Technical Annex to the 10th 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. For an in-depth methodological description please consult: Carrillo, Gomis, Kapsos, Kühn and Mahajan (2022).[1]

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 hours worked 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: labour force survey data, up-to-date high-frequency economic data such as retail sales, administrative labour market data or confidence survey data. Additionally, 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 based on 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 up to the last quarter of 2021 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 hours worked, as well as a de-trending procedure for Google Mobility Reports data, were used. 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

[1] Link: https://content.iospress.com/articles/statistical-journal-of-the-iaos/sji220055

daily based on the Our World in Data online repository.[2] 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. In 2022 the model was modified to include GDP growth estimates, regional trends data, and to take into account time-series properties of hours worked.

The latest data update spanned the period from 22 August 2022 to 30 August 2022, 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. The change in gender gap in hours worked

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). The change in hours worked for country, *i*, sex, *s*, and quarter, *t*, is computed as follows:

$$Change\ in\ hours\ worked\ relative\ to\ 2019\ Q4_{i,s,t} = \left(\frac{\frac{Hours\ worked_{i,s,t}}{Population\ aged\ 15-64_{i,s,t}}}{\frac{Hours\ worked_{i,s,2019\ Q4}}{Population\ aged\ 15-64_{i,s,2019\ Q4}}} \right)$$

The data used for the model includes the country nowcast estimates (see Technical annex 1), country demographic and economic characteristics, and a regional dummy variable. The gender decomposition model is composed of four separate models. First, a model producing estimates from the first quarter of 2020 to the fourth quarter of 2021, for countries with data on hours worked for at least one quarter. 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 during that period. Third, a model producing estimates for the first quarter of 2022. Finally, a model for the projections for the second and third quarters of 2022.[3] The 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. Next, the predictions from the selected models are used to estimate the missing observations of hours worked.[4] 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.

Using the modelled estimates, we calculate changes in the gender gap relative to 2019 Q4. The change in the gender gap is computed as the change in working hours of males minus the change in working hours of females at the country level. Finally, to obtain global aggregates, countries' changes in the gender gap relative to 2019 Q4 are aggregated using each country's female total hours worked in the relevant quarter as weights. Thus, the global aggregate estimate for the gender gap is computed as follows:

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[2] 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]

[3] The different periods were selected due to different availability of reported observations of hours worked.

[4] India was estimated using urban employment levels by sex as a proxy for hours worked as there was timely data available from the Periodic Labour Force Survey.

$$\begin{aligned}&\textit{Global change in the gender gap in hours worked relative to } 2019\ Q4_t\\&= \sum_{i=1}^{i=189}\Bigg(\Big(\textit{Male change in hours worked relative to } 2019\ Q4_{\,i,t}\\&- \textit{Female change in hours worked relative to } 2019\ Q4_{i,t}\Big)\\&\times \frac{\textit{Female hours worked}_{i,t}}{\sum_{i=1}^{i=189}\textit{Female hours worked}_{i,t}}\Bigg)\end{aligned}$$

This aggregation procedure represents a change with respect to the 9th edition of the Monitor. In the previous edition, hours worked and population by gender were summed separately to obtain global estimates and then the gender gap was calculated. This edition's weighting scheme avoids compositional effects that arise from the size of each country's initial gender gap. For example, without the new weighting scheme, two countries could have experienced an increase in the gender gap, but the aggregate of the two could show a decrease purely due to the compositional effect.

Annex 3. Informality estimates

The ILO informality estimates disaggregated by sex provide a complete set of internationally comparable country estimates for the share of informal employment by sex for population aged 15 and older. These estimates include both nationally reported observations and imputed data for countries with missing data. The gender-specific country-level data used for the models includes self-employment and part-time employment rates. The country-level data includes the percentage of people below various poverty lines, the share of employment in agriculture and industry, the urbanization rate, the logarithm of GDP per capita, and categorical variables for geographic region and levels of economic development.

