel, Italy, Japan, Latvia, Lebanon, Lithuania, Luxembourg, Macau-China, Malaysia, Malta, Mexico, Mongolia, Montenegro, Netherlands, New Zealand, North Macedonia, Norway, Occupied Palestinian Territory, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Republic of Korea, Republic of Moldova, Romania, Russian Federation, Rwanda, Saudi Arabia, Serbia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Kingdom, United States, Uruguay, Viet Nam
Extrapolation based on mobility and containment measures	Google Community Mobility Reports (Q2/2020 and onwards) and/or Oxford Stringency Index	Afghanistan, Algeria, Angola, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belize, Benin, Bhutan, Brunei Darussalam, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Central African Republic, Chad, Congo, Cuba, Côte d'Ivoire, Democratic Republic of the Congo, Djibouti, Egypt, El Salvador, Eritrea, Eswatini, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Guam, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyzstan, Lao People's Democratic Republic, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Oman, Pakistan, Panama, Papua New Guinea, Qatar, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, Suriname, Syrian Arab Republic, Tajikistan, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkmenistan, Uganda, United Arab Emirates, United Republic of Tanzania, United States Virgin Islands, Uzbekistan, Vanuatu, Venezuela (Bolivarian Republic of), Yemen, Zambia, Zimbabwe
Extrapolation based on the incidence of COVID-19	COVID-19 incidence proxy, detailed subregion	Armenia, Comoros, Equatorial Guinea, French Polynesia, Maldives, New Caledonia, Saint Lucia, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Western Sahara
Extrapolation based on region	Detailed subregion	Channel Islands, Korea (Democratic People's Republic of)

¹ 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]

Notes: (1) The reference areas included correspond to the territories for which ILO modelled estimates are produced. (2) Countries and territories are classified according to the type of approach used for Q2/2020. (3) For the Philippines, the releases of April 2020 and October 2020 of the Labour Force Survey were used; the data were benchmarked against the April and October 2019 data; the results for the missing months were directly interpolated or extrapolated using Google Community Mobility Reports data. (4) For India, up to the third quarter of 2020 the employment- to-population ratio of workers, excluding those temporarily absent from work, is used as a proxy of hours worked. Evidence from other countries suggests that this proxy is reasonably accurate, though it does tend to underestimate the actual working-hour loss. The data are taken from the Consumer Pyramids Household Survey conducted by the Centre for Monitoring Indian Economy, and in particular from: Marianne Bertrand, Rebecca Dizon-Ross, Kaushik Krishnan and Heather Schofield, "[Employment, Income, and Consumption in India during and after the Lockdown: A V-Shape Recovery?](#)", Rustandy Center for Social Sector Innovation, 18 November 2020. For subsequent quarters, the short-fall of employment is taken as a proxy of the hours shortfall, by assuming that as employment-to-population ratio returns to pre-crisis level so will hours worked.

The latest data update spanned the period from 24 March 2021 to 8 April 2021, depending on the source. The estimates are subject to a substantial amount of uncertainty. The unprecedented labour market shock created by the COVID-19 pandemic and the subsequent recovery are difficult to assess by benchmarking against historical data. Furthermore, at the time of estimation, consistent time series of readily available and timely high-frequency indicators, including labour force survey data, remained scarce. These limitations result in a high overall degree of uncertainty. For these reasons, the estimates are being regularly updated and revised by the ILO.

Annex 2. Labour income loss

This edition of the ILO Monitor presents revised estimates of the labour income losses induced by the COVID-19 pandemic. The new methodology is based on labour incomes reported in labour force surveys, which are available for a total of 19 countries.² In addition, the evolution of labour incomes is approximated using the compensation of employees from national accounts statistics for high-income OECD countries.³ This income includes earnings potentially received while on furlough. Previous editions of the ILO Monitor presented the estimate of gross income loss induced by the reduced number of hours worked before any support measure.

Therefore, the revised estimates are not directly comparable to the previous estimates. While the previous estimates focused on the incomes that are not earned from work, the revised estimates do take substitute incomes into account, in so far as they are received as labour-related income. This means that unemployment benefits are not accounted for, while short-time work schemes, which were used extensively for instance in Europe, do count. Consequently, the revised measure is closer to the actual impact on households, but institutional differences have a strong impact on cross-country divergences in labour incomes.

