Description of the wage projection methodology for the Atlanta Fed's CLIFF tools

This document describes the methodology used to predict the average annual earnings path for a person entering a specific occupation in a specific location, as displayed in the Atlanta Fed's Career Ladder Identifier and Financial Forecaster (CLIFF) tools. These projections are based on a variety of assumptions and are only meant to provide a benchmark for CLIFF tools users. A brief overview of the procedure is provided below, followed by more technical details for the interested user.

Overview of procedure

Wage profiles are generated in two steps. First, an entry-level wage is determined based on granular occupation and location-specific wage percentiles from the Bureau of Labor Statistics' Occupational Employment and Wage Statistics (OEWS).[1] In particular, we assume that wages start somewhere between the 10th and 25th percentiles of the local or state-specific occupational wage distribution. Second, wages are assumed to grow with experience from this starting level by applying returns to experience that are estimated using household survey data from the Census Bureau's American Community Survey (ACS) and standard parametric methods from the labor economics literature.[2] The returns to experience are typically allowed to vary by occupation and by state, except when there is insufficient data to allow for this flexibility (in which case returns to experience only vary by occupation). Annual earnings are obtained by assuming a full-time full-year schedule (40 hours per week for 52 weeks per year).

If there is a training period associated with the chosen occupation, predicted earnings are delayed until the training has been completed and workers are assumed to work part-time in a near-minimum wage job during the training period (specifically a cashier job in the chosen location assuming 20 hours per week for 52 weeks per year). Predicted wage profiles are also shifted upwards to comply with prevailing state minimum wages (both active minimum wages and future increases that have been announced).

Technical details

Let o denote the chosen occupation and c denote the chosen county. The first step in determining the hourly wage path for a person entering occupation o (6-digit SOC codes) in county c is to determine the starting wage of someone with 0 years of experience ($start\_wage_{oc}$). We assume that the starting wage falls somewhere between the 10th and 25th percentiles of the distribution of

[1] OEWS data is publicly available at https://www.bls.gov/oes/tables.htm. In the 2023 data, there are over 800 unique occupations and over 500 unique locations (metro or nonmetro areas), for a total of around 185,000 unique occupation-location combinations.

[2] ACS data is publicly available at https://usa.ipums.org/usa/index.shtml.

hourly wages among workers currently in occupation o in the metro or nonmetro area m containing county c ($p10_{om}$ and $p25_{om}$). These local wage percentiles come from the most of recent release of the OEWS.[3]

To decide whether $start\_wage_{oc}$ is equal to $p10_{om}$, $p25_{om}$, or falls somewhere in between, we leverage data from the ACS.[4] More specifically, we compute the 10th and 25th percentiles of the national hourly wage distribution for occupation o ($p10_o$ and $p25_o$). We then compute the median hourly wage among workers in occupation o who have 0 or 1 year of potential experience ($start\_wage_o$), where potential experience is based on age and years of education as in Lagakos et al. (2018).[5] If $start\_wage_o$ is below $p10_o$, we set $start\_wage_{oc} = p10_{om}$. Analogously, if $start\_wage_o$ exceeds $p25_o$, we set $start\_wage_{oc} = p25_{om}$. If $start\_wage_o$ is strictly between $p10_o$ and $p25_o$, then we set $start\_wage_{oc}$ such that its distance to $p10_{om}$ and $p25_{om}$ is proportional to the distance between $start\_wage_o$ and $p10_o$ and $p25_o$.[6]

The second step is to determine how wages grow with experience. We assume that the growth path from $start\_wage_{oc}$ follows occupation and state-specific returns to experience estimated using the same ACS sample used in the first step. Specifically, we estimate slightly modified versions of the classic Mincer wage equation, which regresses log wages on years of education and a quadratic in potential experience. The first departure from the standard setup is that we estimate these regressions separately by occupation since we are interested in predicting occupation-specific returns to experience. The second departure is that we allow returns to experience to vary by state by including additional interaction terms in the regressions. The third departure is that we additionally include a quadratic term in years of education and cubic and quartic terms in potential experience to better approximate nonlinearities in the data (Lemieux,

[3] Note that for some occupations that are typically paid on an annual basis, the BLS only reports annual earnings percentiles. In those cases, we impute missing hourly wage percentiles by dividing annual earnings percentiles by 2080 hours.

[4] We pool data from the 2019 to 2022 waves of the ACS. We exclude individuals younger than 18, self-employed workers, unpaid family workers, individuals who are enrolled in school at the time of the survey, and workers who usually work fewer than 35 hours a week or worked fewer than 26 weeks in the previous year. We further restrict the sample to individuals with 0 to 40 years of potential experience. Hourly wages are defined as annual wage income last year divided by the product of "usual" hours worked per week and number of weeks worked last year. Wages are deflated using the Bureau of Economic Analysis' Personal Consumption Expenditures (PCE) price index (https://fred.stlouisfed.org/series/PCEPI), and censored below at the federal minimum wage and above at 200 dollars per hour (2023 dollars).

[5] To be more specific, potential experience is defined as age minus 18 for high school dropouts and age minus years of education minus 6 for everyone else. Note that we do not actually observe years of education and must impute it based on respondents' highest degree obtained. We assign the number of years typically required to complete various degrees (e.g., an Associate's degree is assumed to take 2 years, a Bachelor's degree is assumed to take 4 years, etc.).

