Estimating Life Cycle Occupation/Area Specific Wages

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Goals

- CLIFF Tool users select the **career** they want to pursue and their geographic **area**
- Users need to know how their **wages progress** as they gain experience
- Paths of wages differ by:
  1. **Occupation** - each occupation has differing amounts of wage growth potential
  2. **Area** - difference in living costs, regulations and supply/demand fundamentals

Current Approach

- Currently, we use the **Occupation and Employment Statistics (OES) by BLS** to project wages:

  1. Individuals start at the 25th percentile of wages (**proxy for the entry wage**) for a specific area/occupation
  2. Then progress to the 75th percentile of wages **over the period of 17 years** assuming same annual percentage increase

$$g_w = \left(\frac{wage_{ol}^{q75}}{wage_{ol}^{q25}}\right)^{\frac{1}{17}} - 1$$

Disadvantages: this results in

- **convex** wages in years of experience
- same wage growth pattern across occupation or area

Ideal Dataset

Ideal dataset for the life cycle wage growth projection would:

1. Follow individuals over their lifetime
2. Have detailed and timely information on education, occupations, area and wages
3. Have a large enough sample size to get precise estimates for each occupation and area

Data Sources Trade-offs

Data Source	Advantages	Disadvantages
Monthly Current Population Survey (CPS)	• Individual-specific estimates of wages • Information on education and years of experience	• Small sample size – not enough to get area-specific estimates for each occupation • Occupation coding changes over time
Occupation and Employment Statistics (OES)	• Detailed geographic and occupation specific data • Information on typical education level for each occupation • Current workforce system is already familiar with occupations coding	• No individual-level data • Only limited points in the wage distribution (quintiles) • Missing typical amount of experience associated with each point in the wage distribution
American Community Survey	• Detailed individual-level	• Not a panel • Not timely • Occupation coding changes over time

New Methodology: Overview

- **Step I:** Using CPS we estimate the profile of wage levels by years of experience and education level
  - Within education levels, **how many years on average** does it take individuals to achieve 10th, 25th, 50th, 75th, and 90th percentile of wages.

- **Step II:** We then match these obtained education specific estimates of years of experience for each wage level percentile to the OES data by typical entry-level education of job.

Mincer Equation

- Labor economists use **Mincer earnings function** to estimate return to schooling and years of experience

$$\ln(w)_i = \gamma_0 + \gamma_1 YrsofEdu_i + \gamma_2 YrsofExp_i + \gamma_3 YrsofExp_i^2 + \epsilon_i$$

1. Wages are concave in years of experience
2. Slope of years of experience is the same for each education level
3. The squared term allows for wage levels to decline with years of experience