The imputations for missing data are produced through five separate econometric models. First, a model produces estimates from 2004 to 2019 for countries with at least one yearly data point of the share of informal employment by sex. Second, a model produces estimates from 2004 to 2019 for those countries with no data on the share of informality during the entire period. The third and fourth models are used to produce estimates for the 2020 crisis year and the recovery period of 2021, respectively. The final model estimates the projections for 2022. The five distinct models were chosen from an array of candidate models based on cross-validation, which selects the models with the highest accuracy in predicting informality rates in pseudo out-of-sample simulations. The predictions from the models are used to estimate the missing observations of the share of informal employment by sex. Since the models estimate separately the informal rates for the total population, women, and men, the aggregated estimates for women and men may be incompatible with the total population estimates. The subcomponents for women and men are adjusted proportionally to match the total population estimates.

Annex 4. A Structural Vector Autoregression (SVAR) model of vacancies and consumer confidence

To analyse the relationship between economic confidence and vacancies we use a SVAR time series model. This class of models enables the characterization of the joint dynamics of interrelated economic variables. With a minimal set of restrictions, also known as identification schemes, underlying structural economic shocks can be estimated.[5] We use short-run recursive restrictions to identify the relationship between

[5] See Gambetti (2020), "Structural Vector Autoregressive Models", Oxford Research Encyclopedia of Economics and Finance, Oxford University Press, August 2020.

vacancies and economic confidence. The short-run recursive restriction requires an assumption concerning the contemporaneous effects of shocks. This identification scheme has been widely used in macroeconomics, for instance to identify monetary policy shocks.[6]

We assume as a restriction that confidence can react contemporaneously (in the same month) to changes in vacancy postings, but not the reverse. We find this assumption reasonable, as economic confidence is based on sentiment and can react very quickly to economic news and developments, as it only entails sharing a judgmental outlook in response to a survey. In contrast, vacancy postings can be assumed to be more sluggish in responding to recent developments. This is the main identification assumption behind this exercise, and in the case of the bivariate SVAR model, using just vacancies and confidence, the only one.

In addition to a bivariate model, we also use a SVAR model of four variables, namely, inflation, vacancies, interest rates, and consumer confidence. In this case, additional restrictions are needed. The no-contemporaneous effect assumption follows the order in which the variables are mentioned, e.g. consumer confidence is allowed to respond contemporaneously to all variables and inflation to none of them. The ordering of inflation and interest rates is a common practice in the literature concerning monetary policy shocks. The addition of confidence in last place is also related to habitual practice in the literature, where relatively "fast" variables, such as financial indicators, are allowed to react to monetary policy on impact. In this ordering, we place vacancies after inflation and before interest rates as we envisage that price stickiness can constrain changes in prices more than in vacancies and because central banks might use real time vacancy data for decision-making. Other orderings could be reasonably conceived. These were tested and they do not sizably alter the results.

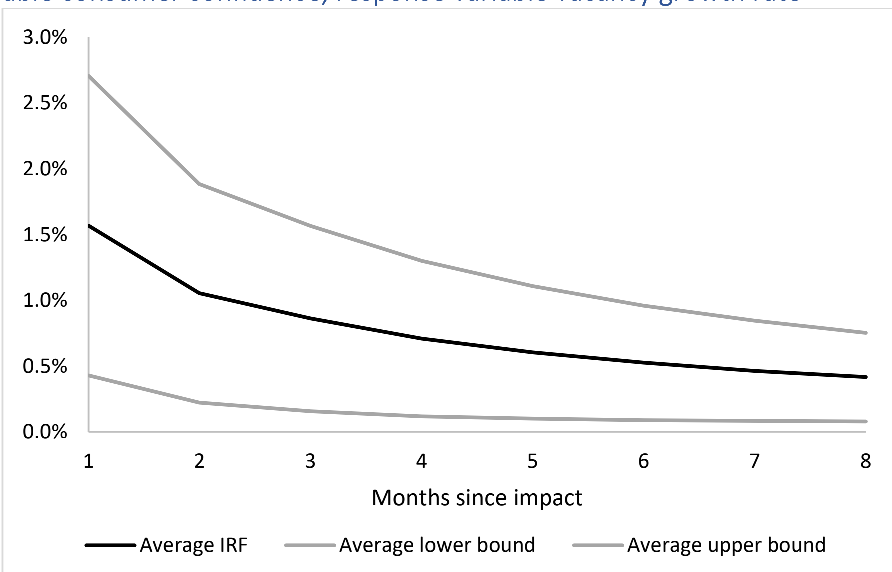
Our preferred specification is the SVAR model with four variables, inflation, vacancies, interest rates, and consumer confidence using the aforementioned identification strategy. Results of the bivariate model of vacancies and consumer confidence are very similar. We use the four variable model to enrich the information set of the bivariate model. Given that the analysis concerns the current turning point in labour markets, it is convenient to add indicators related to inflation and monetary policy – as they also present a recent inflection point. We use a sample of 16 countries[7] with sufficient data to carry out the analysis. The time horizon varies by country, but it generally spans the period 2003M01-2022M07. To ensure stationarity of the variables, we use the differences of inflation (year to year) growth of prices), interest rates and consumer confidence and year to year growth rate of vacancies[8] guided by unit root tests.[9,10]

