Technical annex: World Employment and Social Outlook: May 2024 Update

ILO modelled estimates, May 2024

Estimates of the unemployment rate

This model estimates a complete panel dataset of unemployment rates disaggregated by sex and age (15–24, 25+). For countries for which at least one observation is reported,[1] regressions involving country fixed effects are used. The three best performing models, assessed by cross-validation over a wide range of models, are combined with equal weighting to impute missing values. A separate cross-validation approach is used to select the model that minimizes 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. An additional procedure is used to produce estimates for 2021 which also uses a cross-validation procedure to select models. Finally, for 2022 and 2023, model estimates are calculated using the same approach (using the same models) as for the years up to and including 2019. For countries with no reported observations, models are selected based on a separate cross-validation exercise. Rebalancing the estimates ensures that the implied total rate obtained from summing the demographic breakdowns matches the total rate.

The procedure for unemployment rate projections pools countries in different ways. Three different approaches are used to derive projections, which are then combined into a weighted average. In all approaches the forecast variable of interest is the annual change in the unemployment rate. The first approach uses error correction models, while the second and third approaches do not. The first and second approaches pool countries globally, while the third approach pools countries according to geographical and economic similarity.

Estimates of LU3 and the jobs gap rate

The aim of the model is to provide estimates for the combined rate of unemployment and the potential labour force (LU3) and the combined rate of unemployment, potential labour force and willing non-jobseekers (jobs gap rate) by sex for the population aged 15 or older. The indicators are computed as follows:

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

$$\text{Jobs gap rate} = \frac{(\text{Unemployed} \ + \ \text{Potential labour force} + \text{Willing non-jobseekers})}{(\text{Labour Force} \ + \text{Potential labour force} + \text{Willing non-jobseekers})}$$

where the potential labour force and willing non-jobseekers include persons who were seeking employment and were not available but would become available in a short time (unavailable jobseekers), persons who were not seeking work but were currently available (available potential jobseekers) and persons who were not seeking work and were not available but were willing to work (willing non-jobseekers).

LU3 is estimated first and then these figures are used to estimate the jobs gap rate. The LU3 model uses as the percentage point difference between LU3 and unemployment rates as the target variable. The model uses cross-validation to select the regression models with the best pseudo-out-of-sample performance. The gender-specific country-level data used for the models includes the unemployment rate, economic inactivity rate, and informality rate. The country-level data also includes log GDP per capita, and categorical variables for geographic region and levels of economic development.

The jobs gap rate model uses the percentage point difference between the jobs gap rate and the LU3 rate as the target variable. The model uses the same country-data input as the LU3 model but replaces the unemployment rate with the LU3

[1] 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.

estimates. Moreover, the model (selected by cross-validation) includes the percentage of people aged 65 and older, and social protection rates.

The imputations for countries without LU3 and jobs gap rate data are produced with the predictions of five separate econometric models. First, a model produces estimates from 2004 to 2022 (excluding 2020) for countries with at least one observation of the target variable. Second, a model is used to produce estimates for the 2020 pandemic year. The third model produces estimates from 2004 to 2022 for those countries with no observations of the target variable during the entire period. The final model generates projections for 2023 using a growth approach that includes the change in the unemployment rate and log GDP per capita.

Estimates of labour income by gender

The model estimates a complete panel dataset of the labour income share by gender. The methodology involves two steps. In the first step, imputed labour income for all workers in the sample is estimated at the micro (individual record) level.[2] The imputed labour income takes into account important individual characteristics such as gender, age, education, type of economic activity, residential status and type of occupation. Importantly, the imputed labour income also includes the labour income of the self-employed (i.e. own-account workers, contributing family workers, and employers), and it also adjusts for the selection bias of the self-employed, thus providing unbiased labour income estimates for the self-employed. Having micro level imputed labour income enables the production of estimates of labour income of women and men separately, by aggregating all individual records by sex.