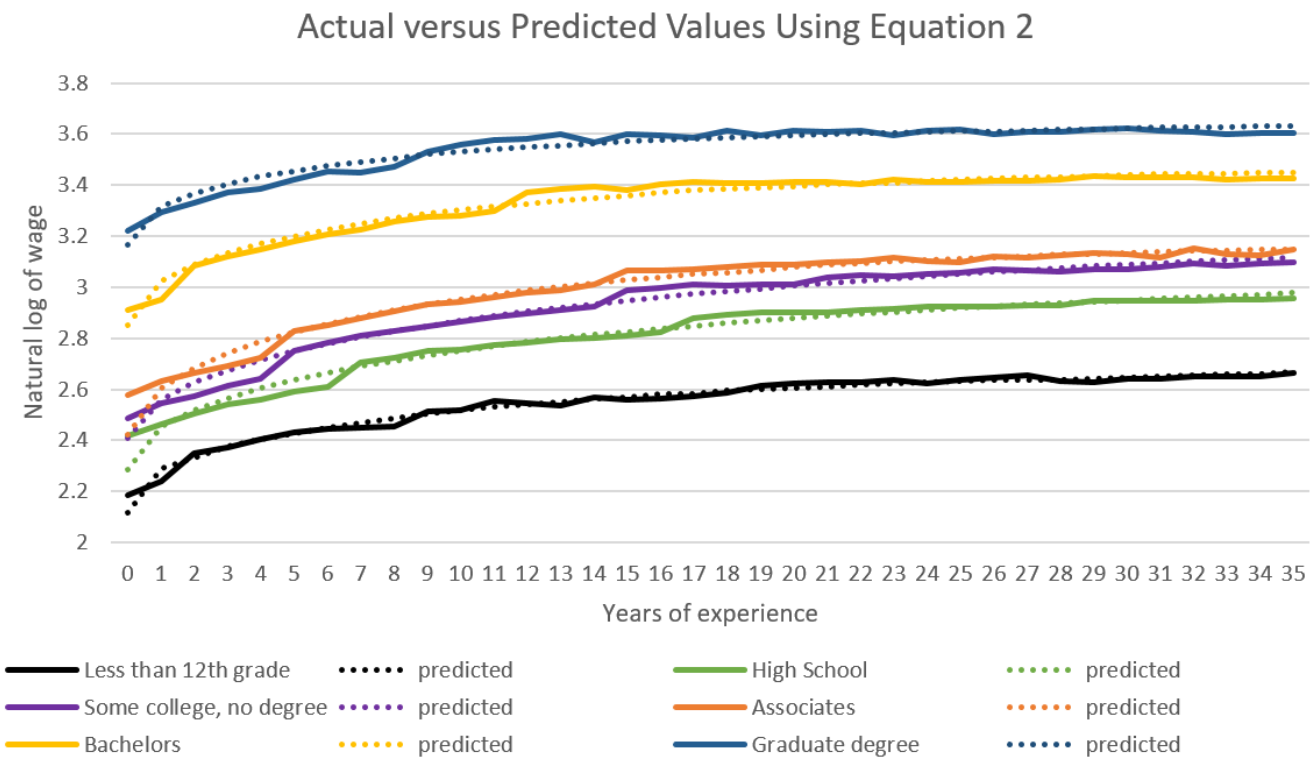
Education Matters

2 and 3 are important restrictions

1. Profile of lifetime wages differ by the education level
   - See **Lagakos et al. (2018)**
2. Wages do not decline with the years of experience **at the individual level** Wage Growth Tracker

Step I: Life cycle Wages by Education Groups

$$\ln(w_{iE}) = \gamma_{0E} + \gamma_2 YrsofExp_{iE} + \gamma_3 YrsofExp_{iE}^{\frac{1}{2}} + \epsilon_{iE}$$



Source: 1994-2019 Current Population Survey, Author's calculations

Step I: Life cycle Wages by Education Groups

Within education levels, **how many years on average** does it take individuals to achieve 10th, 25th, 50th, 75th, and 90th percentile of wages.

Table 1: Years of Experience and Corresponding LN Wage Levels at Each Percentile.

	P10	P25	P50	P75	P90
All Levels					
Less than high school	3yrs	7yrs	18yrs	35yrs	35yrs
High school	3yrs	8yrs	16yrs	33yrs	35yrs
Some college, no degree	2yrs	7yrs	15yrs	28yrs	35yrs
Associates	4yrs	8yrs	16yrs	35yrs	35yrs
Bachelors	1yr	5yrs	12yrs	35yrs	35yrs
Grad school	1yr	4yrs	13yrs	34yrs	34yrs

Source: 1994-2019 Current Population Survey, Author's calculations

Step II: Matching to OES

- Attach years of experience to the wage distribution of each occupation in the OES matching by the typical entry-level education.
- Exclude the 90th percentile
- For each occupation and location we have **two variables** and **four data points**:
  - wage levels at 10th, 25th, 50th and 75th percentiles
  - years of experience at 10th, 25th, 50th and 75th percentiles

Step II: Matching to OES

$$\ln(w_o) = AREA + \beta_1(AREA \times YrsofExp_o) + \beta_2(AREA \times YrsofExp_o^{\frac{1}{2}}) + \epsilon_o$$

- O - occupation
- Fixed effect for each geographic area and an interaction of geographic area with years of experience
- Allows for different progressions of wage growth in different geographic areas

Example: Registered Nurses (RN)