The results[11] of the preferred specification show that on average across the countries, a one-time increase in consumer confidence of 3.7 points (the average standard deviation of the shock in consumer confidence) results, one month afterwards, in an increase of 1.5 percentage points in the year-to-year growth rate of vacancies (see Figure A2). This effect reduces over time: After 6 months the change in vacancy growth is one third the initial size. The result is significant in 8 out of the 16 countries in the sample at the 90 per cent confidence level. Using a 68 per cent confidence level[12] raises the count to 10. Concerning the effect of

[6] For instance, by assuming that monetary policy cannot affect contemporaneously neither inflation nor GDP growth, see Christiano, Eichenbaum and Evans (1996).
[7] The countries are Austria, Chile, Czechia, Finland, Germany, Hungary, Iceland, Israel, Japan, Luxembourg, Poland, Portugal, Spain, Sweden, United Kingdom, United States.
[8] Vacancies are the only variable that shows signs of seasonality.
[9] Unit root tests showed different results across countries in a few instances. We use the specification suggested by most of the results for the sake of comparability.
[10] Concerning the lag length, we choose a one lag model as country results of different lag selection statistical criteria are not conclusive and selecting higher lag orders results in unstable (oscillating) results.
[11] Based on the orthogonalized impulse response function (IRF) from the STATA standard VAR package.
[12] While a 68 percent confidence level is lower than usual, it has to be taken into account that the available data span a short time period starting only in 2003.

vacancies on consumer confidence we find that on average, a one-time increase in vacancy growth of 16 percentage points (the average standard deviation of a vacancy growth shock) results in a decline of 0.5 consumer confidence points on impact, fading after just one month. The effect on impact is significant in 9 out of the 16 countries at the 90 per cent confidence level, and in 11 countries at the 68 per cent confidence level. Notwithstanding the significance, this effect is small in economic terms. The results of the bivariate model are very close to the findings of the preferred specification.

Figure A2. Average results of the orthogonalized impulse response functions: impulse variable consumer confidence, response variable vacancy growth rate



Note: Author's calculations based on the model described. The orthogonalized impulse response function (IRF) represented is the average of the different country results. The averages are used for synthetic value, but the response of vacancy growth as well as its statistical significance should be analysed on a country-by-country basis. The response in the month of impact is zero as imposed by the identification restriction.

The effects discussed are modest in economics significance, with the vast majority of the dynamics of each variable (based on the forecast error variance decomposition) driven by the autoregressive nature of the variables. However, there is some evidence indicating that changes in confidence of greater size have disproportionately large effects. Estimating the dynamic equation for vacancies (in a bivariate VAR via OLS[13]) but splitting the sample into two based on size of changes in consumer confidence (split across the mean) shows markedly different results. In the "high-change" subsample, the reaction of vacancies to consumer confidence is roughly 3 times that of the "low-change" subsample, with the difference being significant at the 95 per cent confidence level. Hence, in the current circumstances, the link between confidence and vacancies could be above the average over the entire time horizon.

[13] Dynamic equations of a SVAR model can be estimated by OLS, simply by estimating each of the VAR equations separately, in this case the residuals cannot be interpreted as structural (orthogonal) shocks.