The methodology to estimate of labour income losses relies on two key components: the estimated labour-related income per hour worked, and the number of hours worked adjusted for population growth. The second component is the output of the ILO nowcasting model, while the first component is estimated in a new model. Both components are expressed as a ratio relative to the fourth quarter of 2019. The basic identity to determine labour incomes is given by:

² Those comprise 5 lower-middle-income countries, 8 upper-middle-income countries and 6 high-income countries, from all continents except Africa.

³ Employees make up the largest part of the workforce in high-income countries, so that this should be a good approximation. Self-employment is much more prevalent outside of high-income countries.

$$LI_t = LI_{19} \left(\frac{LI_t/H_t}{LI_{19}/H_{19}} \right) \left(\frac{H_t/P_t}{H_{19}/P_{19}} \right) \frac{P_t}{P_{19}} \quad (1)$$

The subscript “19” refer to the fourth quarter of 2019, while the subscript “t” refers to the period of interest. LI refers to labour-related income, H to hours worked, and P to the population aged 15 to 64. The first large parenthesis is term to be estimates – the income per hour worked relative to the fourth quarter of 2019. The second parenthesis is the hours worked relative to the fourth quarter of 2019.

In a first step, labour related income – reported in nominal terms in LFS – is deflated to real terms using a GDP price index deflator where available, or a consumer price deflator otherwise. Next, an econometric model is used to establish the factors that drive real labour income per hour. Explanatory variables are the hour worked per employed, a factor capturing the effect of structural change on average incomes in the economy, and productivity per hour worked. Hours worked per employed fell significantly in countries where furlough schemes were used widely, while in those cases labour incomes were at least partially maintained. In addition, the income maintaining capacity is presumably higher in countries of higher income, which is why this component is also estimated with an interaction term with GDP per capita.⁴

Job destruction by the crisis was more focused in some sectors than in others. Such a composition effect can change average incomes, which is why the sectoral composition effect is included. This sectoral composition effect describes the degree to which an economy’s average wage would change, given a change in the sectoral employment structure, but keeping wages constant. In fact, the sectoral composition effect was a primary component of the methodology to estimate the impact on labour incomes in previous editions of the ILO Monitor, and its derivation can be found in Annex 3 of ILO (2020 [6th Monitor]).

An ordinary least squares regression model is estimated at the quarterly frequency, including as a dependent variable the year-on-year change in real labour income per hour, and as independent variables the year-on-year change in hours worked per employed, interacted with GDP per capita, the year-on-year change in the sectoral composition effect and the year-on-year change in GDP per hour worked. The time ranges from the first quarter of 2016 till the fourth quarter of 2021, where observations from 2020 and 2021 receive a double weight in the regression.⁵

The real labour income per hour relative to 2019 Q4 is predicted for a total of 47 countries – including the 38 that have at least partial income data – using quarterly data of employment, hours worked and the sectoral composition. In a second step, the parameter estimates from the regression are applied to annual estimates of hours worker per employed and the sectoral composition effect to obtain estimates of the evolution of real labour income per hour worked for the remaining 142 countries that are part of the ILO modelled estimates series. Just as hours worked, labour incomes relative to the fourth quarter of 2019 that are reported in this document are adjusted for population growth, represented by the term $\frac{LI_t}{LI_{19}} \frac{P_{19}}{P_t}$. For aggregation and to compute the \$US amount of the change in labour income, the total labour income in 2019 is used, which in turn is derived using the ILO estimate of the labour income share and 2019 GDP.

⁴ GDP per capita is rescaled into an interval [0,1], with the lower and upper bound determined by the countries with the lowest and highest GDP per capita in the sample of countries with available data. Any country outside of those bounds is set at the bounds. This assures that no predictions are made outside of the range of observed input data.

⁵ As a robustness check, the estimation period has been restricted to 2020 and 2021. Results are quite similar, but the precision of the estimates is less precise.

Annex 3. Measuring labour market tightness

To measure labour market tightness, we use the ratio of job vacancies to the number of unemployed for the most recent month or quarter between October 2021 and March 2022 for a given country. The percentage change in labour market tightness (measured as the vacancy-to-unemployed ratio) is computed as follows:

$$\frac{LMT_{i,t}}{LMT_{i,t-1}} - 1 = \frac{VAC_{i,t}/UNE_{i,t}}{VAC_{i,t-1}/UNE_{i,t-1}} - 1$$

The above growth rate can be decomposed into separate contributions of unemployment and job vacancies to the change in labour market tightness.