[6] If the local 10th and 25th percentiles deviate too strongly from their analogs at the state level in the OEWS data, we use the state-specific percentiles to determine $start\_wage_{oc}$. The exact condition we impose is that the ratio of the local to the state percentiles must be within 0.8 and 1.2 (failing that, the local percentiles may reflect idiosyncratic differences in the characteristics of workers rather than cost-of-living differences or differences in the demand for specific skills), unless the local percentiles are based on at least 1000 workers or 10 percent of all state employees in that occupation. In addition, if there are fewer than 10 workers with 0 or 1 year of potential experience in a specific occupation (6-digit SOC codes), the adjustment is done at the occupation group level (4-digit SOC codes).

2006). Formally, let i denote individuals, o denote detailed occupations (6-digit SOC codes), and s denote states. The baseline set of regressions take the following form:

$$\log(wage_{ios}) = (\theta_o + \theta_s)\ \mathrm{educ}_i + (\mu_o + \mu_s)\ \mathrm{educ}_i^2 + (\alpha_o + \alpha_s)\ \exp_i + (\beta_o + \beta_s)\ \exp_i^2 + (\gamma_o + \gamma_s)\ \exp_i^3 + (\delta_o + \delta_s)\ \exp_i^4 + \Gamma\ X_i + \varepsilon_{ios} \quad (1)$$

where X denotes fixed effects for basic demographic characteristics (sex, broad race categories, native-born status). These regressions are run separately by broad occupation groups (2-digit SOC codes). As a result, the state-specific terms (and demographic controls) are implicitly restricted to be common across all occupations within a broad occupation group. Note that prior to estimating these regressions, we drop occupations with fewer than 500 observations and states with fewer than 500 observations within the relevant 2-digit SOC code. The predicted return to e years of experience relative to no experience (in percentage terms) in occupation o in state s is then defined as follows:

$$return_{os}(e) = (\hat{\alpha}_o + \hat{\alpha}_s)\ e + (\hat{\beta}_o + \hat{\beta}_s)\ e^2 + (\hat{\gamma}_o + \hat{\gamma}_s)\ e^3 + (\hat{\delta}_o + \hat{\delta}_s)\ e^4 \quad (2)$$

Predicted wages for occupation o in county c in state s at experience level e is then defined as:

$$predicted\_wage_{ocs}(e) = start\_wage_{oc} \times \{1 + return_{os}(e)\} \quad (3)$$

Two alternative sets of returns to experience are estimated at the 4-digit SOC level, one including the state-specific interaction terms (dropping states with fewer than 500 occupations within the relevant 2-digit SOC code) and another excluding them. This serves the purpose of providing returns to experience for all possible occupation-locations, since only around 500 6-digit SOC codes are identifiable in the ACS (and not all of those occupations have at least 500 observations). Returns to experience for broader occupation groups likely provide a reasonable approximation to the returns to experience for more granular occupations.

The final step in the procedure is ensuring that predicted wages are consistent with prevailing state minimum wages, including active minimum wages and future increases that have been announced.[7] This is done using the following procedure. First, if the starting wage in year t is below the previous state minimum wage, the starting wage is raised to the previous state minimum wage. Second, if the state minimum wage went up between year t and year $t-1$, we identify the set of starting wages that are likely to be "affected" by this minimum wage increase, which we assume includes all wages that are below the new state minimum wage in year t and wages that exceed the new state minimum wage by up to 50% of the state minimum wage increase (CBO, 2019). Following Ilin and Terry (2022), the starting wage is then raised by the state minimum wage increase multiplied by a factor equal to the distance between the current starting wage and the upper limit of affected wages divided by the distance between this upper limit and the previous state minimum wage. As a result, starting wages that were initially equal to the previous state minimum wage are raised by the state minimum wage increase, while

[7] Information on current and future state minimum wages comes from the National Conference of State Legislatures (https://www.ncsl.org/labor-and-employment/state-minimum-wages). In Florida, new state minimum wages are scheduled to go into effect on September 30 of 2024, 2025 and 2026. Our projections assume those minimum wages apply to 2025, 2026 and 2027 respectively.

starting wages that were initially higher than the previous state minimum wage are raised by less than the minimum wage increase depending on how far they are from the upper limit of affected wages (the closer they are to that limit, the smaller the increase). Predicted wages in years $t+1$ onwards are then re-calculated using equation (3), plugging in the updated starting wage.

Increases in the state minimum wage after year t are handled in a similar way. While predicted wages are never below the previous state minimum wage by construction, the size of the increase is calculated using the same procedure as above. This increase is applied to all future predicted wages, but returns to experience are not re-applied to these higher predicted wages for simplicity (i.e., we apply a level shift only).

Annual earnings are obtained by assuming a full-time full-year schedule (40 hours per week for 52 weeks per year). If there is a training period associated with the chosen occupation, predicted wages are delayed until the training has been completed and individuals are assumed to work part-time in a near-minimum wage job during the training period (specifically a cashier job in the chosen location assuming a 20-hour work week for 52 weeks).

References

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