In the second step, when microdata is not available, the estimates rely on a regression analysis to impute the necessary data. The estimates for 2004-2019 are obtained using regressions involving country fixed effects (where the labour income share by gender estimates from step 1 are available) or region fixed effects (where the labour income share by gender estimates from step 1 are not available) along with relevant covariates. A separate cross-validation approach is used to select the model that minimizes prediction error in the year 2020 and then again for the year 2021.

Gender gaps in employment: the role of family responsibilities

Gender disparities are evident in workforce participation, where women often face challenges in accessing equal opportunities in securing employment. Recent economic literature (Klaven, Landais and Leite-Mariante 2024; Kleven, Landais and Søgaard 2019) highlights that family responsibilities (i.e. marriage and parenthood) have a greater negative impact on women's employment compared to men, exacerbating gender employment gaps. An empirical specification similar to Klaven, Landais and Leite-Mariante (2024) is run separately for men and women to measure the role of family responsibilities on widening gender employment gaps:[3]

$$\mathrm{Emp}_i^g = \alpha^g + \beta^g \mathrm{Child}_i + \delta^g \mathrm{EverMarried}_i + \gamma^g X_i^g + \epsilon_i^g \qquad (1)$$

Emp_i^g is a binary variable stating whether individual i of gender *g = women, men* is employed. Child_i is a dummy variable that denotes whether the individual i has a child under the age of 6. $\mathrm{EverMarried}_i$ is a dummy variable that states if the individual has ever been married (i.e currently married, union/cohabiting, widowed or divorced/separated). Finally, X_i^g is a vector of control variables that include the age of the individual, education status, residential status of the individual and whether the individual is native or foreign-born. The coefficients β^g and δ^g measure the impact of parenthood and marriage on employment by gender, g. We calculate the difference between estimated coefficients for men and women ($\beta^m - \beta^w$ and $\delta^m - \delta^w$) to measure the disproportionate negative impact of parenthood and marriage on women's employment. For example, a difference of 0.2 between the coefficient associated with parenthood, i.e. $\beta^m - \beta^w$ implies that women are 20 percentage points less likely to be employed compared to men during parenthood, hence increasing the gender employment gap. Finally, we calculate the (negative) impact of family responsibilities (on women) by summing the impact of having children and being married, which is ($\beta^m - \beta^w$) + ($\delta^m - \delta^w$).

The negative impact of family responsibilities on women's employment is estimated using the data from the ILO Harmonised Microdata collection, limiting the sample to individuals aged 25-54. Due to the cross-sectional nature of the data, the precise timing of marriage and childbirth is not observed, posing challenges in separately identifying both the impact of parenthood and marriage in equation 1. For instance, the estimate for the impact of marriage on women's

[2] See ILO 2019 for a complete description of the imputation methodology.

[3] The authors apply a pseudo-event study approach developed by Kleven (2023) by creating a pseudo-panel using matching techniques. However, to measure the impact of marriage and parenthood across all countries, where the precise timing of marriage is not available, the authors use a less granular approach by replacing event/time dummies with single dummies for marriage and having a child as we have done in this study.

employment can capture part of the impact of parenthood due to the anticipation of childcare needs in future and subsequent persistence of women disproportionately exiting the workforce to undertake childcare. By considering both the impact of marriage and parenthood jointly we avoid this issue. Our study exclusively focuses on the employment impact of family responsibilities (combining marriage and parenthood).

We obtain the contribution of family responsibilities to the gender employment gap by taking the share of women that are married and the share of women with children, multiplying these, respectively, with the estimated impact of marriage ($\delta^m - \delta^w$) and parenthood ($\beta^m - \beta^w$), and then summing these components. The gender employment gap in percentage points is defined as the (unconditional) difference in the employment-to-population ratio of men and women.

Informality, job tenure and gender

Experience has long been recognised as an important driver of wages (see the seminal work by Mincer (1958) or for a more recent example Jedwab et. al. (2023). One common approach to measuring experience is the use of a proxy: potential experience. Potential experience considers the age and schooling of an individual to approximate the years of actual experience. We want to study the returns to experience and how this differs for women and men and by formality status.