$$\begin{aligned} \frac{LMT_{i,t}}{LMT_{i,t-1}} - 1 &= \frac{VAC_{i,t}}{VAC_{i,t-1}} \cdot \frac{UNE_{i,t-1}}{UNE_{i,t}} - 1 = \\ &= \left(\frac{VAC_{i,t}}{VAC_{i,t-1}} - 1 \right) \cdot \frac{UNE_{i,t-1}}{UNE_{i,t}} + \left(\frac{UNE_{i,t-1}}{UNE_{i,t}} - 1 \right) \\ &= \left(\frac{VAC_{i,t}}{VAC_{i,t-1}} - 1 \right) + \left(\frac{UNE_{i,t-1}}{UNE_{i,t}} - 1 \right) + \left(\frac{VAC_{i,t}}{VAC_{i,t-1}} - 1 \right) \cdot \left(\frac{UNE_{i,t-1}}{UNE_{i,t}} - 1 \right) \end{aligned}$$

In the main text we present the contributions to the change in labour market tightness by job vacancies as $\left(\frac{VAC_{i,t}}{VAC_{i,t-1}} - 1 \right)$ and the contribution by unemployment as $\left(\frac{UNE_{i,t-1}}{UNE_{i,t}} - 1 \right)$. We do not analyse the smaller contribution caused by the third term, which is the product of the first two. Table A2 summarizes the construction of each variable and their data sources.

Table A2. Summary of variables and data sources

Represented variable	Symbol	Data and source
Contribution of job vacancies to the change in labour market tightness	$\frac{VAC_{i,t}}{VAC_{i,t-1}} - 1$	The change in the number of job vacancies from the most recent available data from October 2021 to March 2022 relative to the baseline month or quarter of 2019. Source: ILOSTAT, EUROSTAT, Trading Economics, Statistics Canada, and UK's Office of National Statistics Note: For Italy the vacancy rate is used as a proxy of the vacancy level due to availability.
Contribution of unemployment to the change in labour market tightness	$\frac{UNE_{i,t-1}}{UNE_{i,t}} - 1$	The number of unemployed from the baseline month or quarter of 2019 divided by the most recent October 2021 to March 2022 month or quarter (same time frame chosen as job vacancies) minus one. Source: ILOSTAT, EUROSTAT, Trading Economics, Statistics Canada, and UK's Office of National Statistics

Change in labour market tightness	$\frac{LMT_{i,t}}{LMT_{i,t-1}} - 1$	Source: ILOSTAT, EUROSTAT, Trading Economics, Statistics Canada, and UK's Office of National Statistics
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Annex 4. Changes in hours worked by gender

The ILO has developed a statistical prediction model that provides a real-time measure of changes in hours worked by sex. The model produces estimates for female and male changes in hours worked adjusted by its relevant population aged 15-64 relative to the respective pre-COVID-19 benchmark. To estimate these changes by gender, the reference period is set to the fourth quarter of 2019 (seasonally adjusted). 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 by gender in the fourth quarter of 2019, before the COVID-19 pandemic, is used.

The data used for the model includes the nowcasting country estimates (see Annex 1), country demographic and economic characteristics) and a regional dummy variable. The model does not directly use high-frequency economic data or mobility and containment as the statistical information of these indicators is already contained in the nowcast results. The gender decomposition model is composed of three separate models. First, a model producing estimates from the first quarter of 2020 to the fourth quarter of 2021, for countries with at least one target data point of hours worked. Second, a model producing estimates from the first quarter of 2020 to the fourth quarter of 2021 for those countries with no hours worked data in that same period. Finally, a model for the projections for the first quarter of 2022.⁶ The three selected models that make up the nowcast by gender were chosen from an array of models based on their accuracy in predicting changes in female and male hours worked adjusted for population aged 15 to 64.⁷ Given that the models estimate the change in hours worked for women and men separately, the aggregated estimates for women and men may be incompatible with the total population estimates of the nowcasting model. To produce compatible estimates, the subcomponents for women and men are adjusted proportionally to match the total loss in worked hours adjusted for population aged 15 to 64 estimated by the nowcasting model.

⁶ All quarters for 2020 and 2021 have sufficient hours worked data points to include quarter fixed effects in the models, which increases the prediction power. Yet, the insufficient number of data points for the first quarter of 2022 requires a different model without quarterly fixed effects.

⁷ India was the only country estimated separately using employment levels by sex as a proxy for hours worked as there was timely data available from the Centre for Monitoring Indian Economy.