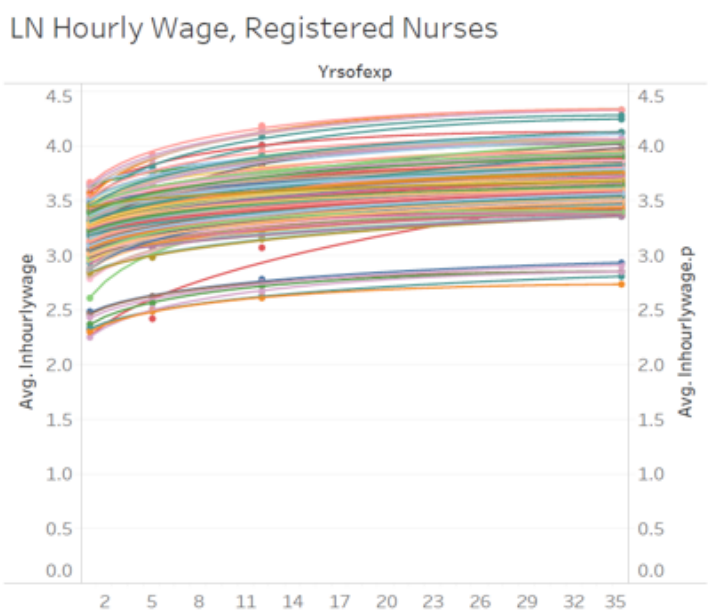
- From OES typical entry-level education for RN is Bachelors degree
- From CPS we know that for people with Bachelors degree:

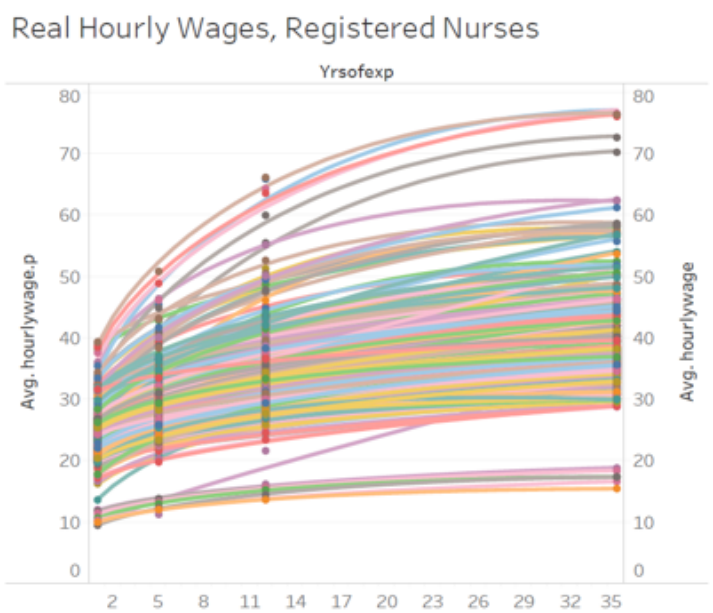
	P10	P25	P50	P75	P90
Bachelors	1yr	5yrs	12yrs	35yrs	35yrs

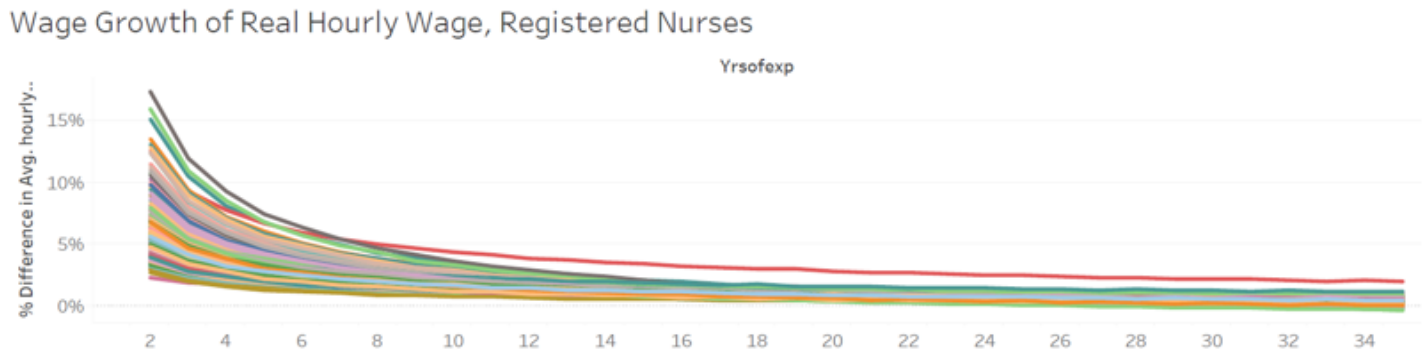
We have information on RN wages in 395 locations:

$$\ln(w_{rn}) = AREA + \beta_1(AREA \times YrsofExp_{rn}) + \beta_2(AREA \times YrsofExp_{rn}^{\frac{1}{2}}) + \epsilon_{rn}$$