Instead of using the potential experience approach, we focus on tenure. Job tenure is defined as the number of years a person has been working in the same job. One potential limitation of the potential experience approach is that gaps in experience due to spells outside of employment cannot be captured and they might be highly relevant for earnings. This is particularly important when exploring differential returns to experience by gender and formality status, given the potential for different incidences of spells outside of employment. By adopting the tenure approach, we can exclude years outside of employment from job specific experience. It is worth highlighting that by taking this approach we are focusing on specific job skill accumulation – as someone with zero years of tenure in a job might have an extended experience elsewhere.

The source of the data for the tenure exercise is the ILO Harmonised Microdata collection. A subset of 20 countries (including 70 different survey observations) are identified as having the required key variables: wages, informality status and job tenure – together with some additional control variables. We focus the analysis on the non-agricultural sector, given that informal employment in agriculture is likely to present marked structural differences with respect to other sectors.

The analysis focuses on differences in tenure by gender and formality status, and its effect on wages, controlling for relevant factors. The objective is to see if tenure could be a sizeable factor in gender pay differences in developing countries (where informal employment is highly prevalent). Note that we do not establish causal effects. Differences in tenure and tenure returns are likely to be endogenous to many factors that we cannot account for. For instance, women working in the informal sector could be working in occupations that have smaller returns to experience. In that case, the ultimate driver of the gender pay gap would be occupational segregation. However, the results are interesting because tenure is one previously unexplored channel through which differences could materialise. Our findings follow.

The first finding concerns accumulation of tenure as a function of age (see Table TA1). We find that men and women in the formal sector acquire tenure at a similar rate (0.48 and 0.43 years per year of age, respectively). In contrast, in the informal sector, while both women and men acquire much less tenure than in the formal sector, women's tenure is especially impacted. Informally employed men acquire 0.27 tenure years per year of age, while informally employed women present the lowest rate, at 0.17. This points to larger job separation rates for informally employed workers, particularly for women.

▶ **Table TA1 – Tenure as a function of age, by gender and formality status**

	Dependent variable: Tenure			
	Women-formal	Women-informal	Men-formal	Men-informal
Independent variable: age	0.4813***	0.1722***	0.4325***	0.2710***
	(0.0238)	(0.0169)	(0.0198)	(0.0212)
Observations	310,650	175,114	436,613	307,035
R^2	0.40	0.23	0.35	0.28
Fixed Effects				
Survey/Time	✓	✓	✓	✓

Note: OLS regression results based on ILO Harmonised Microdata collection. For a given country, all survey rounds are used, but they are scaled so that each country has the same weight in the regression. Standard errors are clustered at the survey/time level and are indicated in parentheses in the row below the regression coefficients. Fixed effects at the survey-time level are included.

The second finding concerns the returns (in terms of wages) to that experience (see Table TA2). Consistent with other studies (ILO 2023), we find that women in informal employment experience lower relative wages compared to their counterparts in formal jobs than men in informal employment do relative to men in formal jobs. With respect to tenure we find, unsurprisingly, that tenure increases wages earned. However, there are marked gender differences. Whereas men who are either formally or informally employed experience similar returns to tenure, women experience sizeably different returns depending on whether they are working in formal or informal jobs.

▶ **Table TA2 – Returns to tenure, by gender and informality status**

	Dependent variable: log(wages)	
	Women	Men
	(2)	(3)
Informal	-0.8685***	-0.6397***
	(0.0318)	(0.0416)
Tenure	0.0206***	0.0148***
	(0.0019)	(0.0019)
Informal × Tenure	-0.0128***	0.0011
	(0.0025)	(0.0038)
Observations	485,764	743,648
R^2	0.95	0.95
Fixed Effects		
Survey/Time	✓	✓
Sector	✓	✓

Note: OLS regression results based on ILO Harmonised Microdata collection. For a given country, all survey rounds are used, but they are scaled so each country has the same weight in the regression. Standard errors are clustered at the survey/time level and are indicated in parentheses in the row below the regression coefficients. Fixed effects at the survey-time level and by economic sector are included.