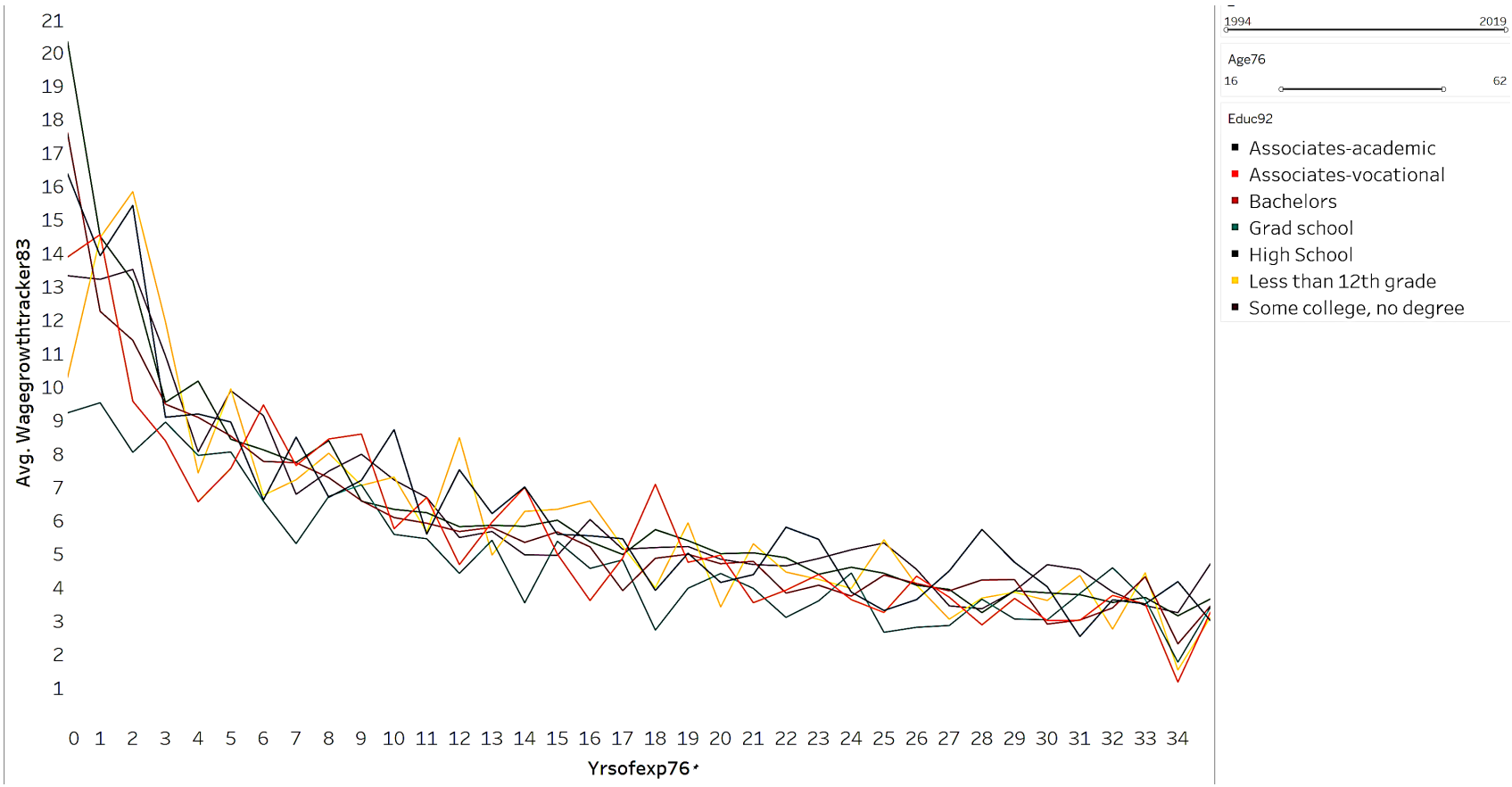
Example: Registered Nurses (RN)







Appendix: Wage Growth Tracker



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